Understanding Customer Behaviour in Fintech

MSc Research Project

Programme Name : MSc In Fintech

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MSc Project Submission Sheet

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Abstract

The research aimed to investigate the key factors (accessibility and trust) influencing consumer behaviour in the Indian fintech sector and predict customer satisfaction in the Indian Fintech services. Machine Learning algorithms and Neural Network models were employed for predicting the customer satisfaction in Fintech services. Among Random Forest Classifiers, ANN, DNN, RNN, and MLP models, RNN with a hyperparameter tuning approach achieved the highest accuracy of 70%. The comparative analysis between the findings generated by the analysis and the findings from the previously existing literature helped to understand the uniqueness as well as the effectiveness of this entire research study related to FinTech and Customer behaviour. Findings of this revealed that geographical location (such as residence in urban or rural areas) had a positive effect on the attitude and intention of customers. Machine learning and deep learning models were found to be highly effective for the prediction of customer behaviour in the fintech industry. In this context, from the developed ML models, random forest with hyperparameter optimization emerged as the best-fitted model due to its highest accuracy.

1 Introduction

1.1 Background of the Study

The customer purchasing behaviour has seen a great improvement because customers have shown reliance on and trust in Fintech companies because of the presence of their advanced security mechanisms. In terms of capital funding and investment, the Indian fintech market gained $270 million of funding in 2016 which has helped in attracting potential consumers (Deloitte, 2017).

On the other hand, fintech companies in India differ from traditional financial organisations in that they operate solely online mode and they have a more consumer centric and agile approach (Migozzi, Urban and Wójcik, 2023). For example, companies like PhonePe, Paytm, CRED and Razorpay use different technologies for streamlining processes and to offer personalised services for potential consumers in the digital age. The following figure 1 states about different benefits of using fintech services. As per the report of Deloitte (2017), that total 77% of Indian consumers prefer fintech services for better return on Investment process. This in turn has displayed a greater customer adaptation and positive customer engagement in Indian Fintech banks even at the time of the pandemic which is continuing.

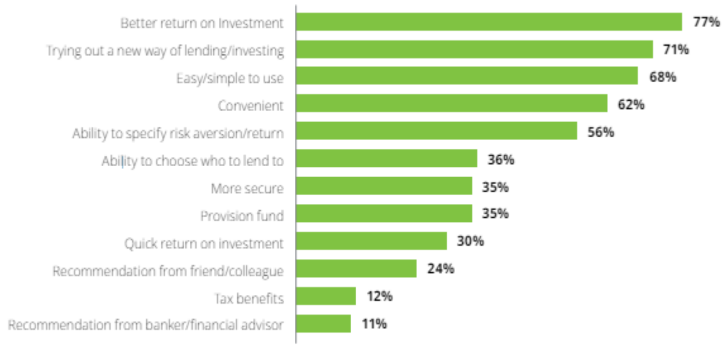


Figure 1: Different benefits of using fintech services in India

(Source: Deloitte, 2017)

The Fintech adoption rate in India has shown a rise in the customer engagement level that in turn foretells positive customer behaviour. Based on the report of PIB (2021), India has the adopted rate of Fintech service that stands at to be 87% while UPI banking interface has recorded the highest banking transactions of over 3.6 Bn transactions. The high rate of adoption mainly accounts to the digital payments and transactions via UPI merchants, especially in the pandemic and the post-pandemic period. The adoption rate of Fintech services in India ranks third against the global average of 64% in FY 2021 (RBSA Advisors, 2021).

1.2 Problem Statement

The Indian Fintech sector though having a sharp rise in the frequency of users in recent times yet experiencing three major challenges that are compatibility, security and appropriate regulatory uncertainty. Based on the report of Statista (2023), IT compatibility and IT security accounts for 61% and 50% of the disrupting functioning of the Indian Fintech sector. The drawbacks the companies are facing with the Indian FinTech can be accounted for by the lack of technological knowledge and expertise of employees in the field of digital banks.

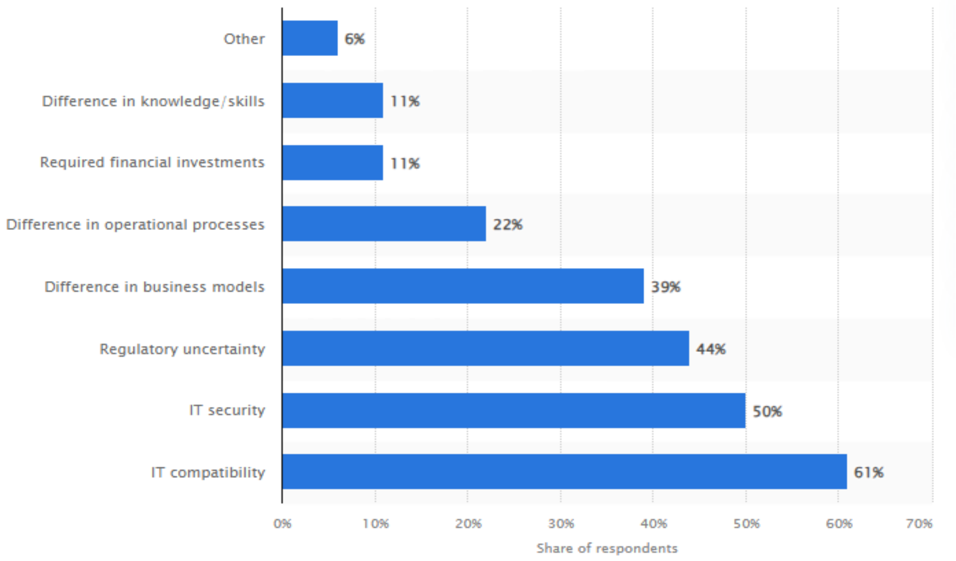


Figure 3: Challenges faced by companies when working with Indian Fintech

(Source: Statista, 2023)

1.3 Research Rationale

The previously done research works lack clarity in providing insights regarding the different strategies needed to cut the low investment issue in the Indian Fintech sector regarding the Russian-Ukraine War. The current research gives the focus on the aspects of customer behaviour under the influence of Fintech applications in Indian companies. In addition to this, the current study has the potential to give insights into the exact reason for the sharp fall in the Indian Fintech investment along with the customer perception of the fall from the government perspective. The main motto of conducting the research study is to have an in-depth idea of the impact of Fintech services and features in India by attaching the response of the Indian people thereby impacting the overall Fintech sector

1.4 Aim and bjectives

1.4.1 Aim

The aim of the research is to investigate the key factors (accessibility and trust) influencing consumer behaviour in the Indian fintech sector.

1.4.2 Objectives

- To evaluate the key factors such as accessibility and trust influencing customer behaviour in the Indian fintech sector.

- To investigate the influence of key factors in terms of adopting Fintech services over traditional banking.
- To identify the challenges faced by different Indian companies in the implementation of Fintech services and customer perception to their business mechanisms.
- To understand the role that Machine Learning plays for the India-based companies to understand the factors which influence and improve the satisfaction level of customers using fintech.

1.5 Research Questions

- What are the key factors such as accessibility and trust influencing customer behaviour in the Indian fintech sector?
- What are the impacts of key factors in terms of adopting Fintech services over traditional banking?
- What are the problems faced by Indian firms for the successful implementation of Fintech services and regulating customer behaviour?
- What roles does Machine Learning play for India-based companies to understand the factors influencing and improving the satisfaction level of customers using fintech?

1.6 Methodology Outline

The research study is going to take a primary quantitative data collection approach for a detailed understanding of customer behaviour in the Indian fintech sector. The study is going to conduct an online survey of 100 customers availing the Fintech services and products in India consisting of 20 questions via Google form. Moreover, the application of positivism philosophy and deductive research approach can be seen along with descriptive research design. Machine Learning analysis is going to place for analysing the quantitative nature of the research data with conducting graphical and machine learning models to understand the factors which helps Indian customers to be satisfied by using fintech.

1.7 Variables Listing

Dependent Variable	Independent Variable
● Fintech Service ○ Investment decision ○ DMT (Domestic Money Transfer) ○ Utility Bill Payments	● Customer Behaviour ○ Consumer experience ○ Customer purchase rate ○ Customer satisfaction

1.8 Research Hypothesis

H0: The Indian Fintech services do not have any kind of significance in the customer behaviour perspective

H1: The Indian Fintech services tend to have a positive impact in the light of customer behaviour management

1.9 Dissertation Structure

Chapters	Description
Introduction	The chapter throws light on the background overview of the study, followed by the problem statement, aims and objectives and methodological overview on the context of Fintech and consumer behaviour.
Literature Survey	The step-by-step understanding of the research topic is displayed by the formulation of distinctive concepts followed by a literature gap, conceptual framework and summary
Research Methodology	The application of primary quantitative research methods is discussed with proper justification in this section.
Design and Implementation Specifications	This chapter throws light on the identification of the output generated from the collected data and also description of the tools for analysing the output regarding the fintech and consumer behaviour.
Evaluation	A comprehensive analysis of the results generated along with the interpretation of findings based on the result analysis and discussion.
Conclusions and Discussion	A concrete discussion on the key finding of the research along with outlining limitations, recommendations and future scope regarding fintech and consumer behaviour.

Table 2: Outline of the study

2 Related Work

2.1 Accessibility of customer behaviour

According to Neves et al. (2023), mobile banking with digital wallets enables users to perform transactions from anywhere at any time, enhancing participation and convenience in the financial system. Additionally, Udeh et al. (2024) have stated the integration of artificial intelligence in customer service such as chatbots has eventually streamlined user interactions which reduces the complexity of accessing financial support and advice. According to the view of Mhlanga (2024), the utilisation of big data analytics allows Fintech companies to adapt services to individual requirements, enhancing user satisfaction and experience.

2.2 Trust Impacting Customer Behaviour

Trust is one of the most critical factors which influences customer behaviour in the Fintech industry. According to Meyliana, Fernando and Surjandy (2019), the perceived trustworthiness of Fintech services can significantly influence customer adoption along with continued usage. Wenxiang et al. (2023) have emphasised that the trust of customers in Fintech platforms is mainly accomplished on security, privacy, and the perceived easiness of use of the service.

Customers who feel confident that their financial and personal information is secure, are more likely to adapt as well as use these Fintech services. .

2.2.3 Machine Learning in Fintech Services

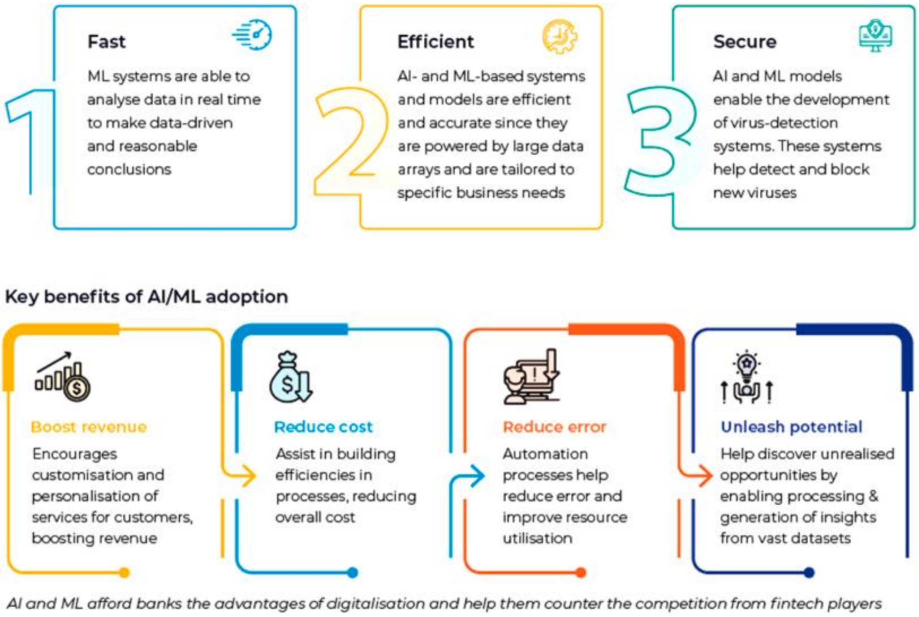


Figure 4: Impact of Artificial Intelligence and Machine Learning in Fintech Services

(Source: Polireddi, 2024)

Machine Learning (ML) algorithms are transforming Fintech services by improving effectiveness, accuracy, and personalisation in financial services. Polireddi (2024) has stated that Artificial Intelligence and ML can easily reduce business risks and enhance operational effectiveness with revolutionary techniques **[*Refer to Figure 4*].** ML approaches are comparatively fast, sage, and effective in analysing data and managing risks to offer customer services in Fintech. Consequently, Olaseni and Familoni (2024) have continuously observed transactions for unusual patterns by using ML systems to identify and flag potentially fraudulent activities in real time which reduces financial losses. Moreover, Huseynov (2023) have emphasised that ML-driven chatbots as well as virtual assistants enhance customer service by offering instant, customised responses to user inquiries, improving the overall customer experience.

2.3 Impact of key factors in adopting Fintech Services

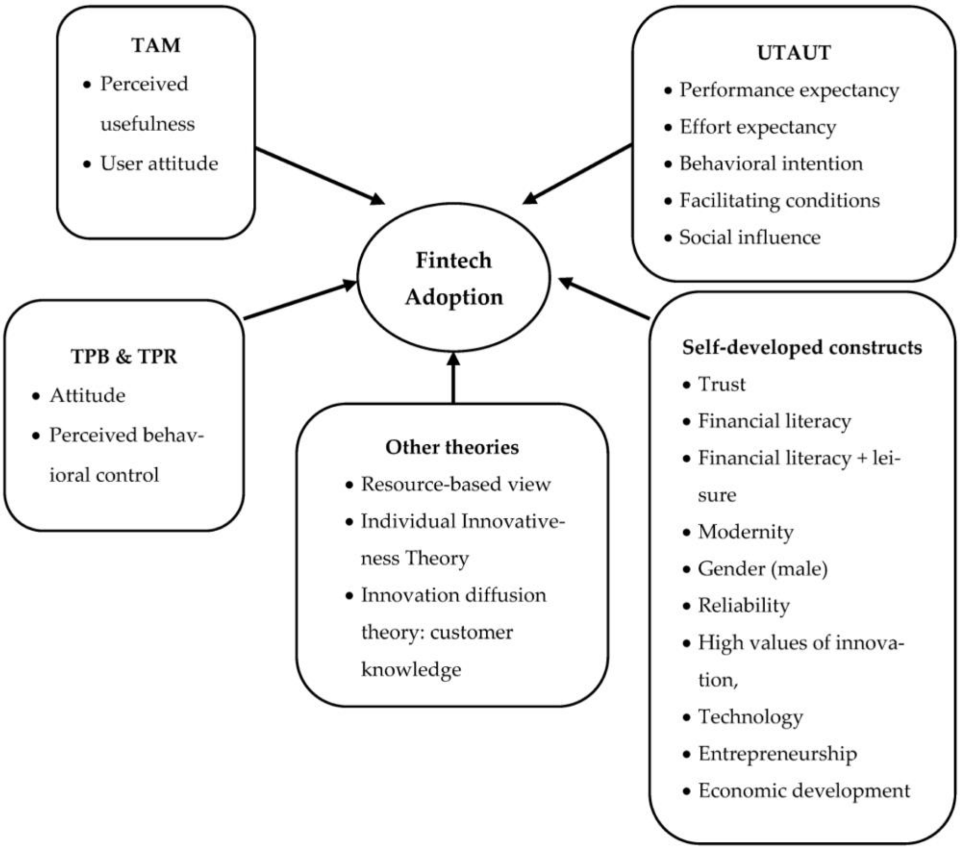


Figure 5: Factors Impacting Fintech Adoption

(Source: Firmansyah et al., 2022)

Figure 5 summarises the factors of Fintech adoption in business as well as management literature which involves five theoretical foundations from which the factors ("Technology Acceptance Model" (TAM), "Unified Theory of Acceptance and Use of Technology" (UTAUT), "Theory of Planned Behaviour" & "Theory of Perceived Risk" (TPB & TPR), and other factors) are derived. This comprehensive overview of the factors impacting Fintech adoption and drawing theoretical foundations helps to understand the multifaceted drivers as well as barriers to Fintech acceptance.

2.4 Comparison Between Traditional Banking and Fintech Services

Rasiwala and Kohli (2021) have emphasised that Fintech services excel in convenience and accessibility and offer 24/7 availability through online platforms and mobile applications, whereas traditional banks often need physical branch visits for services. In addition to that, Barbu et al. (2021) have stated that the user-friendly interfaces of Fintech along with the streamlined procedures enable customers to conduct hassle-free transactions, manage accounts, and access financial advice from anywhere, improving the overall customer experience.

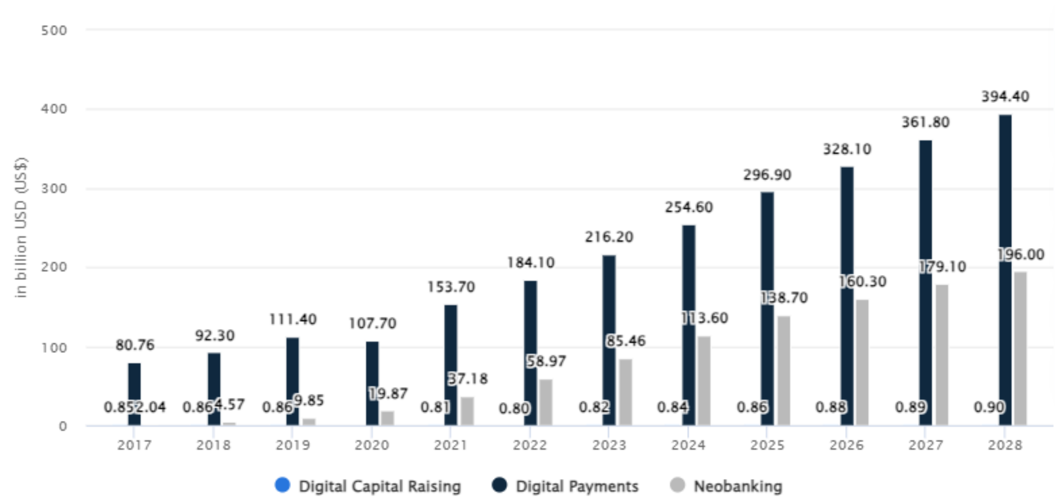


Figure 6: Adoption of Fintech in India over the years

(Source: Statista Market Insights, 2024)

The Digital Investment market would reach a US$1,294.00m AUM ("Assets Under Management") in 2024 with an average AUM per user of US$9.38 **[*Refer to Figure 6*]**. Digital Assets revenue would also grow by 11.81% in 2025 along with Digital payment users would reach 837.20m by 2028 (Statista Market Insights, 2024). These insights reflect the growth potential along with market diversity in Fintech which guides the strategic focus for targeted service offerings.

2.5 Theoretical Underpinning

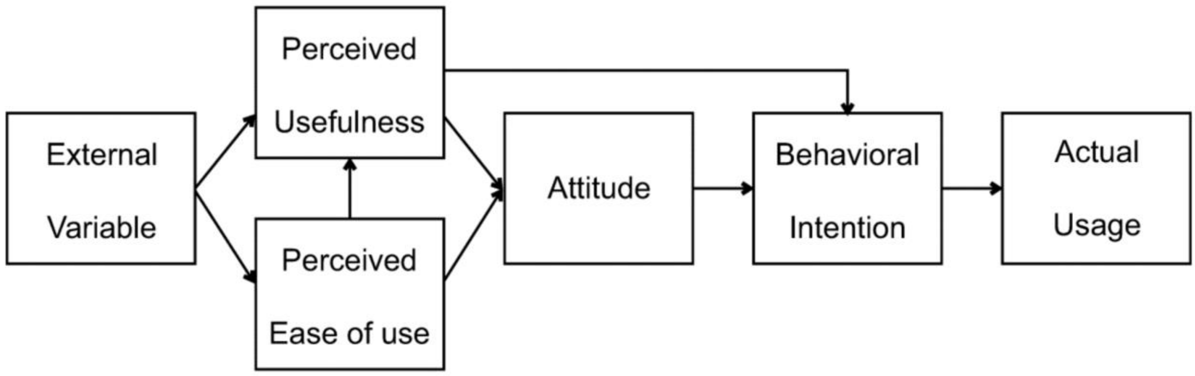


Figure 7: Framework of Technology Acceptance Model (TAM)

(Source: Park and Park, 2020)

The **Technology Acceptance Model (TAM)** offers a robust theoretical framework, especially for understanding the impact of advanced financial technologies on users to make it highly relevant for analysing fintech adoption. TAM was developed by Davis in 1989 in which advances that perceived ease of use as well as perceived usefulness are the primary determinants of technology acceptance (Davis, 1989; Surendran, 2012). In this context of fintech services, TAM mainly helps to evaluate the reason behind certain users being more inclined to adopt digital financial solutions compared to others. Thus, the specific focus of **TAM on Perceived usefulness and perceived ease of usage** helps fintech services to design user-friendly interfaces and signify the advantages of their services which are quite essential for achieving user acceptance.

2.6 Research Gap

Apart from the significant advancements in fintech services, there are also some critical gaps in understanding the intricate dynamics of fintech adoption with its influence on customer satisfaction. Existing literature mainly focuses on broad factors impacting fintech adoption such as technological infrastructure, socio-economic conditions, and regulatory environments (Demir et al., 2020). However, there is a limitation in research related to the interplay between these factors in diverse socio-economic settings, especially in emerging finance markets. In addition to that, the benefits of machine learning algorithms in improving fintech services are well-documented and discussed by endeavours (Brenner and Meyll, 2020). However, the significant mechanisms through which ML drives customer satisfaction require further explorations. There is also a requirement for more empirical studies examining the long-term influence of fintech innovations on financial inclusion, specifically among underserved populations. Consequently, these challenges of regulatory compliance and cybersecurity in fintech remain underexplored, especially in the field of their influence on customer trust and service reliability. Addressing these gaps through comprehensive research can offer deeper insights into optimising fintech services and catering to a more inclusive financial ecosystem.

2.7 Conceptual Framework

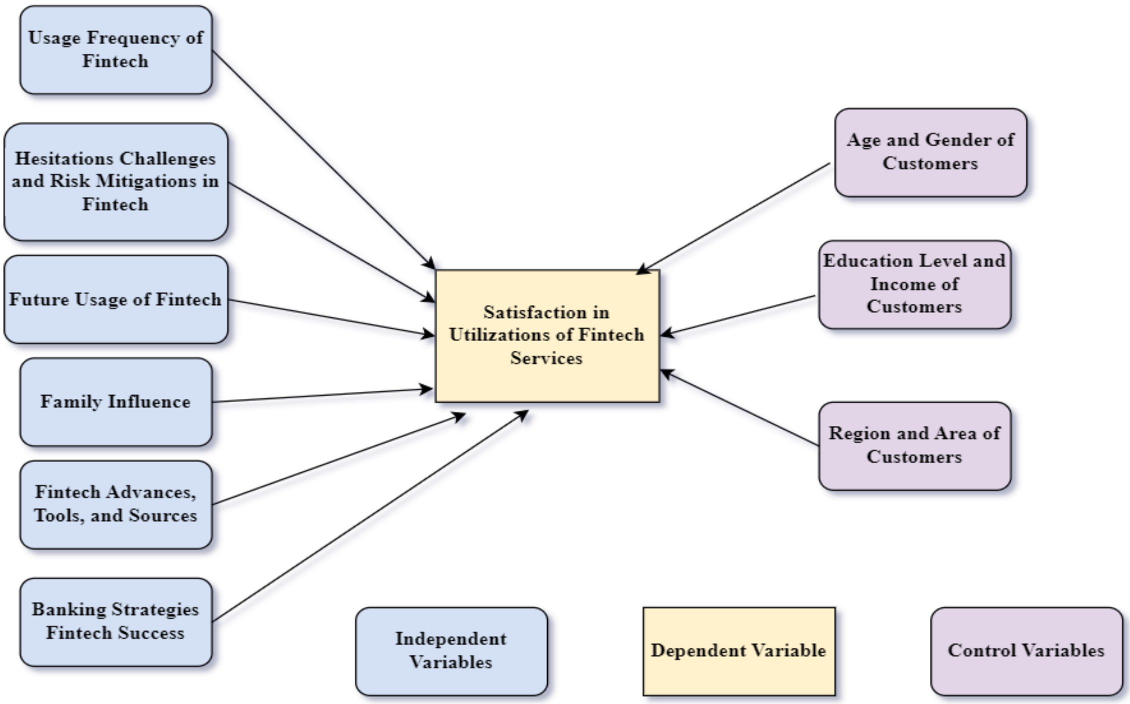


Figure 8: Conceptual Framework

3 Research Methodology

3.1 Research approach

The deductive approach includes formulating hypotheses based on theory followed by choosing the research method that can allow for a hypothesis to be tested (Casula, Rangarajan and Shields, 2020). Empirical research enables the formulation of hypotheses and testing through experiments, which is important when examining new factors affecting consumers in a constantly growing area such as fintech **(*Refer to Figure 9*)**. Specifically for the Indian fintech sector which shows a very high growth rate and shifting consumer behaviour, a deductive approach helps in examining the validity of existing theory regarding technology acceptance and trust in financial services. Therefore, this approach can enable the confirmation or dismissal of the hypothesis and assumption made about consumers in the Indian fintech market.

3.2 Research Ethics

Participants were given clear details of the study objectives and all the participants were given the right to withdraw at any point of time during the research. Consent was asked from all the participants, adhering to the General Data Protection Regulation of the UK and it was ensured that no personal information was being used without primary consent (Government of UK, 2018). Personal data was anonymised to reduce the risk of data breaches and thus ethical requirements by the University related to primary research execution.

3.3 Data Collection

3.3.1 Description of the data

Primary data collection has been undertaken for this research to collect current and specific information related to consumer behaviour and perception in the Indian Fintech market. Secondary data collection has not been considered since it would not provide any real time insights on the consumer behaviour and in contrast, for identifying consumer perceptions, it is essential to connect with them. As a result, a primary survey was created using Google Forms, consisting of 20 close-ended questions covering demographics of the participants, their usage patterns, perceptions, and attitudes towards fintech services. The survey was circulated to 100 individuals, who were selected using non-probabilistic convenience sampling, targeting only Indian consumers with experience in fintech solutions.

Dependent variable	
Fintech service	It evaluates the extent of adoption or the usage level that any financial technology service (such as investment decisions, utility bill payment) receives from customers (Sharma et al., 2024).
Independent variables	
Consumer experience	It refers to the overall user interaction and satisfaction with the fintech service (Al-Emadi, Kassim and Razzaque, 2021).
Consumer purchase rate	This factor reflects how often consumers are buying or making transactions using the fintech service (Bajunaied, Hussin and Kamarudin, 2023).
Consumer satisfaction	This involves evaluating the extent to which consumers are delighted and fulfilled with fintech services (Vijai et al., 2023).

Table 3: Description of variables

3.3.2 Dataset Limitations

The most apparent threat inherent in the dataset is the presence of social desirability bias, as the participants might provide a response that is more appropriate in the perception of the researcher or society, rather than presenting the actual truth. Hence, the method of convenience sampling that was used in this research may lead to a weakness in a generalisation of the results of the research study to the rest of the population of India. Also, the responses to the survey may not be equally distributed geographically across the country, instead, there is a possibility of having several regions over-represented in the study.

3.4 Time Horizon

The cross-sectional framework has been applied, which obtains information about variables at the specific period. This can be proper for the analysis of the present trends in this dynamically growing field of Fintech and its usage. This design is suitable for the accumulation of large data samples and, therefore, the revelation of patterns and links between variables at a given time (Wang and Cheng, 2020).

3.5 Machine Learning Models

Machine learning models capture the complexities and interactions between variables that may not be easily identified by standard statistical techniques such as SPSS, thus giving an additional layer of understanding to the main drivers of adoption and usage of the fintech services. 5 ML classifiers such as Random Forest, Artificial Neural Network (ANN), Deep Neural Network (DNN), Recurrent Neural Network (RNN) and Multi-layer Perceptron have been selected for the statistical analysis of the data which have been explained below in Google Colab:

ML models (With and Without Hyper parameter)	Overview	Justification for selection
Random Forest Classifier	It is an ensemble learning method where an ensemble is built from decision trees and then combined to have a better and more stable projection (Castiello and Tonini, 2021).	Suitable for dealing with data with a higher number of variables and interactions between them.
Artificial Neural Network Classifier	This model seeks to assign an observation to a discrete class based on the inputs (Jena and Majhi, 2018).	Suitable for modelling the relationships between variables effectively and is suitable when the classification of consumer behaviour forecasting is needed.
Deep Neural Network Classifier	It is a unique artificial neuron system capable of classification and generalisation (Sarker, 2021).	Applicable in the analysis of data of consumers and their activities, useful for identifying factors influencing the usage patterns of fintech.
Recurrent Neural Network Classifier	This is a type of neural network in which the output from the previous phase is given as input into the next stage (Tang et al., 2022).	Allows for capturing temporal dependencies in the consumer behaviour.
Multi-layer Perceptron Classifier	This is an artificial neural network made up of numerous layers of neurons (Srinivasa and Thilagam, 2022).	Appropriate for classification problems and capable of modelling in variable interactions.

Table 4: Overview of the selected ML models

4 Design Specification and Implementation

4.2 Design specification

4.2.1 Methodological architecture

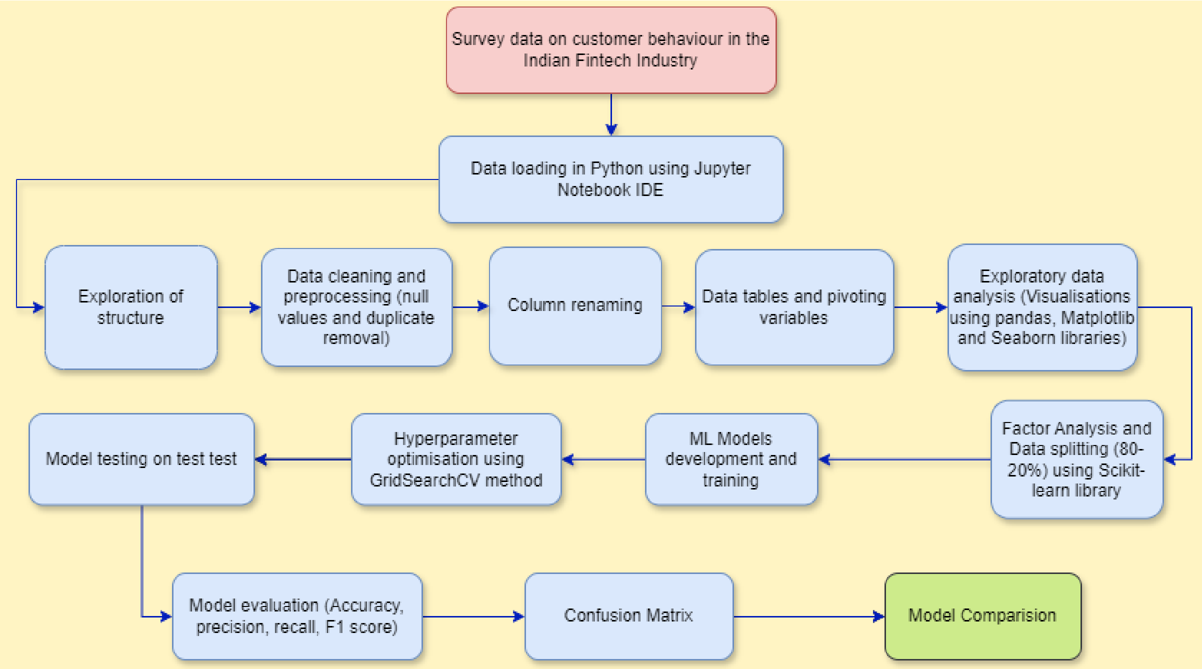


Figure 10: Methodological architecture

Figure 10 demonstrates the methodological (machine learning pipeline) followed in this study to develop, train, and test the ML (Random Forest classifier) and DL models (such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Deep Neural Network (DNN) and Multi-layer Perceptron (MLP) for evaluating customer behaviour in the Indian fintech industry. After performing the ETL process on the survey dataset, data cleaning and transformation (such as treating missing and duplicate values and renaming columns to enhance the interpretability of the dataset) have been performed.

Based on the pre-processed data, exploratory data analysis (data tables, data pivoting and visualisations) has been performed to evaluate the distribution of variables. After factor analysis (for dimensionality reduction and efficient model training), data splitting (80-20% splitting) has been performed. Based on the split data (train set: 80% and test set: 20%), ML models have been developed, trained and tested.

4.3 Implementation/Solution Development Specification

4.3.1 Data Exploration

After loading the dataset (CSV) by 'read' function from pandas' library, head and tail of the dataset have been explored by using the 'head ()' and 'tail ()' functions in Python. The columns of the dataset have been explored to check the name of the columns of the dataset for performing further analysis (data preprocessing, EDA, ML models) From the below figure, it can be observed that the dataset contains a total of 24 columns, which are related to the demographic profile of customers, uses of fintech services, frequency of using fintech services and satisfaction among customers regarding the use of fintech services.

4.3.2 Data cleaning and transformation

The dataset contains three unnecessary columns (Timestamp, Email, Declaration of survey participants), which have no significance in the analysis of customer behaviour. Thus, these two columns have been dropped from the dataset using the ‘drop(columns =)’ function in Python.

Renaming of the columns has been performed by creating a list containing the new column names in Python. After renaming the columns, renamed columns become Age, Gender, Education, Region, Area, Income, Smartphone_use, Fintech_use, Fintech_freq, Banking_Fintech, Family_Influence, Fintech_useful, Fintech_Advantages, Lower_Fees, Fintech_Tools, Fintech_Sources, Attitude_Changes, Banking_Strategies, Fintech_Satisfaction, Hesitations, Challenges, Risk_Mittigation and Future_Use

Null values in the dataset have been checked using the isnull().sum() function in Python to identify if there are any missing values in the variables According to Palanivinayagam and Damaševičius (2023); Emmanuel et al. (2021), missing values cause data inconsistency, which leads to the formulation of information biases in the data analysis process. From the above figure, it can be observed that the variable ‘Fintech_Use’ contains only 1 missing value and other variables contain no missing value. due to the non-existence of missing values in other variables and only 1 missing value in ‘Fintech_Use’, no data points have been dropped from the dataset.

Duplicate values in the survey data have been checked using the ‘duplicated()’ function in Python, from which no duplicate value has been observed in the dataset, indicating non-existence of data redundancy .

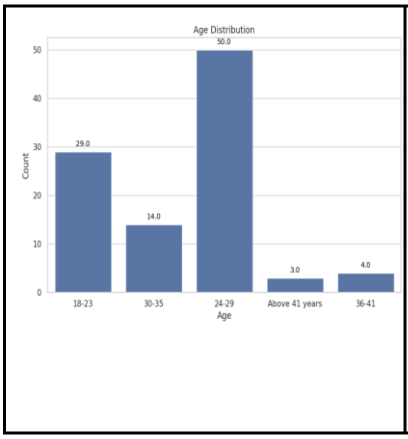
4.3.3 Data tables and Pivot tables

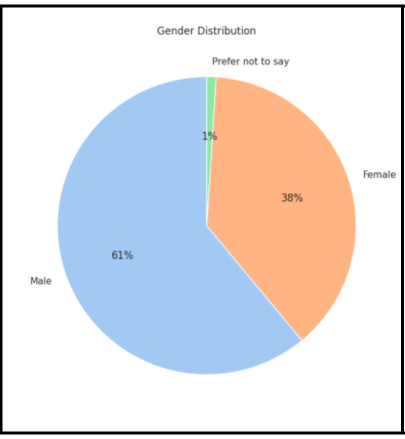
The data tables (containing variables, total observations, and missing values), which have been developed in Python by firstly creating an empty list (data table) and appending the calculated total observations and missing values for each of the variables by executing a for loop. According to Rama (2022), data tables allow for evaluating existing variables, observations, and null values in the dataset. From the developed data tables, it can be observed that the dataset contains 24 variables (100 observations each) with 1 missing value only in the 'Fintech_use' column.

Pivot tables have been developed for all variables to show the distribution of these variables in the dataset. Pivot tables for categorical variables help in demonstrating the distribution of the variables across categories, allowing evaluation of distribution of the overall dataset (Grech, 2018). From the above pivot tables, it can be observed that the majority of respondents are between 24-29 years old (50%), followed by the 18-23 age group (29%). There is a notable gender disparity, with 61% male respondents compared to 38% female. In terms of education and region, most of the respondents have Bachelor's degrees (57%), while most of the respondents reside in the Western part of India (46%), followed by the Northern region (24%). This leads to the indication that the usage of fintech services or awareness of fintech services is considerably higher among the educated population in India (majorly in the western and northern parts of India). This can be further supported by demonstrating the distribution of population (77% from urban areas and 18% from rural areas)

Majority of the respondents (approximately 88%) are comfortable with the use of Fintech services and usage frequency is considerably higher for Fintech platforms like digital banking and mobile wallets.

4.3.4 Data visualisation





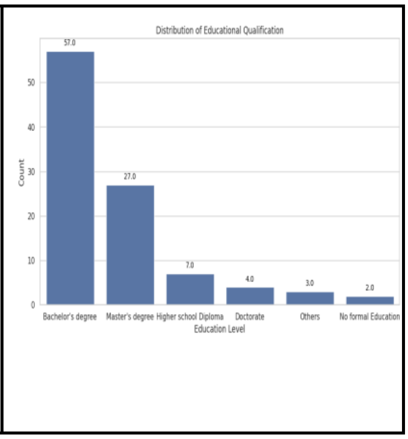


Figure 18: Demographic-wise distribution

The above figures show the demographic-wise (age, gender, and education level) distribution of respondents, from which it can be observed that most of the customers are in the 24-29 years age group with either bachelor’s or master’s degree. This shows that awareness and usage of fintech services (like mobile banking, mobile wallet) are higher among the highly educated young adult population in India.

The distribution of fintech usage frequency, strategies followed by fintech companies in India and user satisfaction for fintech customers is positive. From the analysis, it can be observed that almost 45% of respondents have frequently used fintech services, indicating the usability of fintech services for making seamless transactions.

Label encoding is the process of transforming categorical variables into numerical measures, helping efficient training of ML models (Hancock and Khoshgoftaar, 2020). Due to this, categorical encoding has been performed using the LabelEncoder from the scikit-learn library his has helped in converting the categorical columns into numerical labels, allowing efficient training of ML models.

From the analysis, it can be stated that **Factor 1** has strong positive loadings on ‘Fintech_useful’, ‘Family_Influence’, ‘Future_Use’ and ‘Risk_Mitigation’, suggesting it represents the positive perception and usefulness of Fintech, influenced by family and future intent to use fintech services. **Factor 2** is associated with variables like ‘Smartphone_Use’, ‘Lower_Fees’ and ‘Attitude_Changes’, indicating it can be represented as a technology comfort and cost-effectiveness dimension. **Factor 3** has high loadings on ‘Fintech_Success’ and ‘Risk_Mitigation’, indicating it can be represented by perceived success and risk management in fintech. However, **Fintech 4** (‘Banking_Fintech, Fintech_Sources, and Attitude_Changes) and **Factor 5** (‘Hesitations’ and ‘Challenge’), indicate dimensions related to fintech integration and challenges in fintech integration respectively.

4.4 Results and Critical Analysis

4.4.1 Machine learning models with and without hyperparameter tuning

4.4.1.1 Random Forest Classifier

Random Forest Classifier is initialised from the scikit-learn library with a random state of 42 for maintaining reproducibility. The initialised classification model is then fitted to the training data (X_train and y_train), where it learns the patterns and relationships between features and the target variable. After the development and training of the model, prediction of target variable (Fintech_Satisfaction) was performed on a test set.

Without Hyperparameter optimisation

Classification Report:

	precision	recall	f1-score	support
0	0.79	0.92	0.85	12
1	0.00	0.00	0.00	1
2	0.33	0.33	0.33	3
3	0.67	0.50	0.57	4
accuracy			0.70	20
macro avg	0.45	0.44	0.44	20
weighted avg	0.65	0.70	0.67	20

With hyperparameter optimisation

Classification Report:

	precision	recall	f1-score	support
0	0.83	0.83	0.83	12
1	0.00	0.00	0.00	1
2	0.33	0.33	0.33	3
3	0.60	0.75	0.67	4
accuracy			0.70	20
macro avg	0.44	0.48	0.46	20
weighted avg	0.67	0.70	0.68	20

The obtained accuracy of random forest classifiers is 70% (without hyperparameter) and 70% (with hyperparameters), however, the macro average for F1 score has increased from 0.44 to 0.46 after performing hyperparameter optimisation. This indicates that the implication of hyperparameter optimisation using cross-validation techniques has enhanced the predictive accuracy of the model across different classes of the target variable.

4.4.1.2 Artificial Neural Network (ANN)

The ANN model has been segmented into three layers, which are the input layer, hidden layer and output layer. Within the ANN model (without hyperparameter), a dense layer with the number of units determined by hp.Int('units_input', min_value=32, max_value=256, step=32) and ReLU activation has been used. The implication of the ReLU activation faction has helped in dynamically adjusting the number of units based on hyperparameter tuning.

The obtained accuracy of the ANN (without hyperparameter optimisation) is 55%, while the model accuracy has increased to 60% due to the application of hyperparameter optimisation (

4.4.1.3 Deep Neural Network (DNN) model

Model architecture for DNN models (with and without hyperparameter) has been shown from which it can be observed that DNN models have been developed by using Keras from the TensorFlow library. Within the Dense layer of the DNN model, a hidden layer of units of 256 with ReLU activation function has been used.

<table>
<tr><th>DNN without hyperparameter optimisation</th><th>DNN with hyperparameter optimisation</th></tr>
<tr><td><pre>
Classification Report:
              precision   recall f1-score   support

           0   0.64   0.75   0.69   12
           1   0.00   0.00   0.00   1
           2   0.50   0.67   0.57   3
           3   0.50   0.25   0.33   4

    accuracy   0.60   20
   macro avg   0.41   0.42   0.40   20
weighted avg   0.56   0.60   0.57   20
</pre></td><td><pre>
Classification Report:
              precision   recall f1-score   support

           0   0.69   0.75   0.72   12
           1   0.00   0.00   0.00   1
           2   0.40   0.67   0.50   3
           3   0.50   0.25   0.33   4

    accuracy   0.60   20
   macro avg   0.40   0.42   0.39   20
weighted avg   0.58   0.60   0.57   20
</pre></td></tr>
<tr><td></td><td></td></tr>
</table>

The obtained accuracy of the deep neural network (DNN) model (without hyperparameter optimisation) is 60%, which remains the same (60%) after the application of hyperparameter optimisation

4.4.2 Model comparisons

```
Comparison of Model Accuracies
           Model  Without Tuning (%)  With Tuning (%)
0  Random Forest                70.0             70.0
1            ANN                55.0             60.0
2            DNN                60.0             55.0
3            RNN                60.0             65.0
4            MLP                55.0             65.0

The best fitted model is tuned Random Forest with an accuracy of 70.00%
```

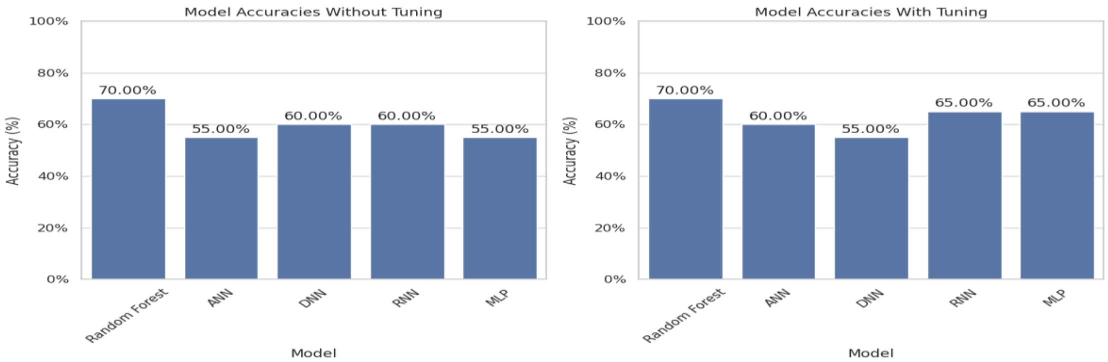


Figure 35: Model comparisons

Figure 35 demonstrates the comparison of the ML models in terms of accuracy for the prediction of customer satisfaction among the fintech customers. The obtained accuracy of the Random Forest model (with hyperparameter optimisation) is the highest (70%), indicating that the random forest model is the best-fitted model for prediction of fintech satisfaction among customers (***Refer to Figure 35***)

5 Evaluation

5.1 Comparing Findings from Previous Studies

Based on the obtained results, it can be stated that the usability of fintech services (like mobile wallets and digital banking) for performing seamless financial transactions has created a positive influence on the adoption of fintech services among customers. The enhanced security in financial transactions in fintech services due to the integration of advanced technologies such as AI, IoT and block has ensured scalability security in fintech transactions. However, the study by Aslam and Abbas (2024) contradicted that ML predictive models have the capability to easily assess creditworthiness more accurately compared to traditional methods, reducing the risk of default to enable more inclusive lending practices. Thus, it can be inferred that machine learning algorithms have the capability to predict behaviour of customers based on multi-dimensional attributes like customer demographics and fintech adoption, technology adoption and perceived challenges in fintech adoption

5.3 Discussion Based on Findings and Research Articles

5.3.1 Evaluation of Key Factors (accessibility and Trust) impacting customer behaviour in Fintech Sector

In addition to that, several studies point out that using big data analytics allows fintech companies to tailor services for individual requirements, improving user experience as well as satisfaction (Mhlanga, 2024). The analysis also explored that easy access to fintech services such as digital wallets and mobile banking significantly improves customer engagement. The 24/7 easy access to fintech services through digital platforms and mobile banking makes traditional physical visits to the banks much easier. Clear communication about data and security measures improves customer trust in Fintech (Aldboush and Ferdous, 2023).

5.3.3 Identification of Challenges Faced by Indian Companies in the Incorporation of Fintech Services and Customer Perceptions

Compliance with financial regulations is crucial for acquiring consumer trust with legality assurance (Oyewole et al., 2024). However, the exponential evolution of technological innovation in Fintech outpaces regulatory frameworks, creating potential legal risks as well as uncertainty for companies. The analysis mainly explored that the regulatory landscape remains a significant challenge for Indian FinTech companies. Trust is also a critical factor in consumer adoption of Fintech services and many users remain sceptical about the security as well as reliability of Fintech platforms compared to traditional financial services (Gupta, Wajid, and Gaur, 2023)

Conclusion and Future Work

6.1 Linking with Objectives

The level of technological infrastructure plays an essential role in the adoption of Fintech services. High internet access, widespread smartphone utilisation, and advanced digital payment systems (mobile wallets, biometric authentication) are crucial for encompassing Fintech adoption. Main challenges associated with the traditional bank syingstems in India include increased security breaches, strict regulations of Anti-Money Laundering (AML) and limitations in terms of providing convenient services. (**fulfilling research objective 2**).

Consequently, with the enhanced digitalisation of financial services, cybersecurity has become one of the most important concerns in this context. Previous studies have found that companies in India have faced critical challenges like cyber-attacks, and data and security breaches. Findings of this study revealed that as fintech companies collect and store sensitive financial and customer data, they become at a higher risk of cyber-attacks, data and information breaches. (**fulfilling research objective 3**)

6.2 Validity, scope, and generalisability

The data collected from customers having experience of using fintech services in India, thus, the information provided can be considered as reliable and valid.

6.3 Implications

The implication of this study can be beneficial for fintech companies to understand the influence of usability, trustworthiness, and perceived ease of use of fintech services in the adoption of fintech across the consumers in India.

6.5 Limitations

- The study is based on a quantitative survey, thus, causing limitations in terms of demonstrating qualitative viewpoints regarding challenges in fintech adoption and customer acceptance. This has led to a limitation in the generalisability of overall findings.
- The study fails to include factors like technology acceptance among the customers and the technological landscape within the fintech ecosystem. This can limit the generalisability of this study in demonstrating the impact of technological factors in the adoption and scalability of fintech services among customers in India.

6.6 Scope for future studies

- Future studies can incorporate technological factors like technology acceptance among the customers and stakeholder involvement in advancing technological infrastructure in the fintech ecosystem.
- Future studies can focus on development of advanced DL models like DNN, RNN along with baseline models like Logistic Regression, Random Forest, Naive Bayes, and Gradient Boosting to show model comparison in prediction of customer behaviour.

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