

Project Dissertation Report on

DEBT TRAPS CAUSED BY UNSECURED FINTECH LOAN APPLICATIONS AMONG YOUNG BORROWERS IN INDIA

Submitted By

S M Mozammil

24/DMBA/199

Under the Guidance of

Dr. Deep Shree

Professor



DELHI SCHOOL OF MANAGEMENT

Delhi Technological University

Bawana Road Delhi 110042

CERTIFICATE

This is to certify that the Major Research Project titled “Debt Traps Caused by Unsecured Fintech Loan Applications Among Young Borrowers in India” is submitted by S M Mozammil is an authentic piece of work carried out under the supervision of Dr. Deep Shree, 2024/DMBA/199 to Delhi School of Management, Delhi Technological University, in partial fulfillment of the requirement for the award of the degree of Masters in Business Administration during the academic year 2025–2026.

Dr. Deep Shree

Delhi School of Management

Delhi Technological University

Student’s Signature

DECLARATION

S M Mozammil, student of DMBA, bearing enrollment number 2024/DMBA/199, hereby declare that the project dissertation report titled " Debt Traps Caused by Unsecured Fintech Loan Applications Among Young Borrowers in India " is an original piece of work carried out by me under the guidance of Prof. Deep Shree, Delhi School of Management, Delhi Technological University. I further declare that this work has not been submitted for the award of any other degree, diploma, fellowship, or similar titles.

S M Mozammil

2024/DMBA/199

Delhi School of Management

Delhi Technological University

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EXECUTIVE SUMMARY

India's fintech lending revolution did what banks failed to achieve; it brought credit to millions of youths whom the official banking sector could never see. In Noida, for instance, a college student can access up to Rs. 10,000 within just three minutes using only a smartphone and his or her Aadhaar identity. This access is very much real, and it has benefited many. However, the reason for this study is that access alone cannot be taken for granted.

This research project, entitled 'Debt Traps Triggered By Unsecured Fintech Loans Applications Amongst Young Debtors in India', was undertaken as a Major Research Project in the context of MBA program at Delhi School of Management, Delhi Technological University. The research was undertaken in the Delhi-NCR area amongst individuals aged between 18 to 30 years who have accessed at least one fintech unsecured lending application within the last two years. A total of fifty respondents answered the surveys which were circulated using Google Forms.

The research attempted to address four major questions concerning factors influencing excessive usage of payday lending apps. Namely, do financial illiteracy and lack of knowledge cause late payments, can certain characteristics of the app itself cause individuals to borrow more, how does social media impact attitudes towards borrowing money and which populations suffer from this problem the most. To explore these questions, three specific hypotheses were tested during the research. Although the first one showed an interesting trend that people lacking basic knowledge about interest rates missed payments almost twice as frequently as financially literate individuals, there wasn't enough evidence to prove a statistically significant correlation. However, the last hypothesis proved to be very relevant in terms of its contribution to the results. Specifically, the analysis showed that people who scored high on platform design susceptibility borrowed significantly more averaging 1.48 loans in the past 12 months compared to 0.62 for the low susceptibility group ($p = 0.005$). Surprisingly, even though social media did not increase the likelihood of borrowing among participants in the experiment, 68% percent of young users considered using such applications as normal behavior.

These are the three recommendations that arise from the above observations. Firstly, fintech platforms must by regulation display the total cost of the loan in rupees within one page before any loan is concluded. Secondly, financial literacy especially on the reading of an APR and calculating the total costs repaid must be included in university curricula. Finally, RBI's guidelines on digital lending must be followed strictly as there is enough room for improvement according to the data gathered thus far. Financial inclusion which exposes youths to financial products they barely comprehend cannot be considered true financial inclusion at all.

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INTRODUCTION

1.1 Background

Not many years back, the whole process of borrowing money was an intricate process. If a college student in Delhi needs Rs.10, 000 to pay for a semester textbook or a month's rent, there are very few options. Banks required salary slips, proof of employment, and credit history documents that most youth did not possess. Friends and family were the more realistic option, although asking them was an awkward matter itself. For a significant part of the youth population of India, formal credit was not much option.

That changed quietly but quickly, and by 2016, there was a new financial product on Indian smartphones. These were financial products offered by fintech lending firms based on the user's data and an algorithmic evaluation of their creditworthiness; the app could get funds into a user's account within minutes. All this took to onboard a user was an Aadhaar number, a PAN card, and a few selfies. No bank branch, no paperwork, no waiting. But this was the first time young Indians could access credit on their own terms.

What happened next was a growth. "The Reserve Bank of India said that digital loans given in the country went up from around Rs. 11,671 Crores in 2017-18 to more than Rs. 1.41 Lakh crore, in 2021-22." In four years, there was a more than tenfold growth of the market. This growth was primarily fueled by the 18-30 age-group of borrowers who were mostly young students or fresh graduates, workers in the gig economy, or salaried young employees who relied mainly on such apps for their personal credit needs. Not many of them were an extra financial tool for the fintech financing. All of the tool set was engaged.

These applications were assisting a true credit issue for India. They had all been disappointed by years of banking policy by first-generation, low-income families, or by those employed in the unorganized sector. This deficit was filled by the fintech loans, often helpful in real terms. These apps gave a handy solution which only the organization offered to students wishing to pay an exam fee prior to the receipt of the scholarship and for the regular workers needing funds to buy supplies, etc. This is no small matter. Credit, when harnessed properly, changes lives.

But the same features that made these apps useful also made them dangerous for a certain group of users. The friction that traditional lending created the time it took, the documents it required, the rejection it sometimes delivered was not entirely useless. The friction that traditional lending created the time it took, the documents it required, the rejection it sometimes delivered was not entirely useless. "When an app removes that friction and replaces it with a one-tap approval, it removes the thinking pause that cognitive self-control needs." (Thaler and sunstein,2008).

For most young borrowers venturing into credit for the first time, there were no such answers to be given. There is very little coverage of personal finance in a practical sense within school curricula in India. A student of economics at plus-two can enlighten you about demand and supply curves but is sure to fail to answer what the effective annual interest rate on a fintech loan means or how to work out total repayment liability from a quoted monthly rate. This is a study that highlights some of

the primary issues of disconnection, not only between reality and schooling, but between the two components of schooling, as well.

Another issue was the system architecture. Another problem was design of platforms. They are specifically crafted to maximize disbursements as it is a facet of the company structure. In the case of a lending app, the maximum amount allowed is already inputted when a user opens the app; that is not a blunder. The series of push messages sent and received that provide a "limited-time rate" offer are not random. Dark pattern layouts, identified by interface experts as layouts that support the business, rather than the user, have been found (Brignull, 2010). The negative trends capitalize on inexperience in the product by the first time consumer, who cannot easily identify when the product is pushing in a manner that they may not have chosen.

A third dimension was introduced by social influence. Similar to other popular applications, fintech applications grow by word of mouth, referral bonuses and by everyone around you using it. Such advice can also have an impact if a friend states that a loan app is quick and simple. It's biased, too. Only the experience of getting the money is shared by friends. They seldom ever discuss what transpired when the time for payback arrived and there was a deficiency in the banking account.

Early in the 2020s, borrowers, investigators, or regulators started to notice a darker side to what had started off as a true story of financial inclusion. Strict loan recovery techniques were reported in the news. "In 2021, the Reserve Bank of India issued emergency warnings, and in 2022, it issued more comprehensive regulations for digital lending." News reports highlighted young people, such as students and those who had recently started their first jobs, who were unable to manage their debts and were caught in cycles of borrowing money from one app to pay another. The fintech debt trap had a name, and some people were caught in it.

This work examines the disparity among the actual advantages of fintech lending as well as the actual damage it has caused to a large number of young Indian consumers. Rather, it looks closely at the reasons why young borrowers are more prone than other to become caught in debt loops when utilizing such apps. It also examines what this trend reveals about the shortcomings in platform design, financial instruction, as well as enforcement of regulations that all make it simple to slip into a bind and difficult to climb out.

1.2 Problem Statement

If you walk into any college campus in Delhi and ask students if they have used a fintech loan app a lot of them will say yes. Then ask them what interest rate they were charged per year. Most of them will not know. Ask them if they have ever missed a payment or taken a loan to cover the first one. You will find that many of them will say yes. This shows a pattern. Something is going wrong from the moment a young person starts using a fintech lending app to the moment they realize the loan is a problem they cannot easily solve.

The problem is the gap between getting a loan and being able to manage it. Fintech lending in India has really helped a lot of people get access to money that they would not have gotten from banks. That is an achievement. The same thing that made fintech lending successful has also created a problem that is not being talked about enough: young borrowers, many of whom are borrowing money for the first time and do not know much about finances are getting into debt that they cannot get out of.

The problem is not just that interest rates are high even though many of them are. It is not that young people spend money recklessly even though there is a lot of pressure to spend money on lifestyle things. The problem is that there are three things that are not working together: young borrowers do not know enough about finances to understand what they are getting into; the loan apps they use are designed to get them to borrow more money rather than to borrow wisely; and the people around them including friends and social media make it seem normal to use fintech credit without thinking about it.

Other researchers have studied parts of this problem. They have not put all the pieces together. Some researchers have shown that people make mistakes when they borrow money for the term at high interest rates. Others have shown that people who do not know much about finances are more likely to have debt. Some have shown that many fintech apps are designed to make it easy for people to get loans without thinking about it. These results are not all in one location as well as were not examined collectively in a single effort that concentrates on Indian youth consumers.

India's position is distinct and significant. Investigations on fintech obtaining have been conducted in several nations, including the United States and the UK. India is not like that. People are less knowledgeable about money; hence the regulations are looser. People have varied perspectives about credit. A 22-year-old engineering graduate in Noida who recently took out his fourth loan from an alternative app is not covered by what we know regarding fintech debt in other nations.

The goal of this investigation is to close that gap. It asks why young individuals in the Delhi-NCR area who use fintech loan apps are more prone to fall into debt problems. Three factors are examined: young borrowers lack the financial knowledge necessary to make wise judgments; the layout of loan applications encourages people to take out larger loans than they should; and social media and friends make borrowing money seem commonplace. Additionally, it asks whether a few demographics such as those with salaries or students are more prone than others to accumulate debt.

These are not only inquiries. Every month thousands of people in India take out their first fintech loan. Many of them will pay it back without any problems. A lot of them will find themselves a few months later with debt that they cannot pay and they will not know what to do. Understanding why this happens and what causes it is the step, to figuring out how to help the next group of borrowers who use a loan app for the first time.⁴

1.3 Objectives of the Study

The four objectives listed below come only from the gaps found in the literature review. Every goal is tied to a specific unanswered question in the current research on fintech lending and youth debt in India.

RO1: To assess the impact of financial literacy on debt accumulation and repayment difficulties among young unsecured fintech loan users in the Delhi-NCR region.

► *LR Gap:* — “Lusardi & Mitchell (2014) established financial literacy as a predictor of high-cost borrowing”, but no India-specific empirical study has tested this relationship for fintech borrowers.

RO2: To examine how specific platform design features of fintech lending applications including pre-filled loan amounts, push notifications, and gamified interface elements influence the borrowing frequency and volume of young users.

► *LR Gap:* “Brignull (2010) documented dark patterns in fintech platforms globally”, the susceptibility of young Indian borrowers to these specific features has not been empirically measured.

RO3: To evaluate the influence of social media exposure and peer referral on borrowing behavior and the normalization of digital credit among young adults aged 18–30 in India.

► *LR Gap:* “Festinger (1954) and Bianchi & Braver (2020) link social comparison to impulsive borrowing”, this mechanism has not been empirically tested in the Indian fintech lending context.

RO4: To examine the combined and integrated effect of financial literacy, platform design susceptibility, and social influence on debt trap vulnerability among young fintech borrowers in India.

► *LR Gap:* — The research gap explicitly identifies the absence of any integrated model testing all three factors simultaneously in the Indian context. Most Indian studies examine these variables in isolation.

1.4 Scope of Study

Every research study has its limits. It looks at some things closely. Leaves out other things. Being clear about these limits is what makes the findings of the study trustworthy. This section explains what this study is about and what it's not about so that anyone reading the findings knows what to expect and what not to expect.

This study focuses on people who're between 18 and 30 years old living in the Delhi-NCR region and have used at least one fintech lending app to borrow money in the last two years. This age group was selected because it represents the period when most people encounter formal credit for the first time and financial habits are still forming. At 18 most people are borrowing money for the time and do not know much about debt. By the time they're 30 most people have gained some experience with money and know what to expect. The 18 to 30 age group is where people learn about debt for better or for worse. Fintech lenders have also targeted this age group because younger borrowers are comfortable using apps and do not question the terms and conditions.

Within this age group the study looks at four types of borrowers: students with no income students who work time people with salaried jobs and people who are self-employed or work in the gig economy. These four groups are different because they have financial situations, different incomes, different relationships with employment and different experiences with financial institutions. Determining maybe each of these categories is also susceptible to debt traps or whether certain are more susceptible than others is one of the objectives of this investigation.

The Delhi-NCR area, which includes Delhi, Noida, Greater Noida, Gurugram, Faridabad, as well as Ghaziabad, provided the study's information. This region was chosen because it has a number of fintech lending app users, a big student population and good access to smartphones and the internet. The findings of this study may also be relevant to cities like Mumbai, Bengaluru and Hyderabad which have similar demographics and fintech adoption. However, the study does not cover cities, -urban areas or rural markets where the borrower profile and financial literacy are different.

The financial product that this study looks at is the loan that is given through a mobile application. Apps like KreditBee, LazyPay, MoneyTap, mPokket, Navi, Slice, CASHe and PaySense are the kinds of platforms that are included in this study. Other types of loans such as home loans, vehicle loans and digital loans offered by banks are not part of this study. The reason for this is that unsecured fintech personal loans have a combination of features that create a kind of debt risk that this study is investigating. They are approved quickly require documentation have high interest rates and are designed to make borrowing easy.

The study looks at three factors: how financial knowledge a borrower has and how it affects their debt how the design of fintech app interfaces influences borrowing behavior and how social media and friend referrals affect a young persons attitude toward fintech borrowing. These three factors were chosen because previous research has shown that they are important. They have never been studied together in a study focused on India The primary objective of this study is to comprehend the debt vulnerability, which's a combination of borrowing frequency, repayment difficulties and need to take a new loan to repay an existing one.

This study is conducted in the period 2021-2024. The period saw a massive surge in Indian fintech users which led to the RBI releasing its 2022 guidelines for better transparency and accountability. This study investigates how borrower experience varied prior to and after these guidelines were established.

There are some things that this study does not cover. It does not look at how fintech companies make their credit decisions or what happens to a borrowers life after a debt trap experience. It also does not compare debt vulnerability across cities. These are topics that require research. The goal of this study is to understand why young fintech borrowers in one of Indias urban lending markets fall into debt traps and what drives this process. The study focuses on fintech borrowers in the Delhi-NCR region and its findings can help us understand the debt trap issue in this region. The study is about fintech borrowers and their experiences with debt. It seeks to give a clear image of the Delhi-NCR region's debt trap problem, specifically with regard to fintech consumers.

LITERATURE REVIEW

2.1 The Rise of Fintech Lending and Financial Inclusion

The notion that fintech loans may make services accessible to more people sparked the conversation. Arner, Barberis, and Buckley (2016) examined the evolution of the fintech sector. They claimed that it went through three stages: initially, technological assisted banks; secondly, fintech firms began to compete with them; and now, technology firms are turning into their own financial service firms. They felt that this adjustment made it more affordable to provide loans to those who previously couldn't obtain them from banks.

In nations where financial institutions did not assist low-income individuals and those employed in the unorganized sector, fintech financing quickly expanded. Mobile loans swiftly gained enormous popularity in countries like the Philippines, Kenya, as well as India. This occurred as a result of the banking system denying individuals access to credit. Although the privilege was genuine, there was a risk associated with it when any conditions were not made apparent.

2.2 Behavioral Economics and the Decision to Borrow

The behavioural economics can help explain why young people take out excessive loans from fintech companies. People constantly prioritize immediate incentives above superior long-term results, a tendency known as hyperbolic discounting, according to research by Laibson (1997). When borrowing money, individuals often underestimate the expense of repaying it later in favour of obtaining it now. When borrow funds, individuals prioritize receiving it over repaying it afterward. This is particularly true when loan is fast and easy, such with a mobile application.

Even when the basic alternatives are the same, Thaler and Sunstein (2008) shown that how choices are laid out influences people's decisions. When a lending app recommends a loan quantity, it is pushing the borrower in the direction of a particular result rather than providing objective data.

A third motivation is explained by Festinger's (1954) social comparison theory. In the age of social media, young people constantly evaluate them to their peers, and such evaluation is biased against aspiration purchasing. Fintech credit provides a rapid bridge for those who are unable what their peers seem to have. The decision to obtain is not necessarily based on necessity. Maintaining up is important at moments.

2.3 Platform Design and Manipulative Interface Practices

Some researchers are investigating how fintech companies build their platforms to influence consumers' financial decisions. Brignull (2010) referred to these dark patterns as interface choices that go against the user's interests while benefiting the company. In fintech lending apps, they take very specific forms, such as loan quantities quoted quarterly instead of annually, green animations that make approval feel joyful, or push alerts scheduled for afternoons when users are more inclined to consider deeply before swiping.

This is an issue for creditors because being excellent with technologies does not imply being adept at handling their money. Fintech companies are benefiting from convincing individuals that being tech-savvy is equivalent to being economically informed.

2.4 Financial Literacy and its Role in Debt Outcomes

Lusardi and Mitchell (2014) discovered that financial literacy is the single most consistent predictor of whether individuals spend excessively. People who comprehend how cost operates are considerably less likely to have high-interest debt, even after adjusting for income or degree.

In India, the RBI working group study (2021) discovered that many young fintech borrowers do not grasp the conditions of their borrowing. Most had no idea the rate of interest they were being billed, as well as many were uninformed that if they skipped a due date, they were going to incur a punishment. This isn't as they lack intelligence. Perhaps they were not taught about finance in school, so fintech firms make it difficult to comprehend.

2.5 Regulatory Gaps

"As the RBI has issued rules for digital lending in 2022, implementation has still been sporadic." The previously noted structural issue, in which "Zetsche et al., (2017)" refers to fintechs exploiting the gap among digital regulation and financial regulation, is only partially fixed.

2.6 Research Gaps Identified

Most research on fintech lending or debt has been conducted in the US, UK, or East Asian economies. There is very little research on the Indian applicant, and what is available typically focuses on sector-level growth rather than individual borrower experiences. Within the existing behavioral study, the three primary elements of financial literacy, system layout, and peer impact have been explored separately rather than collectively. There has never been single empirical research in India that evaluated all the 3 concurrently. This study fills both voids. It addresses young fintech consumers in Delhi-NCR and evaluates all three parameters in a single framework. The purpose is useful: to create data that will directly affect Indian regulatory policies, educational institutions, and product creation requirements.

RESEARCH METHODOLOGY

3.1 Introduction

This chapter highlights the methodology used in gathering the data. It will give an overview of the type of data gathered, from whom, through what means, and how it was concluded in arriving at its findings. There is nothing random in these decisions since each of them is dictated by the nature of the research itself, as well as by the specifics of the task to work with a student community in the Delhi-NCR area within the framework of an MBA project.

As such, the study poses a problem that requires a measurement of two types of aspects. One relates to statistical measures of behavior, such as frequency of borrowings, awareness of interest rates, susceptibility to application design. The second aspect pertains to the experience gained from borrowings themselves. Such factors as unexpected loans, the perception of debt accumulation, and recommendations for friends joining the market may help in answering the research question.

3.2 Research Design

Quantitative methodology is applied in this research design with the main focus on structured survey questionnaires as the primary data collection tool. This survey included multiple choice and Likert-scale ratings as well as scenarios in order to receive closed-ended feedback from 50 eligible participants. Data received from the survey will be used to perform three statistics tests aimed at testing each hypothesis.

This research is essentially descriptive and analytical in terms of content. On one hand, it is about describing the borrower profile of fintech youth borrowers, the mechanisms behind their borrowing and their knowledge or unawareness of the product's benefits and risks. On the other hand, it examines the relationship between certain variables and borrowers' behavior or vulnerability to debt. The research makes no attempts to manipulate or experiment with any variable in particular.

3.3 Type of Research

The research is mostly descriptive and analytical. The former will include defining the demographic profile of the target audience, their financial behavior and awareness. The latter will include checking whether the associations found in the literature indeed exist in the current sample.

Since the research deals with a rather limited sample (50 participants), the choice of statistical tests is based on the fact that they are non-parametric and distribution-free where necessary. Such an approach to the analysis will be more realistic for the actual sample, rather than use tests that do not fit the current situation.

3.4 Sampling Strategy and Sample Size

The study's target population is people aged between 18 and 30 years living in Delhi-NCR who have used at least one fintech lending app in the last two years prior to distribution of the survey questionnaire. Fintech lending app users do not form a

population listed in any centralized directory; therefore, a probability sample could not be selected. The study relied on convenience sampling, where participants were contacted using university WhatsApp and Telegram groups, LinkedIn contacts, and social media connections.

A total of 50 responses were received from the survey distribution. While this is a relatively small sample size compared to most tests, this is explicitly stated in the discussion of results whenever the sample size becomes an issue in interpreting the findings. However, a sample size of 50 is sufficient to undertake the non-parametric tests selected for this research.

3.5 Research Instrument

3.5.1 The Questionnaire

The main research instrument used for the gathering of information is a 22-question structured questionnaire which will be disseminated using Google Forms. Four parts were included in the questionnaire. The first part involves information about respondents' demographic data including age, gender, occupation, monthly income, and social media usage per day. The second part will obtain details regarding the fintech lending experience such as number of loans borrowed, purpose of borrowing, how they first became aware of the application that they currently use, if they are aware of the annual interest rate prior to borrowing, and if they have missed repaying the loan.

The third part of the questionnaire includes nine items of Likert scale that are rated from Strongly Agree to Strongly Disagree, consisting of three clusters of themes. The first three items focus on financial literacy, behavior, and awareness which is aligned with Hypothesis 1 while the second three items will assess susceptibility to platform features such as pre-filled amount of loan and notifications. Finally, the last three statements will focus on social media influence and the normalization of borrowing among peers, related to Hypothesis 3.

The final segment included four case inquiries designed to investigate how participants would respond in practical lending circumstances instead of simply evaluating their self-statement.

3.5.2 Likert Scoring

The five-point Likert scale was converted into a numerical rating from 1 to 5: strongly agree with 5, then strongly disapprove with 1. The numerical scores allowed for the production of composite scores for each category, including financial literacy score, platform architecture susp score, or a social influence rating.

3.6 Data Analysis Process

The survey data was then moved to an Excel spreadsheet so that we could convert from text to number format and classify respondents into groups (i.e. repeat vs. new

borrowers). We performed the standard quantitative analysis using SPSS, and produced all the graphs necessary for Chapter 4 using standard statistical tests.

The level of significance was $p < 0.05$. Due low number of respondents in our sample, it is possible that we missed some of the trends. But we have taken these in consideration rather than declaring the result complete failure.

3.7 Validity and Limitations of the Methodology

In order to maintain the reliability of my data, I improved my questions in terms of clarity and presented respondents with situations from real life that made their answers more genuine. Nevertheless, there are several aspects that should be mentioned as possible weaknesses of this research. For example, because I conducted the survey among only 50 people, certain trends may have been overlooked due to the small sample size, while the fact that my pool is quite technologically-minded suggests that it does not fully reflect the entire youth population in India. Furthermore, people might sometimes misrepresent or even forget about certain issues when responding to the questions asked.

3.8 Ethical Considerations

All participation in the survey was entirely voluntary. Each participant was first introduced to the purpose of the academic survey, the anonymity of their answers was assured, and they were informed about the option to stop participating whenever they wished without consequences. None of the personal identifiers, such as phone numbers, email addresses, or any account-related information, was collected during the survey.

The full name field was an optional one provided by the Google Form; however, it was never used for any type of analysis. All data is stored safely and only the researcher has access to the results.

ANALYSIS AND FINDINGS

4.1 Introduction

This chapter will give details of the empirical findings gathered through the survey questionnaire. A total of fifty valid responses have been obtained from fintech loan takers in the age group of 18 to 30 years residing in the Delhi-NCR area. The findings are presented in six sections. First, the demographic profile of the sample is explained. Second, the borrowing pattern of the respondents is described. Third, the answers to the Likert scale questions based on themes are provided. Fourth and fifth, the outcome of the hypothesis testing has been explained. Sixth, a cross-tabulation analysis is conducted to test research objective four.

In instances where there was no statistical significance, this fact is explicitly stated, and the probable explanations for this have been made. The small size of 50 respondents limits the statistical power of the tests used. Real associations present in the larger population may fail to meet the required statistical threshold in this sample.

4.2 Demographic Profile of Respondents (RO4)

The sample size of 50 people gives us a fair representation of the target audience. A majority (64%) belong to the age group 23-27, followed by 18-22 years (20%) and 28-30 years (16%), which is close to the average profile of a fintech customer in India. The sample consisted of 70% males and 30% females, which could be due to higher penetration amongst males in the NCR region.

Occupation-wise, students with no job (32%) constituted the majority, followed by salaried workers (30%) and students with part-time employment (26%), with the remaining being either self-employed or freelance. As expected, incomes were comparatively low, with 68% earning less than Rs. 30,000 per month. In terms of social media consumption, 88% spend more than an hour on these websites per day, with 22% spending more than four hours.

Table 4.1: Demographic Profile of Survey Respondents

Demographic Variable	Distribution
Age: 18–22 years	10 respondents (20%)
Age: 23–27 years	32 respondents (64%)
Age: 28–30 years	8 respondents (16%)
Gender: Male	35 respondents (70%)
Gender: Female	15 respondents (30%)
Status: Student (no income)	16 respondents (32%)
Status: Salaried / full-time	15 respondents (30%)
Status: Student (part-time income)	13 respondents (26%)
Status: Self-employed / gig worker	6 respondents (12%)
Income: Below Rs. 15,000	15 respondents (30%)

Income: Rs. 15,001 – Rs. 30,000	17 respondents (34%)
Income: Rs. 30,001 – Rs. 40,000	10 respondents (20%)
Income: Above Rs. 40,000	8 respondents (16%)
Social media: Less than 1 hour/day	5 respondents (10%)
Social media: 1 – 2 hours/day	19 respondents (38%)
Social media: 2 – 4 hours/day	14 respondents (28%)
Social media: More than 4 hours/day	11 respondents (22%)

4.3 Borrowing Behavior Profile

Out of 50 people, 27 had obtained loans from financial technology companies in the previous year, with more than 25% taking numerous loans. The pattern indicates that borrowing regularly has grown into a habit, even within the young population. The majority of people took out loans to cover their daily expenses or personal tastes. Unexpectedly, six people obtained loans to repay earlier debts. Other people were acting aggressively.

Another concern is a lack of information about the rate of interest. Approximately 36% were uninformed of annual interest rates, whilst the majority were only familiar with monthly the rate of interest. This trend resulted in practical difficulties for borrowers, as 22% of the sample had failed to make payments. People found the loan application through personal search engines, referrals from friends, or adverts on social media platforms.

Table 4.2: Borrowing Behavior Summary

Indicator	Count and Percentage
Never borrowed (past 12 months)	23 respondents (46%)
First-time borrower	13 respondents (26%)
2–3 loans in past 12 months	10 respondents (20%)
4 or more loans in past 12 months	4 respondents (8%)
Borrowed for daily expenses	6 respondents (22% of borrowers)
Borrowed for lifestyle purchases	5 respondents (18.5% of borrowers)
Borrowed to repay another loan	6 respondents (22% of borrowers)
Borrowed without planning (impulse)	6 respondents (22% of borrowers)
Knew APR before accepting	32 respondents (64%)
Only saw monthly rate / did not check	18 respondents (36%)
Missed repayment at least once	11 respondents (22%)
Discovered app via peer referral	16 respondents (32%)

Discovered app via social media/ad	15 respondents (30%)
Discovered app via own search	16 respondents (32%)

4.4 Breaking Down the Likert Scores

Nine statements on the Likert scale were categorized into three groups based on their themes. Each individual gave his/her rating for each statement on a scale of one to five, with one being strongly disagree and five being strongly agree.

Table 4.3: Likert Scale Mean Scores

Statement	Mean Score (out of 5)
L1: I always check total repayment before accepting [H1]	4.00
L2: I understand the difference between monthly and annual rate [H1]	3.92
L3: I know the penalty for missing a repayment [H1]	4.04
L4: I usually borrow the pre-filled app amount [H2]	2.92
L5: I have borrowed after a push notification [H2]	2.60
L6: Countdown timers make me want to borrow faster [H2]	2.88
L7: I borrowed after seeing social media content [H3]	3.04
L8: I feel comfortable because trusted people use the app [H3]	3.16
L9: Fintech borrowing feels normal among people my age [H3]	3.40
Financial Literacy Composite Mean	3.99
Platform Design Composite Mean	2.80
Social & Peer Influence Composite Mean	3.20

4.5 Hypothesis Testing

The three hypotheses have been tested through three tests of statistics. Tests have been chosen depending upon the nature of variables as well as the number of respondents. Parametric test could not be applied to the test as it did not satisfy the conditions needed for applying parametric test.

Hypothesis 1- Financial Literacy and Debt Vulnerability [RO1]

H₀: There is no significant association between financial literacy and repayment problems faced by young borrowers of fintech loans.

H₁: Young borrowers with poor financial literacy will be more prone to encounter repayment problems compared to young borrowers with good financial literacy.

Type of test used: Chi-Square Test of Independence: The financial literacy question on Awareness of the Annual Percentage Rate (APR), asking whether the respondents had known the annual interest rate of their loan prior to taking the loan, was employed as the categorical variable for financial literacy. This was correlated with the missed repayment question. Chi-Square test is appropriate here since both are categorical variables.

Table 4.4: Chi-Square Test

Group	Never Borrowed Always on Time Missed Once Missed Multiple
Knew APR (n=32)	14 12 3 3
Did Not Know APR (n=18)	4 9 3 2
Chi-Square (χ^2)	3.2835
Degrees of Freedom	3
p-value	0.350
Decision	H ₁ Not Supported at $p < 0.05$

As I looked at the square test result, I saw that the p-value is more, than 0.05, actually 0.350. This means that we cannot prove a link so H₁ is not supported by statistics. If I look at the numbers they tell a different story. As I mentioned earlier people who do not know much about the interest rate have a percentage of not paying back their loan around 33%. In comparison the rest of the population has a percentage, only 19%. This shows that not knowing the loan terms can lead to problems a difference of 14%. The reason we do not see significance here is that our sample size is relatively small. This is because 18 people who took our survey had never borrowed money before.

4.5.2 Hypothesis 2 - Platform Design and Repeat Borrowing [RO2]

H₀: The impact of platform design on loan frequency among young users is insignificant.

H₁: More susceptible young borrowers take more loans than less susceptible young borrowers as a result of platform design influence.

Test performed: Mann Whitney U test. Subjects were categorized into two groups according to the Platform Design Susceptibility score – high susceptibility (>median) and low susceptibility (<= median). Then, the amount of fintech loans obtained during the last 12 months was compared between these two groups. The Mann Whitney U test was used as it is the nonparametric alternative for the independent samples t-test,

which is suitable for comparing two groups regarding an ordinal or skewed variable regardless of the lack of normally distributed data. **Table 4.5: Mann-Whitney U Test**

Group	n Mean Loans Median Loans
High Platform Susceptibility	21 1.48 1.0
Low Platform Susceptibility	29 0.62 0.0
Mann-Whitney U Statistic	427
p-value (one-tailed)	0.0052
Decision	H2 Supported — Significant at $p < 0.05$
Group	n Mean Loans Median Loans
High Platform Susceptibility	21 1.48 1.0
Low Platform Susceptibility	29 0.62 0.0
Mann-Whitney U Statistic	427
p-value (one-tailed)	0.0052
Decision	H2 Supported — Significant at $p < 0.05$

As for the Mann-Whitney U test results, $p = 0.0052$, which is significantly less than our threshold, thus providing support for H2.

This discrepancy is truly significant as those people who were more affected by design were more likely to borrow more frequently—nearly 1.5 times compared to others. Moreover, the median of borrowing frequencies for people whose decision-making was less affected by design was even equal to 0, while among the other participants, this rate reached 1.

This is the most interesting result from the entire experiment. Indeed, such factors as push notifications and pre-defined loan amounts were found to actually affect decision-making regarding borrowing, thus providing another piece of evidence to support the existence of dark patterns influencing users' decisions in app interfaces.

4.5.3 Hypothesis 3 - social media, Peer Influence, and Borrowing [RO3]

Ho: There is no significant association between social media usage and peer referral and the behavior of borrowing.

H1: The higher social media usage and peer-referred app adoption influence repeat and impulse borrowing behaviors.

The tests conducted for H3 comprised two parts: Part A and Part B. In Part A, we performed the Spearman Rank Correlation test to determine whether there was a positive correlation between daily social media hours and the Social and Peer Influence Score generated from the responses given on the five-point Likert scale. We did not choose Pearson's correlation coefficient for our analysis because the variable "social

media hours” was ordinal, rather than interval or ratio, and it also doesn’t require linearity and normality assumptions. Part B involved performing the Chi-Square Test of Independence test.

Table 4.6: Chi-Square Test

Referral Channel	Non-Repeat (0–1 loan) Repeat Borrower (2+ loans)
Peer Referred (n=16)	13(81.2%) 3 (18.8%)
Other Channel (n=34)	23(67.6%) 11 (32.4%)
Chi-Square (χ^2)	0.438
Degrees of Freedom	1
p-value	0.508
Decision	H3 Part B Not Supported at $p < 0.05$

Our square test result was 0.508, which means H3 Part B is not significant. We were surprised to find that people who found the app through ads or searches borrowed money often (32.4%) than those who got it from friends (18.8%).

One possible reason for this difference is the persons goal. For example if someone searched for a loan app they probably wanted to borrow money. On the hand if a friend recommended the app the person might not have had a specific goal, in mind. This is a finding that we should look into further. The source of information and the persons goal are both factors to consider.

4.6 Demographic Analysis - Debt Vulnerability by Sub-group (RO4)

Research Objective 4 explores if vulnerability to debt traps is a "one size fits all" concern or if specific youth borrowers are vulnerable compared to others. The main criterion for measuring vulnerability was missed repayments, which were compared against different types of jobs and different income levels.

4.6.1 Occupational Status and Repayment Difficulty

For those with no income, five out of the sixteen participants (31.3%) had failed to repay. Salaried employees came second, recording twenty percent non-repayment of loans (three out of fifteen). Students who worked part-time had the lowest non-repayment rate; only one individual (7.7%) had skipped paying back their debts. However, the high percentage of non-repayment among self-employed and gig workers (33.3%) might be misleading since the sample size was only six individuals.

These results indicate that students with no source of income are the most susceptible groups of debtors. Unable to cushion themselves against unforeseen expenses, they borrow money to meet basic needs that their employed counterparts can finance

through salaries. Additionally, a part-time job seems sufficient to create repayment capability for students, putting them ahead of those with no income.

Table 4.7: Repayment Difficulty by Occupational Status

Occupational Status	n Missed Repayment Rate (%)
Student (no income)	16 5 31.3%
Salaried / full-time employed	15 3 20.0%
Student with part-time income	13 1 7.7%
Self-employed / gig worker	6 2 33.3%
Total	50 11 22.0%

4.6.2 Income and Repayment Difficulty

This section of the study is exactly as expected. 33.3% of people earning below Rs. 15,000 did not repay, which is the highest percentage of any group. There tends to be a reduction in the difficulty of repaying with higher income levels, the lowest being 12.5% for people earning more than Rs. 40,000 and 17.6% for the Rs. 15,001-30,000 income bracket.

There exists a direct correlation between income and repayment difficulties. Although it was expected that this would happen, the conclusion is significant because it shows that Chapter 5's policies should recognize the importance of income when helping young borrowers. The success of these policies or education will only be achieved if the focus is on the lower income brackets.

Table 4.8: Repayment Difficulty by Income Bracket

Monthly Income / Allowance	n Missed Repayment Rate (%)
Below Rs. 15,000	15 5 33.3%
Rs. 15,001 – Rs. 30,000	17 3 17.6%
Rs. 30,001 – Rs. 40,000	10 2 20.0%
Above Rs. 40,000	8 1 12.5%
Total	50 11 22.0%

4.7 Scenario-Based Question Analysis

Four different scenarios helped understand the way people operate regarding loans in their everyday life; the results obtained were more authentic as opposed to answers given in the questionnaires. First, when respondents were asked whether they might take bigger sums than initially intended due to automatic filling of fields by apps, 30% answered that they might indeed fall victim to such manipulation. It was also discovered that around 40% of loaners admitted not calculating the cost of taking money and simply guessing the sum required to pay back on the go. Finally, when discussing the way of managing several debts at once, 20% of those surveyed declared

their readiness to use another application for obtaining money even though they had some other loans active. All these facts suggest that apps' design and behavior patterns as well as absence of calculations prior to loans can contribute to the development of a debt trap.

4.8 Summary of Findings

Four insights emerged from my analysis that provided me with a good understanding of the relationship between youth and fintech debt. Firstly, although the results of my analysis were not entirely convincing due to the limited data, one thing that became evident was that consumers who did not understand their interest rates were about twice as likely to make late payments. It would seem that financial ignorance has serious consequences. Secondly, my analysis demonstrated that the app's design has the greatest influence on debt. Users who are easily influenced by features such as "one-click" approval borrow much more frequently.

It is important to note that although individuals perceive borrowing as "normal" in their social groups, an increase in social media usage does not necessarily result in more borrowing behavior. Therefore, social influence appears to have more of an underlying effect on financial borrowing behavior rather than triggering more borrowing behavior. Lastly, it is important to note that debt does not affect all individuals equally. Individuals without income and those who earn less than Rs. 15,000 are most affected by borrowing debt from various social media platforms. It means that any intervention should target the high-risk individuals rather than all young people aged between 18 and 30 years old.

H	Description	Test Used	Statistic	Decision
H1	Financial Literacy → Debt Vulnerability	Chi-Square	$\chi^2=3.28$ $p=0.350$	Not Supported
H2	Platform Design → Repeat Borrowing	Mann-Whitney U	$U=427$ $p=0.005 \checkmark$	SUPPORTED
H3a	Social media → Peer Influence	Spearman Corr.	$\rho=-0.171$ $p=0.241$	Not Supported
H3b	Peer Referral → Repeat Borrowing	Chi-Square	$\chi^2=0.438$ $p=0.508$	Not Supported

CONCLUSION

5.1 Overview of the Study

This study was conducted with the purpose of determining the reason behind high vulnerability to debt traps of young loan consumers via fintech apps from the Delhi-NCR area. The four core objectives of the paper were assessing the effect of financial literacy, understanding how app design influences users, analyzing the impact of peer pressure, and specifying the most vulnerable subgroups from the age range of 18-30. To conduct this research with fifty participants and three tests, certain research gaps had been defined.

Based on the analysis, the study managed to produce one significant finding, a clear directional trend, and an unexpected discovery. Overall, this combination of results reflects the truth about the vulnerabilities of young Indian loan borrowers through fintech apps without resorting to only the success statistics.

5.2 Key Findings

It is possible to state that the most important outcome of the study is associated with the crucial role of app features on the borrowing frequency among teenagers. The participants whose behavior was influenced by such features as pre-calculated loan amount and push notifications borrowed 1.48 times per month while those who were not significantly affected by the mentioned factors borrowed only 0.62 times per month. Hence, the relationship is statistically significant with $p=0.005$ meaning that such an application cannot be regarded as merely a neutral technology.

Even though the relationship between personal financial literacy and debt turned out not to be statistically significant, the pattern could hardly be overlooked. Namely, participants who lacked knowledge about their interest rates failed to make timely repayments at a rather high rate – 33.3% of people versus 18.8% of people among the latter group. It appears that such a high discrepancy might have been caused by the insufficient sample size.

Regarding the issue of social media and peer pressure, the direct tests do not reveal any correlation between social media usage and borrowing; however, the survey results indicate that the majority of the respondents perceive borrowing these amounts of money as entirely "normal" amongst their peers. The evidence presented above indicates that social media and peer pressure influence the perception of debt as a practice, making it acceptable.

Lastly, the demographic analysis reveals the uneven effect of debt traps on various groups of borrowers. For instance, the survey found learners with zero income or incomes of Rs. 15,000 or less fail to pay back their loans. Such an observation proves critical when addressing the problem because the proposed intervention measures should target high-risk, low-income individuals.

5.3

Recommendations

Pre-Lending Disclosure: Every mobile application should be compelled to display one non-skippable page prior to finalizing the loan. All details of the loan repayment cost in rupees, the APR, associated fees, and the penalty per missed installment must be displayed. The technology is already available; the need is only for regulatory action.

Financial Education at Undergraduate Level: A course module should be introduced at the college level, educating students on how to compute the actual cost of borrowing. Emphasis should be placed on practical applications, such as converting monthly to annual rates, especially in areas with high prevalence of student loans, such as the Delhi-NCR region.

RBI Regulatory Enforcement: The 2022 RBI guidelines for digital lending are well-written; however, their implementation remains erratic. Regulators can put an end to predatory practices by publishing instances of non-compliance and enforcing fines.

5.4 Limitations of the Study

While the above conclusions offer a definite idea of the borrowing environment, there are a few drawbacks that must be mentioned. The first one is the small sample size of only 50 people, which decreases the strength of the statistics used to confirm our trends. The second drawback is related to the type of sampling used, namely convenience sampling, which means that the outcomes favor educated users living in the urban environment. Lastly, due to the nature of self-reporting, it is possible that some respondents could have had difficulties recalling specific amounts or were a little reserved when answering questions regarding payment delays or debts.

5.5 Directions for Future Research

There are three obvious areas for future research stemming from this study. A replication study using at least 150 respondents will be able to provide the requisite statistical power to confirm all three hypotheses, especially H1. A longitudinal study would show the development of the debt trap phenomenon over time and can only be seen via longitudinal data, not cross-sectional data. A comparative study in other cities within India will allow the researcher to see what part of the phenomenon is unique to Delhi-NCR and what might be seen nationally in India.

5.6 Closing Remarks

Teenagers who use fintech apps are not acting foolishly; rather, they are functioning in an ecosystem in which having has become cheap while the true cost of debt has been masked. This is the major result of this study article, which indicates that users' sensitivity to fintech application design is the most important predictor of continuous loan. Solving the problem does not require restricting poor individuals of credit possibilities. On the other hand, it includes holding fintech app developers liable for clear disclosure of financing charges as well as the execution of relevant legislation designed to safeguard customers. Neither task is technically complicated; ultimately, it all boils down to priorities.

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ANNEXURE



Debt Traps in Unsecured Fintech Lending Among Young Borrowers in India

This survey is part of a **Major Research Project (MRP)** for the MBA program at **Delhi Technological University (DTU)**.

Purpose: The objective of this study is to analyze how the rapid proliferation of instant credit apps (such as Slice, Ring, CRED, etc.) impacts the monthly saving habits and spending patterns of digital consumers.

Confidentiality: All responses will be used solely for academic research purposes. No personal financial data or identifiers will be shared. Your honest participation is vital to understanding the evolving digital debt landscape in India.

Estimated Time: 5–7 minutes.

Researcher: S M Mozammil

Full Name

Your answer _____

Age Group *

- 18-22
- 23-27
- 28-30

What is your gender? *

- Male
- Female
- Prefer not to say

What is your current status? *

- Student (no income)
 - Student with part-time income
 - Salaried / full-time employed
 - Self-employed / freelancer / gig worker
-

What is your monthly income or allowance? *

- Below Rs. 15,000
- Rs. 15,001 – Rs. 30,000
- Rs. 30,001 – Rs. 40,000
- Above Rs. 40,000

What is your current status? *

- Student (no income)
 - Student with part-time income
 - Salaried / full-time employed
 - Self-employed / freelancer / gig worker
-

What is your monthly income or allowance? *

- Below Rs. 15,000
- Rs. 15,001 – Rs. 30,000
- Rs. 30,001 – Rs. 40,000
- Above Rs. 40,000

How many hours do you spend on social media per day? (Instagram, YouTube, Snapchat, etc.)

- Less than 1 hour
 - 1 – 2 hours
 - 2 - 4 hours
 - More than 4 hours
-

How many fintech loans have you taken in the past 12 months? *

- 0
- 1 (first time)
- 2 – 3 loans
- 4 or more loans

What was the main reason for your most recent fintech loan? *

- Daily expenses or bills
 - Lifestyle - gadget, travel, dining, or clothing
 - To repay another existing loan
 - No specific reason - I borrowed without planning
 - Not taken any loan
-

Did you know the annual interest rate (APR) of your loan before accepting it? *

- Yes, I knew the annual rate
- I only saw the monthly rate, not the yearly cost
- I did not check before accepting
- The lender did not clearly disclose the annual rate to me

Have you ever missed a repayment or been charged a penalty on a fintech loan? *

- Yes - once
 - Yes - more than once
 - No, I always paid on time
 - I have never taken a fintech loan
-

	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
I always check the total repayment amount including all fees before accepting a loan.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I understand the difference between a monthly interest rate and an annual interest rate (APR).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I know what penalty I will be charged if I miss a repayment on my fintech	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

When the app shows a pre-filled loan amount, I usually borrow that amount without reducing it.

I have taken a loan after receiving a push notification, even though I had not planned to borrow.

Countdown timers or 'limited offer' messages on loan apps make me want to borrow

I have taken a fintech loan to buy something I wanted after seeing similar content on social media.

I feel comfortable using a fintech loan app because friends or family I trust also use it.

Among people my age, borrowing from fintech apps is completely normal and widely accepted.

A fintech app approves you for Rs. 20,000 at '2% per month.' You only need Rs. 10,000. The app pre-fills Rs. 20,000. What do you do?

- Borrow Rs. 20,000 - it is already approved
- Reduce it to Rs. 10,000 - I take only what I need
- Take something in between like Rs. 15,000
- Close the app and reconsider

Before taking your last fintech loan, did you calculate the total amount you would have to repay (including all fees)?

- Yes - I calculated it completely
- I checked roughly but not in detail
- No - I accepted without calculating
- I have never taken a loan like this.

How did you first start using your fintech lending app? *

- A friend or family member recommended it
- I saw it on social media or an ad
- I searched for it myself when I needed money
- I got a notification from a payments app I already used

You already have one active fintech loan. A friend tells you about another app with a better rate. What do you do?

- Sign up and take a loan from the new app too
- Check it carefully but probably wait until the first loan is repaid
- Ignore it - I avoid having two loans at the same time
- Ask my friend more details before deciding

In one sentence, what is the biggest advice you would give to someone who is just starting to use apps like Slice or Cred?

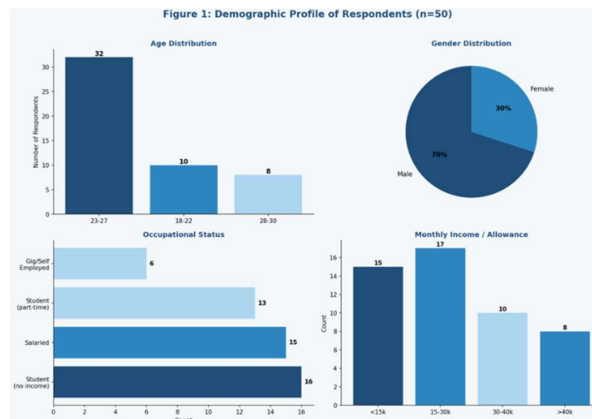


Figure1

Figure 2

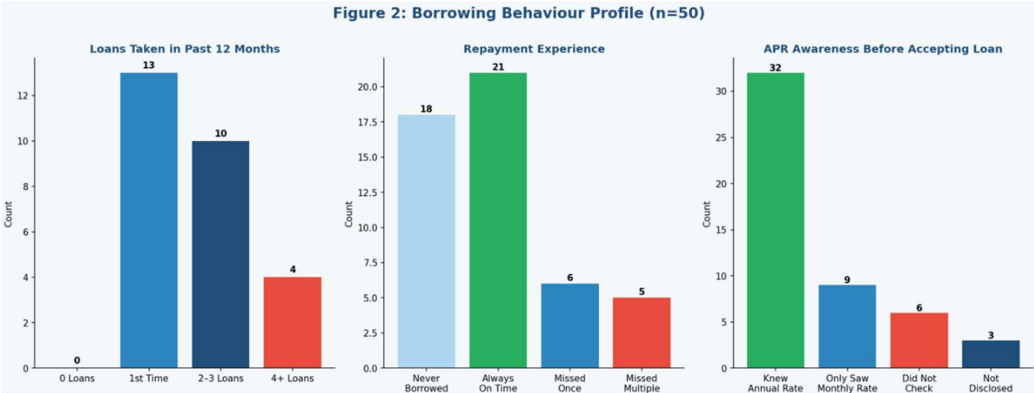


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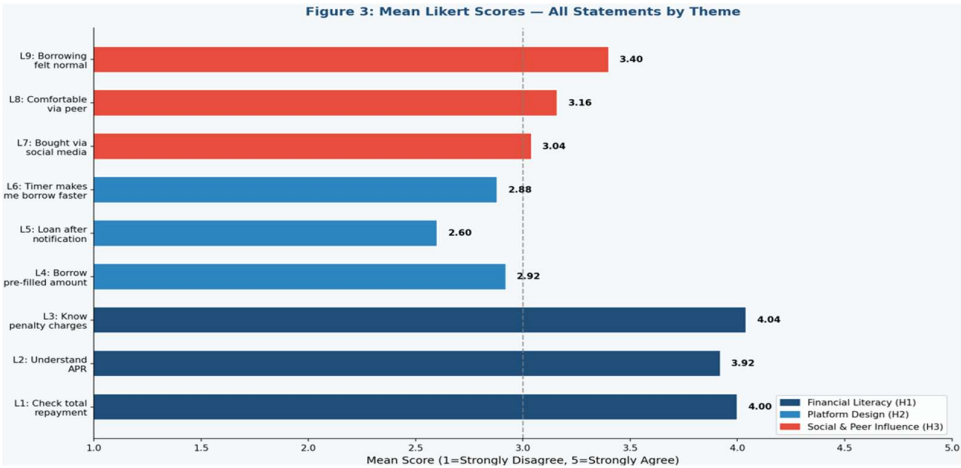


Figure 4

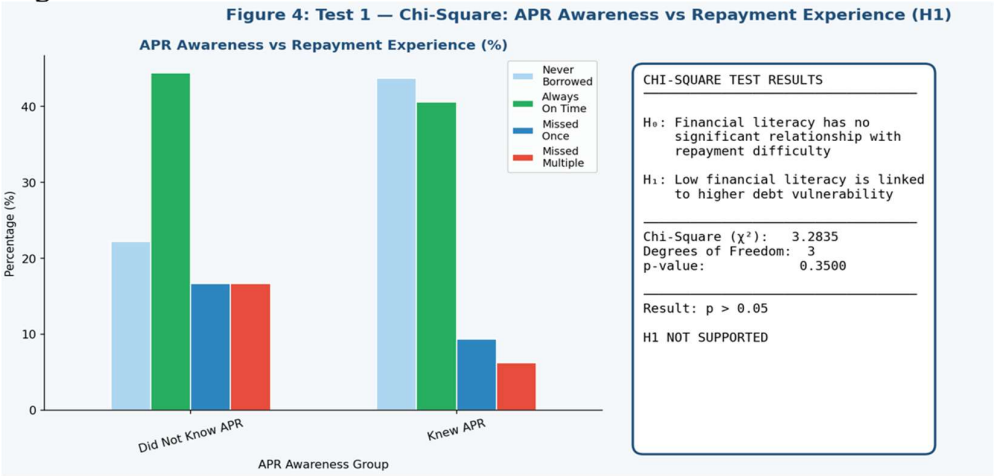


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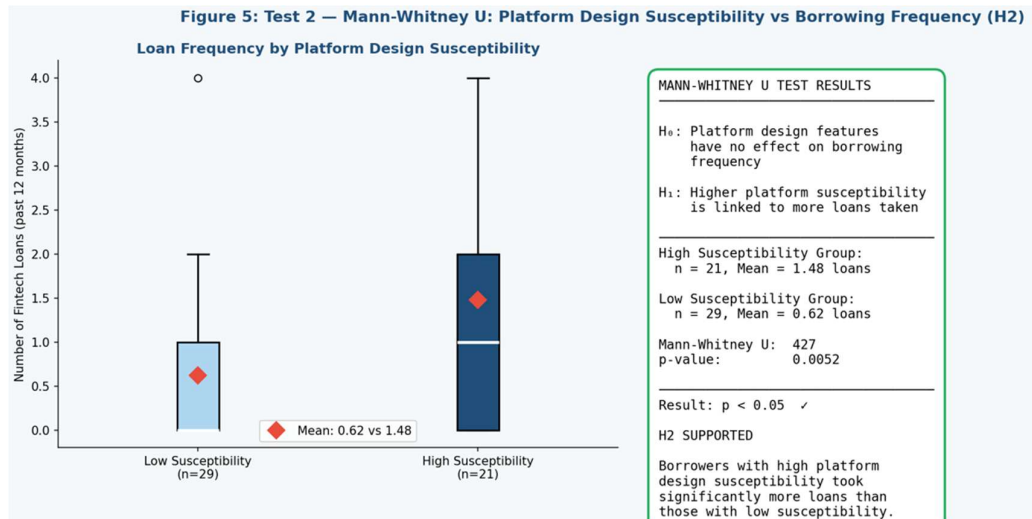


Figure 6

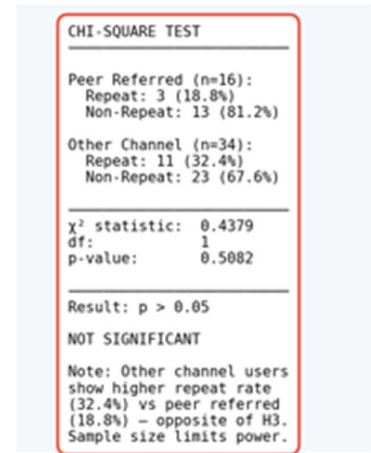
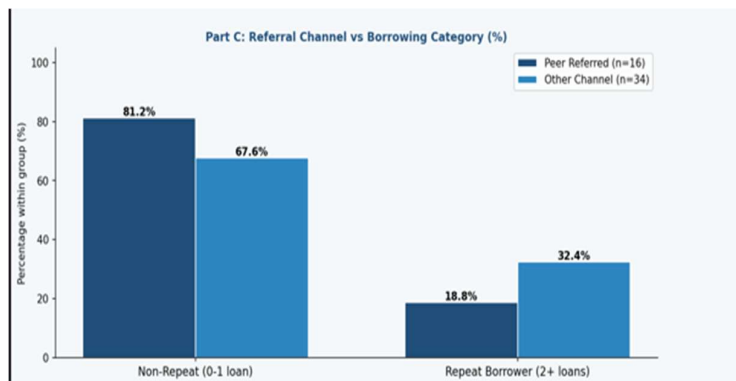
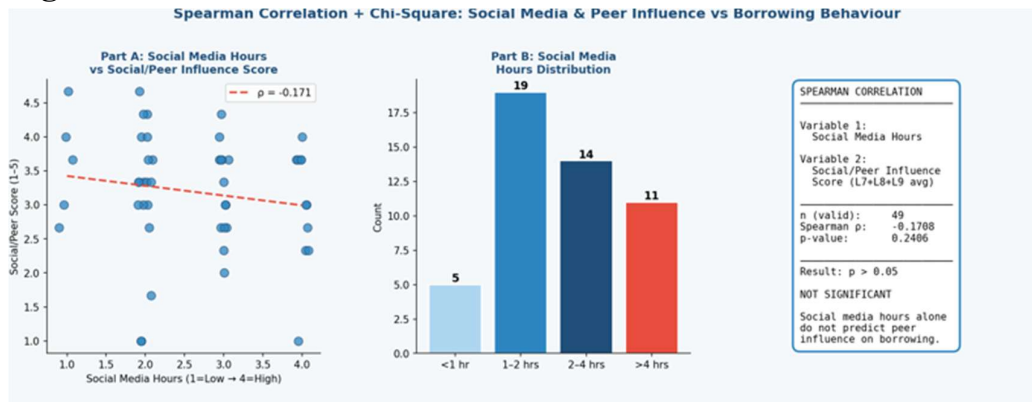


Figure 7

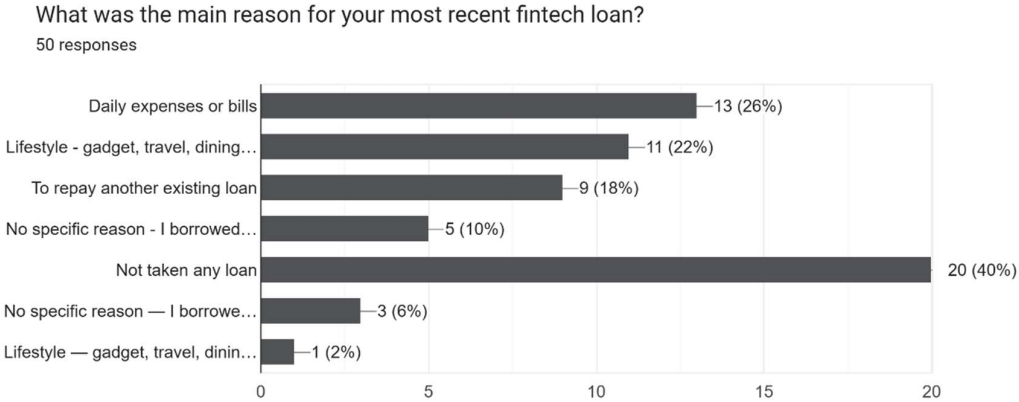


Figure 8

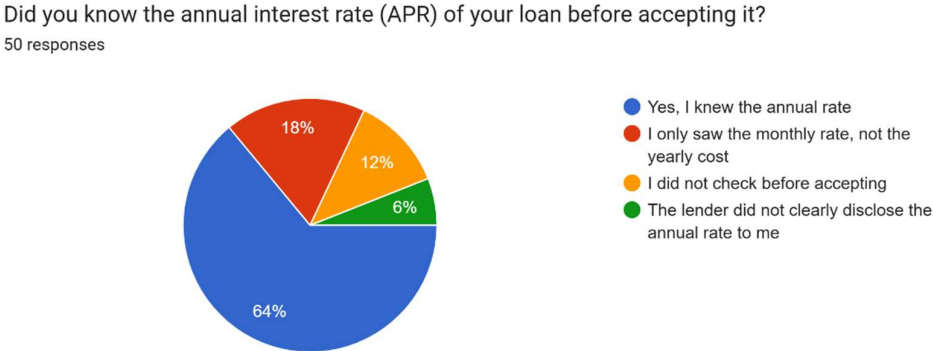


Figure 9



Figure 10

"Please rate your agreement with the following statements regarding your habits when taking out a fintech loan."

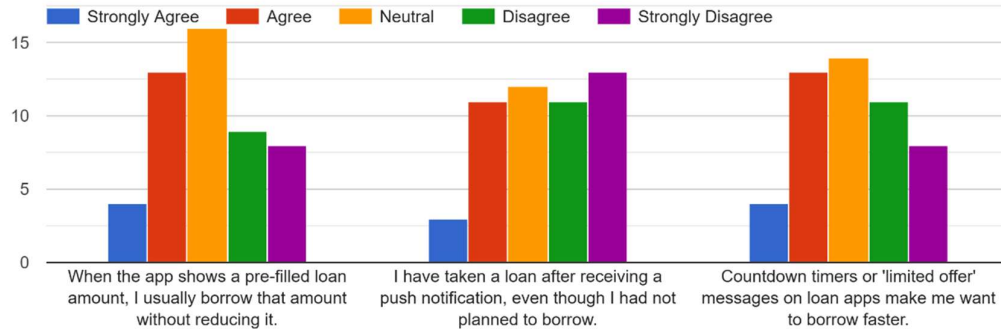


Figure 11

"Please rate your agreement with the following statements regarding your habits when taking out a fintech loan."

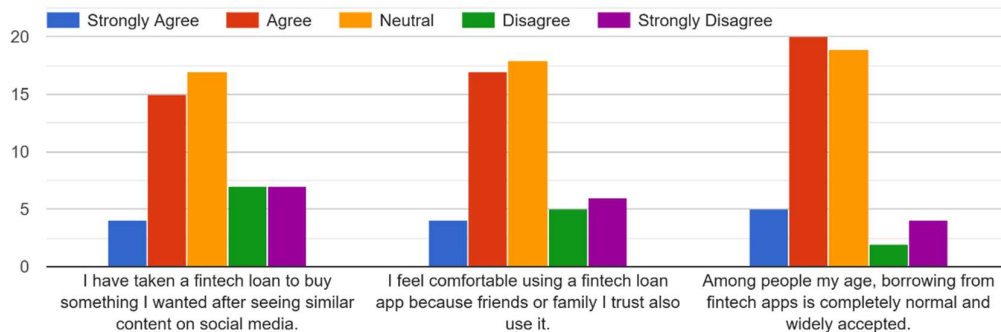


Figure 12

A fintech app approves you for Rs. 20,000 at '2% per month.' You only need Rs. 10,000. The app pre-fills Rs. 20,000. What do you do?

50 responses

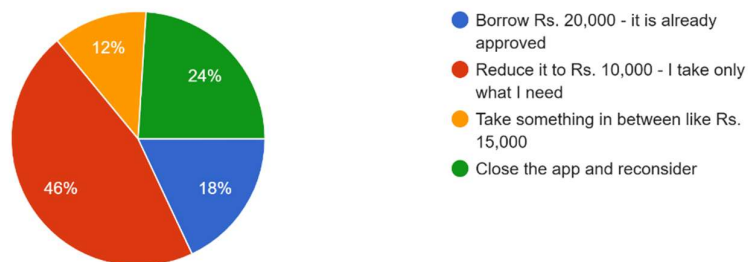


Figure 13

Before taking your last fintech loan, did you calculate the total amount you would have to repay (including all fees)?
50 responses

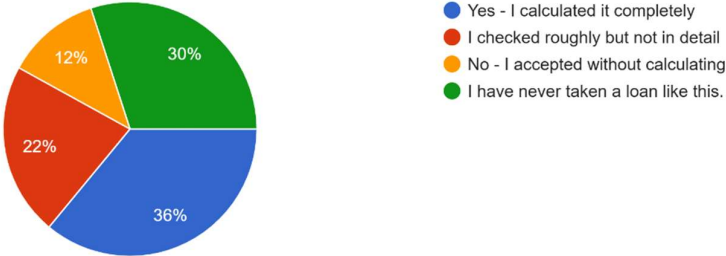


Figure 14

How did you first start using your fintech lending app?
50 responses

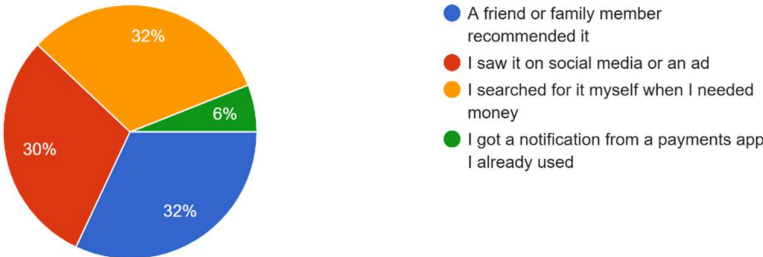


Figure 15

You already have one active fintech loan. A friend tells you about another app with a better rate. What do you do?
50 responses



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