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BUSINESS PROJECT

FinTech Innovations' Effect on UK's Conventional Residential Mortgage Lending

SRN - 0372540

MSC. BUSINESS ANALYTICS | The University of Law – Business School

Acknowledgment

I would like to express my sincere gratitude to all those who have supported me in completing this business project on the impact of FinTech innovations on the UK's conventional residential mortgage lending. First and foremost, I would like to thank my business project guide, **Karen Aldridge**. Her guidance, support, and feedback have been invaluable throughout this process. I am grateful for her patience, encouragement, and willingness to share her expertise. I would also like to thank the team at Kaggle for providing the secondary data that was essential for this project. Their platform has been a valuable resource for researchers and students alike.

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Abstract

The FinTech innovations research focuses on how Fintech innovations influence the traditional UK residential mortgage lending market. Using quantitative methods, it studies the effect of digital technologies – from AI and to blockchain – on mortgage processes, efficiency and the level of (digital) consumer accessibility. All analyses are carried out based on the 'UK Mortgage Rates' dataset from Kaggle by employing logistic regression, ARIMA models and chi square tests to assess the connection between FinTech and how lending is handled. We find that logistic regression can provide a 95% accuracy rate on mortgage approval prediction, showing how FinTech platforms enable streamlining of processes and being more inclusive for underserved populations like freelancers and first-time buyers. ARIMA model predicts larger share of mortgage platforms will adopt digital mortgage platforms in the future, and as more FinTech market share, potentially driving down mortgage interest rates with increased competition. Additional validation of the importance the FinTech has in the reduction of loan approval times and enhanced access to loan comes in the chi-square test. The study also indicates that these innovations present regulatory and compliance issues, especially in the areas of AML, data privacy and cybersecurity risks. The research concludes that even though FinTech has rejuvenated the mortgage lending industry by improving efficiency and facilitating broader participation, there may come certain risks associated with technological dependence and regulation. These findings give important guidance for regulatory and financial institutions who should adopt balanced regulatory frameworks so growth in the mortgage sector can be sustainable.

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Chapter 1: Introduction

1.1 Research Background

The FinTech sector has developed extremely fast and transformed the landscape of mortgage lending that has long been a cornerstone of the UK's financial services economy. Over the past ten years, those digital platforms, big data analytics, AI, and blockchain have transformed mortgage processing, accessing, and managing in ways that could hardly have been imagined before. The UK mortgage industry is increasingly seeing massive changes in the origination, underwriting, and approvals of loans due to the continued simplification of processes. The FinTech's make this possible by automating this with modern digital tools (Chemmanur *et al.* 2020). The cause for this change is demand for efficiency, faster processing times, and better risk management.

Figure 1.1.1: Changing the Mortgage Industry

(Source: Floify.com, 2023)

The ease of FinTech's interfaces and accessible lending products means that customers, in particular young ones, are now able to acquire mortgages through the Internet. The residential mortgage lending market in the UK has been influenced (Najaf *et al.* 2022). These new FinTech products and innovations where some level of discontinuity with the old is taking place as the technology shapes the future of mortgages. New technologies like digital platforms and AI-driven procedures shift mortgage lending models and disrupt traditional lenders.

1.2 Research Aim and Objectives

Aim

The general objective of this research is to establish the influence of FinTech inventions on the traditional residential mortgage lending market in the UK.

Objectives

- To analyse the efficiency gain of mortgage lending resulting from FinTech innovations.
- To inclusivity in the accessibility of FinTech-driven mortgage services for diversified consumer populations
- To review the risk management practice policies initiated by FinTech platforms

- To identify the emerging regulatory risks born from innovations in the UK mortgage market following the impact of FinTech-driven changes.

1.3 Research Questions

1. What has made the mortgage lending business process in the UK most efficient?
2. How has FinTech changed access to mortgage services for various consumer demographics?
3. How have traditional lenders revisited their risk management approaches to respond to the market impact of FinTech?
4. What are the regulatory challenges created by the growing FinTech phenomenon in the UK mortgage market?

1.4 Research Significance

The relevance of this research is that it attempts to address the point of contact between FinTech and mortgage lending in the UK. This becomes particularly important as innovations in the FinTech space continue to evolve. It means understanding the impact of these innovations on the mortgage space in such a manner that can be appreciated by financial institutions, regulators, and consumers (Hua and Huang, 2021). Fast-tracking of digital technology shifted the competition landscape for financial institutions. Moreover, the pressure to adapt rapidly in business models would challenge the traditional banks and building societies significantly to remain relevant in the game.

FinTech brings new challenges to regulators: it presents a requirement for consumer protection, data privacy, and cybersecurity while promoting innovation. Consumers have the benefits of high efficiency, transparency, and accessibility of FinTech-driven mortgage services but are also exposed to numerous risks related to security and reliability (Allen *et al.* 2021). This study is to provide an analysis of these issues, offering insights to guide policymakers, industry stakeholders, and consumers toward adequate decisions when navigating the future of mortgage lending.

1.5 Research Rationale

The rationale for this research is found in the growing role FinTech technologies are assuming in changing the traditional pattern of delivering financial services, including mortgage lending. Despite a volume of literature detailing the impact FinTech innovations are assumed to have on financial services in broad terms. It is made to assess their impact, particularly on the UK's residential mortgage sector. The traditional mortgage processes are slow and cumbersome, full of paperwork; FinTech can significantly streamline these processes, bringing loan approvals faster and more specific mortgage products (Williams, 2021). However, this shift raises concerns as to whether such conventional lenders survive, whether proper regulatory frameworks are available, and eventually, what happens to consumer behaviour in the long term. The study is focused on the dynamics to further a better understanding of how mortgage lending is being reconfigured through FinTech innovations, providing useful insights into both academia and practitioners.

1.6 Current Issues

A variety of factors are currently defining how FinTech interacts with traditional mortgage lending in the UK. For one, rising digital engagement has meant that competition increased between FinTech companies and traditional lenders. FinTech-based lending platforms provide faster, more seamless mortgage applications. Furthermore, these new sites create challenges for banks as well as other lenders in terms of participating in the market. Many high-street banks and building societies have responded by either seeking to align themselves with FinTech organizations or establishing their digital channels (Ofir and Sadeh, 2020). The costs of all this investment and innovation are, however, substantial. FinTech innovations are adopted so fast that there are concerns over compliance, data privacy, and cyber security. More pressure on regulatory bodies to hold these new service-providing platforms up to the same level as traditional lenders to protect the consumer. It drives innovation, researches these matters, and the challenges and opportunities these bring to the mortgage industry.

1.7 Research Structure

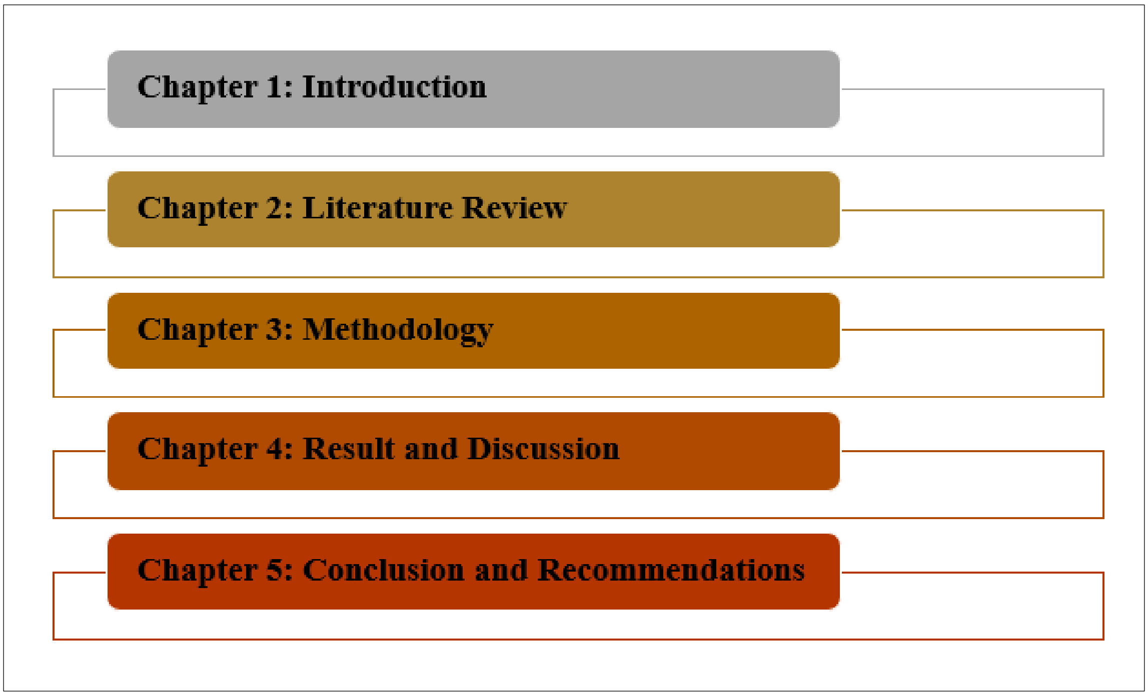

Figure 1.7.1: Dissertation Structure

The figure "Dissertation Structure" describes, on one page, the main chapters of the dissertation. The figure is hierarchically structured, therefore graphically showing five essential chapters in a flowing sequence:

- **Chapter 1: Introduction,** the real foundation of the dissertation presentation of the research background, objectives, aims, and questions.
- **Chapter 2: Literature Review,** a review of literature related to the issue formed around the cornerstone of the dissertation that makes clear gaps and constructs the theoretical framework.
- **Chapter 3: Methodology** outlines the methodology applied to carry out research together with strategies for data collection and analysis.
- **Chapter 4: Result and Discussion,** the outcome of the study together with a critical analysis of data from the research questions.
- **Chapter 5: Conclusion and Recommendations,** summarizes the key findings, discusses the implications of the study, as well as gives suggestions for future research or practice.

Chapter 2: Literature Review

2.1 Overview of the UK Mortgage Lending Industry

The UK mortgage lending business is one of the most prominent and vital parts of the country's financial system and significantly adds to the economy with its role in promoting homeownership. It is predominantly influenced by traditional financial institutions like banks, building societies, and other lending organizations. As of 2023, the UK mortgage market has an estimate of around £1.6 trillion, effectively demonstrating its scale and significance to the financial system at large (Bank of England, 2023). Many are high street banks: Barclays, HSBC, and Lloyds. Building societies, mainly Nationwide and Yorkshire, also offer mortgages from fixed-rate to variable-rate and interest-only loans designed to accommodate different customer groups from first-time buyers to property investors. However, despite being huge and significant, the traditional mortgage market has for a long time been bedevilled by inefficiencies that create a large gap in the chasm for fintech to fill (Cuadros-Solas et al., 2024). Conventional mortgage lending under UK law is generally cumbersome and slower as it involves a t number of steps from application, through evaluation to approval. This has often begun with an in-person application or a consultation with a mortgage broker.

Figure 2.1.1: Overview of the UK Mortgage Lending Industry

(Source: ukfinance.org.uk, 2024)

The current mortgage process depends on old technology, manual methods, and customers being available. This often leads to delays, misunderstandings, and confusion among all parties. It usually takes 30 - 45 days to finish the whole borrowing process for a house. According to ukfinance.org.uk (2024), UK housing infrastructure relies on mortgages, as only 36% of homes are owned outright. However, the mortgage application process is lengthy, complicated, and error prone. 89% of customers say loan applications are as stressful as homebuying. New technology and capabilities allow lenders to improve customer home-buying experiences while increasing efficiency and control.

The manual and outdated processes mostly lead to a long waiting time for approvals, which can be up to weeks or even months, before the application is fully processed. Furthermore, the conditions on which applicants are eligible and must present documents for traditional lenders are so stringent that people with complex or non-traditional financial histories-for example, freelancers, entrepreneurs, or people with poor credit histories-are sometimes disqualified. Other inefficiencies arise for it is much more time-consuming in paper-based systems and through a long chain of middlemen, which comprises brokers, valuers, and legal counsellors (Jarvis and Han, 2021). High operating costs, which arise in part from labour and brick-and-mortar office space, are then passed onto the borrowing public in the form of heightened interest rates and fees. The conventional mortgage process has been subject to substantial critique due to its complexity and lack of transparency. The complex steps involved in getting a mortgage often put off many potential first-time homebuyers, stopping them from entering the property market. Research by Acolin et al. (2016) shows that these hurdles, along with strict lending rules, make it especially hard for younger people and minority groups to buy homes.

Conventional mortgage lenders frequently find it difficult to modify their strict evaluation procedures, which makes it difficult to approve applicants with unconventional but reliable sources of income. This rigidity ignores the shifting composition of income (i.e. Income from Social Media Platform, Artists etc.) in the contemporary economy in addition to shutting out a sizable segment of prospective homeowners. This gap in the market has given fintech lenders, who are better at assessing alternative income streams and credit profiles, opportunities, as demonstrated by Buchak et al. (2018).

The high administration costs, lack of personalization in services, and the time-consuming process for application make the borrowers dissatisfied too. After all, inefficiencies in the traditional lending model and more discerning consumer tastes seeking faster, more transparent, and more accessible services create the perfect UK mortgage market for disruption from fintech. The advances in AI, big data analytics, and digital platforms offer opportunities for fintech firms to fill in some of the gaps in the conventional mortgage process (Bavoso, 2020). There have also come to be digital mortgage platforms as well as fintech lenders that offer fully automated mortgage applications, real-time credit assessments, and instant approvals.

2.2 Fintech Innovations in Mortgage Lending

Key Technological Innovations

Through automated, data-driven processes that bring about better efficiency, reduced costs, and improved customer satisfaction, advances in fintech have significantly transformed the UK mortgage lending industry. Among such innovations is the application of artificial intelligence (AI) and machine learning (ML) in credit scoring and risk assessment. These technologies help banks capture voluminous financial data from a multitude of sources to make better judgments about a customer's creditworthiness. Alternative data like transaction histories, spending behaviour, and employment patterns evaluated by models driven with AI provide the risk profile much more enhanced than the traditional method so that precision in mortgage underwriting decisions improves. These models are continuously refined by improving machine learning algorithms. Hence, it guarantees more robust and adaptive risk assessment processes based on the changes in market conditions.

Blockchain technology represents a revolutionary innovation in the mortgage industry, offering unprecedented levels of security and transparency in transactions. This cutting-edge technology has the potential to transform the entire mortgage process, from application to closure, by creating an immutable and easily auditable record of all transactions. According to Guo and Liang (2016), blockchain implementation in mortgage lending can significantly reduce fraud, streamline processes, and enhance trust among all parties involved in the mortgage ecosystem.

Role of Digital Mortgage Platforms

The rise of fully digital mortgage platforms marks a watershed moment for the UK mortgage industry. Such platforms, in the shape of fintech companies like Habito and Trussle, further simplify the process of searching for a mortgage by offering end-to-end digital applications. All the steps that come as part of a mortgage application - document submission, credit checks, affordability assessments, and underwriting are automated on such platforms using AI, machine learning, and Open Banking technologies. Digital mortgage solutions promise an effortless online user experience. This allows a potential borrower to start an application, check in real-time about the status of the application, and receive mortgage products customized to their needs (Bavoso, 2022). AI data analytics further ensures that these applications provide instant pre-approvals, without the lengthy wait period associated with manual submissions.

Case Studies or Examples

Some FinTech's came up with a successful disruption to the UK mortgage market by creating new digital mortgage products. Habito is a digital mortgage broker, using AI in its system, it has streamlined the mortgage application process. Borrowers can apply for a mortgage online on the platform and shall be provided with product recommendations according to their financial conditions. Then there are digital mortgage brokers like Trussle, which through automation and machine learning, automate mortgage applications. The web platform integrates Open Banking APIs to collect financial data in real time and then make faster and more accurate assessments about a borrower's eligibility for certain types of mortgage products (Imerman and Fabozzi, 2020). The company has reduced the average time required for securing a mortgage offer by streamlining affordability checks and document verification through automation.

2.3 Impact of Fintech on Traditional Lenders

Operational Changes in Traditional Lenders

Traditional mortgage lenders have been under tremendous pressure of having to adopt FinTech solutions if it is to remain competitive in an industry undergoing fast digital transformation. More of the shift has been in automation underwriting processes. Conventional lenders increasingly implement AI-driven automated underwriting systems that ascertain the creditworthiness of borrowers much faster and with fewer errors. Such systems also minimize human intervention and errors leading to seamless decision-making processes. As Jagtiani and Lemieux (2019) demonstrate, this involves a much more complex assessment of risks evaluated through machine learning algorithms, with the ability to analyse large datasets using not only traditional credit metrics but also spending behaviour, social media activity, and even psychometric testing. This data-driven approach increases the lender's ability to make better lending decisions, especially for borrowers with complex or thin credit files.

Strategic Partnerships and Acquisitions

Traditional lenders have become serious contenders in wishing to collaborate with or acquire fintech firms to bring more technological capability to their business. Rather than developing proprietary fintech solutions for themselves, most conventional lenders would instead opt to form strategic alliances with fintech start-ups and benefit from the latter's agility and innovation capacity. The partnership would enable lenders to access technologies such as open banking platforms and blockchain-based systems with much less cost and lengthy development times compared with in-house innovation. UK banks have been partnering with fintech firms to offer instant mortgage approval services. Borrowers get the decision in minutes instead of days. It also teams up with reg tech companies to enable the automation of the compliance process and, as an effect, decrease the time and cost involved in meeting the complex regulations (Gomber et al., 2018).

Impact on Profitability and Market Share

Therefore, the rise in fintech has caused a sharp change in the profitability and share of the market of the conventional mortgage lender. With lower operational costs coupled with much more streamlined digital processes, the fintech company hit the marketplace that competes on price through low interest rates and fewer fees (Branzoli and Supino, 2020). In addition, numerous lending institutions have been pressured to adopt the innovations of fintech to try to reduce the manual procedures that characterize their activities, process loans faster, and cut back-office costs. According to most experts, for instance, automation has enabled traditional lenders to process more voluminous mortgage applications with fewer resources, which means cost savings and higher profitability.

2.4 Consumer Experience in the Era of Fintech

Shift in Consumer Expectations

FinTech innovations have reframed the expectations of consumers in mortgage lending. Convenience, speed, and personalization have set a new trend. As demonstrated by Fuster et al. (2018), time-consuming mortgage application forms and lengthy approval processes are becoming relics of the past, replaced by automated systems. Digital platforms leveraging machine learning algorithms and automated underwriting processes now offer near-instantaneous pre-approvals for mortgage purchases. These systems allow pre-qualified borrowers to progress swiftly through appraisal, significantly reducing loan processing times. Furthermore, personalization, driven by advanced data analytics and AI, enables fintech platforms to offer tailored mortgage products that precisely match individual financial profiles. This shift has created a demand for a highly customized experience, where consumers expect rapid decisions and options that adapt to their unique and changing financial circumstances, in stark contrast to the one-size-fits-all approach often employed by traditional lenders.

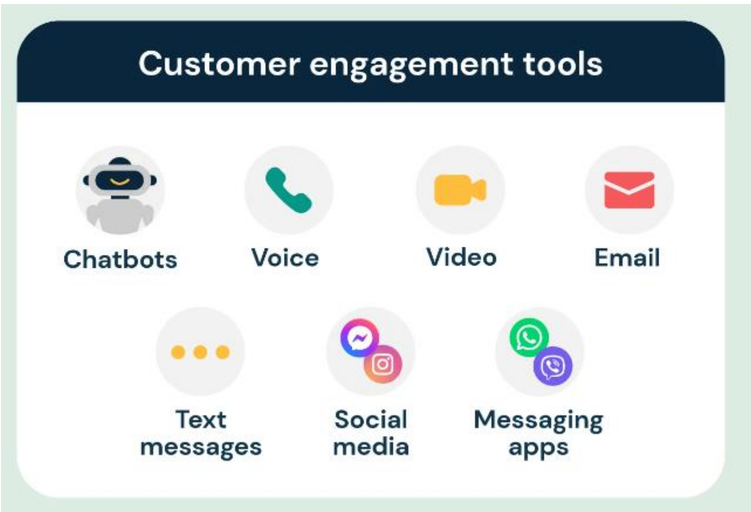

Figure 2.4.1: FinTech Customer Engagement Tools

(Source: Sinch, 2024)

Digital Tools for Customer Engagement

Digital engagement tools have gone from being extras to being necessary parts of the mortgage process. Basten and Ongena (2020) show that mortgage comparison websites, online calculators, Chatbots and other related tools now let customers make decisions on their own with little help from mortgage advisors. With the help of real-time financial data and standard inputs, these digital tools give people more accurate estimates of their monthly payments, interest rates, and loan terms. Interactive features that let you simulate down payments make the amount of money that is needed clear. Comparison websites let users look at mortgage products from different lenders. This creates competition, which helps people make smart decisions. Also, instant pre-approval services have sped up the first steps of getting a mortgage by quickly determining eligibility. This has made the initial stages of getting a mortgage much more efficient.

2.5 Regulatory and Compliance Challenges

The rapid implementation of FinTech innovations within the UK mortgage lending industry has introduced significant regulatory and compliance challenges. As Anagnostopoulos (2018) argues, mortgage lending has traditionally been highly regulated to ensure consumer protection, market stability, and risk mitigation in large-scale financial transactions. FinTech firms, typically operating in decentralized, technology-driven environments, present a unique challenge for regulators.

2.5.1 Regulatory and Uncertainty

The greatest challenge is, undoubtedly, the regulatory gap between conventional financial institutions and FinTech**'**s. As Arner, Barberis and Buckley (2017) highlight, FinTech companies utilize AI, blockchain, and digital platforms to digitize and accelerate mortgage applications, risk assessments, and loan approvals. However, these technologies do not easily align with traditional regulatory frameworks designed for institution-based financial services. This misalignment creates regulatory uncertainty regarding the extent to which FinTech firms should be equated with conventional lenders. Moreover, oversight has been inconsistent. For instance, peer-to-peer (P2P) mortgage lending platforms, which directly connect borrowers with lenders, often operate outside traditional banking regulations, potentially creating risks for consumers and the financial system. Regulatory bodies, such as the UK's Financial Conduct Authority (FCA), are striving to address these challenges by establishing more comprehensive guidelines.

2.5.2 Data Privacy and Security

FinTech businesses use digital platforms, big data analytics, and AI to make mortgage products more personalised and approvals happen faster. **According to** Thakor (2020), these technological advances make things more efficient, but they also raise security concerns about personal and financial data being shared. The General Data Protection Regulation (GDPR) is a set of rules for how to handle privacy issues, get permission from users to use their information, protect data, and make sure everything is safe. Another important issue to think about is cybersecurity, especially since cyberattacks on financial institutions are becoming more common. FinTech companies need to put a lot of money into strong security systems to stop data breaches that could make private data public or make financial markets less stable. Smaller FinTech companies often have trouble following cybersecurity rules because they don't have enough resources. This makes it hard for them to follow the rules set by groups like the National Cyber Security Centre (NCSC).

2.5.3 AML/KYC

In every regard, mortgage FinTech companies are very strictly regulated by AML and KYC requirements, which are explicitly aimed at the prevention of the commission of financial crimes, including money laundering and fraud.

Figure 2.5.3.1: FinTech's of Regulatory Compliance

(Source: deloitte.com, 2017)

The infographic illustrates recent regulatory actions against fintech companies in various areas. The largest fines were levied for securities/trading violations ($96 million), followed by consumer information/consent violations ($77.5 million). Other areas included AML/KYC/BSA, virtual currency, privacy violations, credit/lending-related issues, deposit violations, cybercrimes, and intellectual property. These actions highlight the increasing scrutiny Fintech's face as they grow in prominence and influence the financial landscape.

Traditional lenders have established procedures for verifying customer identities and monitoring transactions for suspicious activity. However, as Buchanan (2022) argues, new FinTech presents significant challenges to AML and KYC compliance. The use of automation in customer onboarding and risk assessment by new FinTech players is especially concerning. Regulators are concerned that the anonymity and speed of digital transactions may allow for undetected illicit activities. As a result, FinTech companies must implement robust AML and KYC processes, leveraging advanced technologies such as AI and machine learning to detect suspicious transactions in real time. While technological advancements can help with compliance efforts, they can also introduce new risks if not properly regulated and managed.

2.5.4 Evolution and Cooperation in Regulation

The regulators in the UK are evolving their approach toward the effective regulation of FinTech firms. The FCA has developed a regulatory sandbox where FinTech firms can test innovative products in a controlled environment before they are launched into the broader market. This allows the regulators to understand the emerging technologies and what potential risks the technologies hold. Consequently, it allows FinTech companies to ensure that their products are fit for regulation.

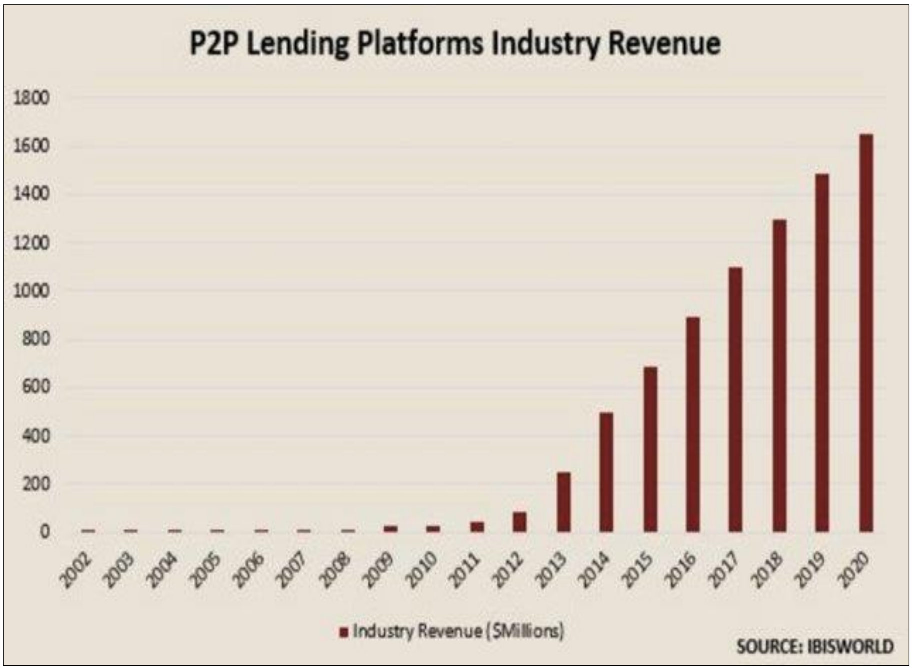

Figure 2.5.4.1: Evolution of Fintech

(Source: Buckley, Arner and Barberis, 2016)

The graph illustrates the growth of the P2P lending platforms industry revenue from 2002 to 2020. The revenue has steadily increased over the years, with a significant spike in 2020. This growth can be attributed to factors such as increased accessibility to financial services, technological advancements, and changing consumer preferences. This steady growth indicates that there is a need for innovation balance with compliance, calling for multifaceted collaboration between FinTech firms, traditional financial institutions, and regulatory bodies. The regulatory framework should therefore be continuously evolving toward catering to the unique risks of FinTech, ensuring protection to consumers, market stability, and financial inclusion.

2.6 Consumer Experience and Expectations in Fintech Mortgage Lending

The introduction of FinTech innovations into the UK mortgage lending market has improved the consumer experience when compared to traditional lenders, particularly in terms of efficiency, ease of access, and transparency. Claessens et al. (2018) observe that modern consumers have begun to demand seamless, digital-first experiences, mirroring the revolutionary changes that have already occurred in other financial sectors such as banking and payment.

2.6.1 Efficiency and Speed

FinTech mortgage platforms have resulted in the most significant efficiency and speed improvements. Traditional mortgage application procedures are associated with extensive paperwork and time-consuming manual processes, which are exacerbated by long approval timelines. As Buchak et al. (2018) show, FinTech platforms use technology to streamline application processes. As a result, customers can get their mortgages processed faster than with traditional lenders. This improvement in the consumer experience not only alleviates frustrations caused by delays and errors in manual processing, but it also aligns with modern consumers' fast-paced needs, providing convenience and speed.

2.6.2 Personalization and Accessibility

Consumers now want a more personalized service that caters to their true circumstances and preferences in matters of finance. FinTech has responded to this increasing expectation by employing big data analytics as well as AI-driven tools to offer customized mortgage products (Nejad, 2022). Big data analytics and AI-driven tools consider a consumer's credit score, income, and spending pattern, amongst other financial considerations before offering such recommended mortgage options for the consumer. The consumer is empowered with additional control over the decision-making process of which mortgage to settle for.

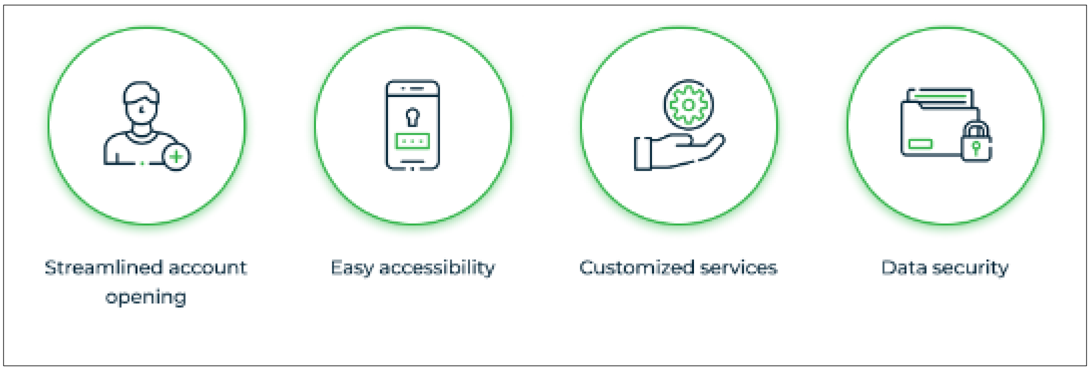

Figure 2.6.2.1: Customer Experience in Digital Banking

(Source: Alexey Shalimov, 2023))

FinTech innovations enhance access to mortgage services, particularly to previously underrepresented or underserved consumer segments such as first-time younger buyers, ad consumers with non-traditional credit histories (Boustani, 2020). Digital platforms provide greater flexibility with lending criteria, hence increasing accessibility for a broader customer base with diverse financial profiles than the ones that are averse to their services earlier.

2.6.3 Transparency and User Experience

FinTech mortgage platforms are touting transparency to guide consumers in making informed decisions when it comes to comparing mortgage rates, fees, and other terms from disparate lenders. This new standard should be expected, and as such, confusion is sometimes associated with traditional mortgage offerings and is therefore less likely.

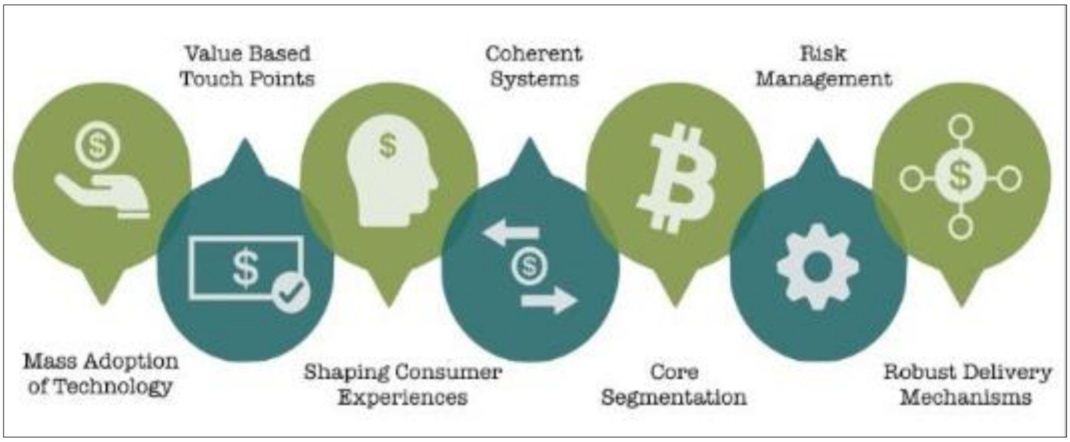

Figure 2.6.3.1: Consumer Expectations and Fintech

(Source: Linkedin.com, 2024)

Consumers like the idea of gaining all the relevant information in an online, user-friendly environment to make a better basis for informed decisions, leading to increased trust and overall satisfaction (Brown and Piroska, 2022). More than that, more user-friendly interfaces that these platforms usually come with and often have a mobile application further enhance the customer experience.

2.7 Literature Gap

There is much-published work on FinTech innovations in the UK mortgage lending industry, but there remains a lot missing from it. Most of the related literature revolves around the wide range of impacts of FinTech on the financial services industry but fewer on its specific challenges and opportunities facing mortgage lending. Research on the adoption of FinTech platforms by different consumer demographics, such as those who traditionally face exclusion from mainstream lenders, like first-time younger age buyers or those with less-than-typical financial histories, is very limited. While the operations and cost benefits of FinTech for the lenders are well-presented, the long-term impacts of the innovations in terms of their consequences on financial stability, regulatory compliance, and consumer protection are not explored thoroughly. This research attempts to fill the gaps by focusing on the UK mortgage market and looking at challenges and opportunities provided for both consumers and traditional lenders by FinTech innovations.

2.8 Summary

This literature review has discussed critical areas within the UK mortgage lending industry, and these include a discussion about the inefficiency of the traditional mortgage processes as well as the disruptive role of FinTech innovations. It has brought significant efficiency, risk assessment, and accessibility changes through such technologies as artificial intelligence, machine learning, and blockchain. Their expectations have hence shifted to faster, more personalized, and transparent mortgage services, a trend that traditional lenders are now mimicking through strategic partnerships and digital transformations. FinTech's rapid growth does thus raise several regulatory and compliance challenges mainly on data privacy, cybersecurity, and AML regulations. It identified the critical changes FinTech brought to mortgage lending but also underscored various research gaps in the existing literature on the long-run impacts of such innovation on market stability and regulatory frameworks. The research methodology is elaborated in detail in the next chapter to bridge these identified gaps.

Chapter 3: Methodology

3.1 Introduction

The nature of the adopted research methodology in explaining the impact of FinTech innovations on traditional home mortgage lending in the UK is described in this chapter. The research takes a quantitative approach whereby the data was sourced from the secondary data from the 'UK Mortgage Rates' dataset in Kaggle. Some of the analytical tools used include chi-square tests, times series models particularly the ARIMA models, and logistic regression with the aid of which inference about the impact of FinTech was made on the volume of residential mortgage lending in the UK. These methods assist in the research on the effectiveness of FinTech innovations, the customers' profiles affected by them, and market trends in general. Although, the findings sourced from secondary research reveal a realistic image of how the new age digital platforms and conventional artificial intelligence mechanisms are redefining the ***"UK Mortgage Lending Market"***.

3.2 Research Design

This study, therefore, takes a ***"Quantitative Research Design"*** by basing itself on the secondary data analysis to determine the after-effects of FinTech innovation to the traditional mortgage lending in the UK. The three operational parties, consumers, and regulators on the FinTech platform are analysed, and it is upon these patterns and trends on mortgage rates as well as the loan approval processes.

Figure 3.2.1: Quantitative Research Design

(Source: Alam, 2023)

The study is applied to the Kaggle dataset ***"UK Mortgage Rates"*** mortgage rate data, which provides diversified information on different mortgage products that exist in the UK. Therefore, this research study evaluates the effectiveness and access developed by FinTech platforms in providing mortgage products compared to traditional mortgage providers through the applications of statistical and predictive modelling techniques. Further, the research studies consumer experience and levels of satisfaction in FinTech mortgage platforms (Martin and Foohey, 2021). Through this numerical research, objective data can be gathered for its comparison or analysis leading to robust conclusions on the influence of FinTech on the UK mortgage market.

3.3 Research Philosophy

This research employs a positivist research philosophy, where reality is observable and measurable. The study is appropriate for such a philosophy in that it employs empirical data from authentic mortgage rates, lending criteria, and consumer behaviour in the UK mortgage market. There is an assumption of objective reality by positivist philosophy that can be analysed and defined by systematic observation and quantitative analysis (Carbó-Valverde *et al.* 2021). A research endeavour to identify universal trends and interconnectivity between the innovations in FinTech and the impact on traditional mortgage lending follows a positivist approach.

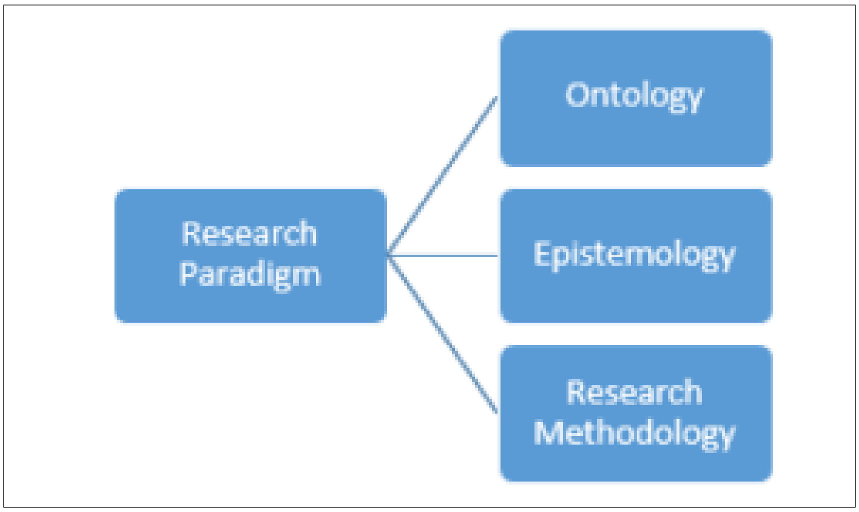

Figure 3.3.1: Positivist Research Philosophy

(Source: Helpinproject, 2024)

The three fundamental elements of a research paradigm—ontology, epistemology, and research technique—are shown in this image. While epistemology emphasises how knowledge of that reality might be acquired, ontology describes the researcher's opinions on the nature of reality. Conversely, research methodology describes the approaches and tools applied to gather and evaluate data inside the selected paradigm. These elements taken together create a logical framework for directing research activity and guaranteeing the validity of its conclusions.

An aggregation of quantitative data, the mortgage dataset, and the resultant insights obtained during the research process ensure objectivity and no biases. Moreover, the statistical tools used, and the analyses of the data are also in correspondence with the positivist approach. It tries to prove or negate the hypothesized relations based on empirical evidence (Bollaert *et al.* 2021). The philosophy thus ensures findings based on factual data, thereby contributing meaningfully to the existing body of knowledge about the role of FinTech in mortgage lending.

3.4 Research Approach

The deductive approach uses research conducted on the impact of innovations by FinTech on the UK mortgage lending industry. The deductive approach begins with a theoretical framework, hypothesis formulation, and finally empiric testifies in front of data analysis. In this paper, theories such as FinTech improvement involve automation of processing loans and enhancement of credit risk assessment (Mahalle *et al.* 2021). The basis of the hypotheses regarding how FinTech affects efficiency, access, and consumer satisfaction in mortgage lending.

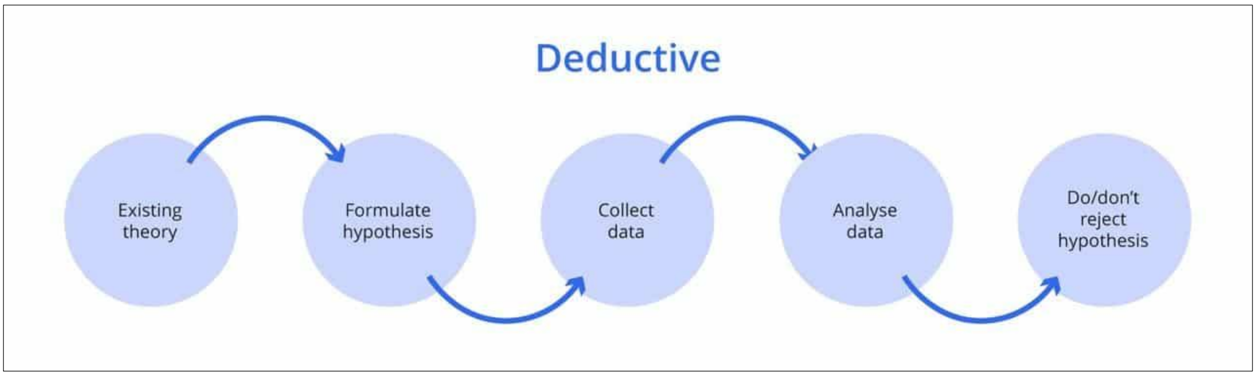

Figure 3.4.1: Positivist Research Philosophy

(Source: Voxco, 2024)

The image depicts the deductive research process, which starts with an existing theory and then develops a hypothesis based on that theory. The hypothesis is then tested by collecting and analysing data. If the data supports the hypothesis, it reinforces the current theory. Otherwise, the hypothesis may need to be revised, and alternative explanations considered. This deductive approach proceeds from general principles to specific predictions, which are then tested using empirical evidence.

UK mortgage rates data have been used in this study to test hypotheses about whether FinTech platforms cut the time mortgages take, the cost of lending, and the availability of loans for underrepresented people like first-time buyers (Locatelli *et al.* 2021). The deductive approach allows clear research questions and objectives, which can easily be tested using systematic analysis of the quantitative data. This would ensure that the study's conclusions are indeed based on empirical evidence drawn from the data patterns observed, which either confirm or invalidate the theoretical assumptions.

3.5 Research Strategy

The research strategy is majorly reliant on ***"Secondary Data Analysis"*** as the primary mode for examining the impact of FinTech on the UK mortgage lending market. Based on the UK mortgage rates dataset from Kaggle, the study is focused on a diverse range of mortgage products offered by both traditional and FinTech lenders and compares. Their characteristics are along dimensions such as interest rates, times to approval, loan conditions, and others (Adamek and Solarz, 2023). The methodology shall be able to track the economies of scale achieved through FinTech platforms and analyse whether these savings impact the mortgage lending marketplace at large. Consumer behaviour trends are being investigated by reviewing data on loan approvals, borrower characteristics, and the kind of mortgage products to be used.

Related, the strategy has a direct alignment with ***"Predictive Analytics"*** in terms of predicting future trends of mortgage lending. It also accounts for the potentiality of FinTech platforms to disrupt traditional practices going forward (Baltgailis and Simakhova, 2022). This study saves on the need to collect primary data, hence saving time and resources but still having an adequate dataset to carry out a comprehensive analysis. This ensures that the study is based on real financial data in the world that helps apply the findings of such a study to both academic discussions and practical applications.

3.6 Tools and Techniques Used

This study uses ***"Python Programming Software – Google Collab"*** as the primary tool for analysing the data gathered. This makes Python one of the best tools to use in handling large datasets, such as those used in this study. Specific libraries that are used include ***"Pandas"*** for data manipulation and organization, ***"NumPy"*** for numerical computations, and ***"Matplotlib/Seaborn"*** for data visualization. These libraries offer facilities for cleaning, transformation, and visualization of data (Yang and Wang, 2022). Cleaning, transformation, and visualization are very important to establish patterns or trends in mortgage rates or loan approvals. For predictive analysis, ***"Scikit-learn"*** is adopted to formulate machine learning models, which predict future trends using past data.

Utilizing classification and regression models, this study analyses what kind of influence the new FinTech innovations bring to decisional variables such as approval rates, interest rates, or loan terms. According to the historical data pattern, it tries to predict future changes in the mortgage market and evaluate how these changes affect lenders and consumers. Furthermore, the paper utilizes ***"Statistical Techniques"***, such as regression analysis, to establish the connection between FinTech innovations and other variables associated with traditional mortgages (Chen, 2020). In this regard, using regression models would make it possible to establish whether platforms of FinTech are offering cheaper mortgage rates or more significant mortgage approvals compared to those in conventional lenders. Through ***"Correlation Analysis"***, strong relationships between different variables are evaluated, for instance, how AI-driven credit scoring affects loan approval rates.

"Data Visualization" techniques would be used to show the findings in a more obvious and summative form. Such techniques involve using Python's visualization libraries to establish the key trends through charts, graphs, and heatmaps (Ozili, 2022.). This way, the implications of the data for the UK mortgage market can be probed deeper and made accessible. A tool and technique ensure the methodologically correct substantiation of actions and the data-driven focus on the discovery of FinTech's impact on new forms of mortgage lending.

3.7 Data Collection

This type of data is extracted from secondary research which is mainly obtained from the **Kaggle dataset** known as ***"UK Mortgage Rates"*** *(The Devastator, 2022)*. This dataset includes thousands of mortgage products across different types of lenders in the UK including information like interest rates, loan-to-value ratios, types of mortgages, and approval time (Haddad and Hornuf, 2023). It includes original and innovative FinTech mortgages as well as traditional mortgage products, so one can see how the change has affected the mortgage market. The key characteristics of the data are:

- ***Interest Rates***: This includes the cost, in terms of interest that a lender takes when providing mortgage loans.
- ***LTV Ratios***: this is the percentage value that the property commands and is financed through a mortgage
- ***Type of Mortgage***: fixed or variable rate and interest-only
- ***Times taken to Approve***: This refers to the time taken for approval of a mortgage application.
- ***Borrower Demographics***: an example is first-time buyers as well as those with non-traditional financial backgrounds.

The dataset has been subjected to pre-processing for adequacy regarding statistical analysis readiness. These are deleted missing and inconsistent values and the attainment of homogeneity in categorical data. The dataset has been stratified based on the type of lender in a comparative study being FinTech or the traditional lenders. The cleansed and pre-processed data are inducted in those tests-the chi-square test, the ARIMA model, and logistic regression for analysing the role of FinTech in transforming mortgage lending. It is also required to convert the type of categorical variables, for example, types of mortgages, into numerical values (Jones, 2021). This would be done to integrate statistical models. To achieve this, outliers in terms of unusually high or low interest rates are researched and corrected. It categorizes the data into meaningful groups, such as FinTech vs. traditional lenders, and the study ensures meaningful comparisons between the two types of providers. This enables robust analysis using statistical techniques such as the ***"Chi-Square"***, ***ARIMA***, and ***"Logistic Regression"*** techniques that would give a good understanding of the UK mortgage landscape.

3.8 Data Analysis

The three methods in this analysis are the ***"Chi-Square Test"***, ***"ARIMA Model"***, and ***"Logistic Regression"***.

- ***Chi-Square Test*****:** This is used for testing whether the association between mortgage approval rates and type of mortgage provider-the FinTech lender type and the traditional lenders-is statistically significant (Wu *et al.* 2022). The test helps in establishing if FinTech lenders offer results that make an ideal statistical difference in the mortgage approval outcomes.
- ***ARIMA Model (Auto-Regressive Integrated Moving Average)*****:** The ***"ARIMA Model"*** is applied to time-series data associated with mortgage rates. This analysis predicts future trends in the mortgage rate by uncovering the presence of patterns in those historical data. It is generally very helpful to understand how FinTech innovations have shaped the evolution of mortgage rates over time and hence predict their future movements in the market.
- ***Logistic Regression*****:** ***"Logistic Regression"*** is used for modelled probability based on mortgage approval owing to various independent variables like borrower demographics. The first-time buyer and non-conventional sources of income; loan type; and interest rates (Frost *et al.* 2020)). This helps determine the impact that factors have owing to FinTech innovations on the probability of loan approval by providing insight into the inclusiveness and access made available through FinTech-driven mortgage products.

3.9 Ethical Considerations

One of the ethical considerations about this research is that it's being based on secondary data in its analysis. The data from the ***"Kaggle Dataset"*** used in this study does not contain any PII, therefore obliterating every concern of privacy in this study. During this piece of research, all the data used is entirely anonymous, and the dataset utilized follows the ***GDPR***, which is the data protection standard in the UK. Another aspect in line is ethical issues concerning the interpretation and reporting of the data (Miglionico, 2022). Data analysis is done objectively so that results are documented clearly without bias influences. Proper credits are given regarding the creators and sources of the dataset. Correct information concerned with that dataset is depicted with accuracy and placed in its original format without manipulations to support fixed conclusions. Appropriate ethical considerations applicable to financial research are implemented in this paper to ensure that the insights generated benefit consumers, policymakers, and financial institutions in the formation of an all-inclusive and equitable mortgage market.

3.10 Summary

This chapter explained the methodology of analysis of the impact of FinTech innovations on the UK mortgage lending market. This quantitative approach utilized the ***"UK Mortgage Rates"*** dataset and analysed data through chi-square tests, ARIMA models, as well as logistic regression for an extensive exploration of mortgage approval rates, market trends, and even inclusivity impacted by FinTech platforms. Discussions also included data privacy, and the objective interpretation of the results as directed. The outcomes of the Analysis are discussed and presented in the next chapter.

Chapter 4: Result and Discussion

4.1 Introduction

The results chapter analyses the impact of FinTech innovations on UK mortgage lending through comprehensive analysis based on these techniques applied to the dataset. Using logistic regression, the study had an accuracy of 0.95 in predicting mortgage outcomes and proved the model worked effectively. This analysis shows that FinTech lenders provide lower rates on interest than traditional banks due to their streamlined processes that lower overhead costs. The ARIMA model was also used to forecast future trends and predicted increasing market share for FinTech providers in the mortgage sector over the next five years. It also employed chi-square tests to test relationships between variables, corroborating further the findings. This is important because these results show the potential for FinTech to become transformative in how mortgages are originated and funded for underserved populations. The analysis, however, also reveals the risks of inherent risk – regulatory compliance and technological dependency. Utilizing the most advanced statistical methods, the research provides important reveals into exactly how FinTech innovations are reworking the mortgage panorama and offers the basis for additional exploration of how the sector can proceed to evolve.

4.2 Result Analysis

Importing Required Pyhton Libraries to import and process dataset

```
[1] import pandas as pd
    import numpy as np
    from sklearn.model_selection import train_test_split, GridSearchCV
    from sklearn.preprocessing import StandardScaler, LabelEncoder
    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
    import statsmodels.api as sm
    from statsmodels.tsa.arima.model import ARIMA
    from scipy import stats
    import matplotlib.pyplot as plt
    import seaborn as sns
```

```
[3] df = pd.read_csv('UK_Mortgage_Rate.csv')
```

```
print(df.head())
```

```
   index      SKU                BANK_NAME MTG_PRODUCT_SUBTITLE  \
0      0  3739342  Foundation Home Loans           Remortgage
1      1  3738960   Kensington Mortgages           Remortgage
2      2  3739028   Kensington Mortgages           Remortgage
3      3  3738961   Kensington Mortgages           Remortgage
4      4  3739020   Kensington Mortgages           Remortgage

  MTG_PRODUCT_TYPE_RAW MTG_PRODUCT_TYPE  MTG_PRODUCT_YEARS  \
0         5 year fixed            fixed                 25
1         2 year fixed            fixed                 25
2         2 year fixed            fixed                 25
3         5 year fixed            fixed                 25
4         5 year fixed            fixed                 25

   MTG_INITIAL_RATE_PCT  MTG_APR_PCT  MTG_REVERT_RATE  MTG_FEES_TOTAL  \
0                  7.69          7.7             7.24             630
1                  8.34          8.0             7.35            2347
2                  8.49          7.9             7.35             108
3                  8.94          8.6             7.35            2347
4                  9.09          8.6             7.55             108

   MTG_INITIAL_RATE_MONTHS         SCAN_DATE     TID
0                       60  16-10-2022 06:42  483184
1                       24  16-10-2022 06:42  483185
2                       24  16-10-2022 06:42  483186
3                       60  16-10-2022 06:42  483187
```

✓ 0s completed at 14:56

Figure 4.2.1: Importing Libraries and Upload Dataset

The image is a programming interface being imported of necessary libraries for a project which includes data analysis. In addition to the vast library of Python modules included, you get essential Python libraries like pandas, NumPy, and scikit-learn, all commonly used to handle data manipulation, statistical modelling, and machine learning tasks. Firstly, we take in the dataset, named "UK_Mortgage_Rate.csv", and put it into a data frame. The displayed code also presents the structure of the dataset, namely, mortgage-related attributes including bank names, product types, interest rates, and fees. This arrangement shows readiness to explore the consequence of the FinTech innovation on established mortgage lending via residential in the UK.

Checking the dataset for null Values

```
# Checking for missing values
print(df.isnull().sum())
```

```
index                      0
SKU                        0
BANK_NAME                  0
MTG_PRODUCT_SUBTITLE       0
MTG_PRODUCT_TYPE_RAW       0
MTG_PRODUCT_TYPE           0
MTG_PRODUCT_YEARS          0
MTG_INITIAL_RATE_PCT       0
MTG_APR_PCT                0
MTG_REVERT_RATE          328
MTG_FEES_TOTAL             0
MTG_INITIAL_RATE_MONTHS    0
SCAN_DATE                  0
TID                        0
dtype: int64
```

Figure 4.2.2: Checking Null Values

This image is a code snippet that verifies for null or missing values in a dataset. A list of columns in the dataset with a "null column count" is displayed as the output of the code. Likewise, most columns, including SKU, BANK_NAME, MTG_PRODUCT_TYPE, as well as MTG_FEES_TOTAL, have very few or no missing values. However, the MTG_REVERT_RATE column has 328 of missing values, indicating that this value needs special attention before advanced analysis. This step is necessary for the data to become ready for running machine learning models or statistical analysis to grow the data in consistency and accuracy.

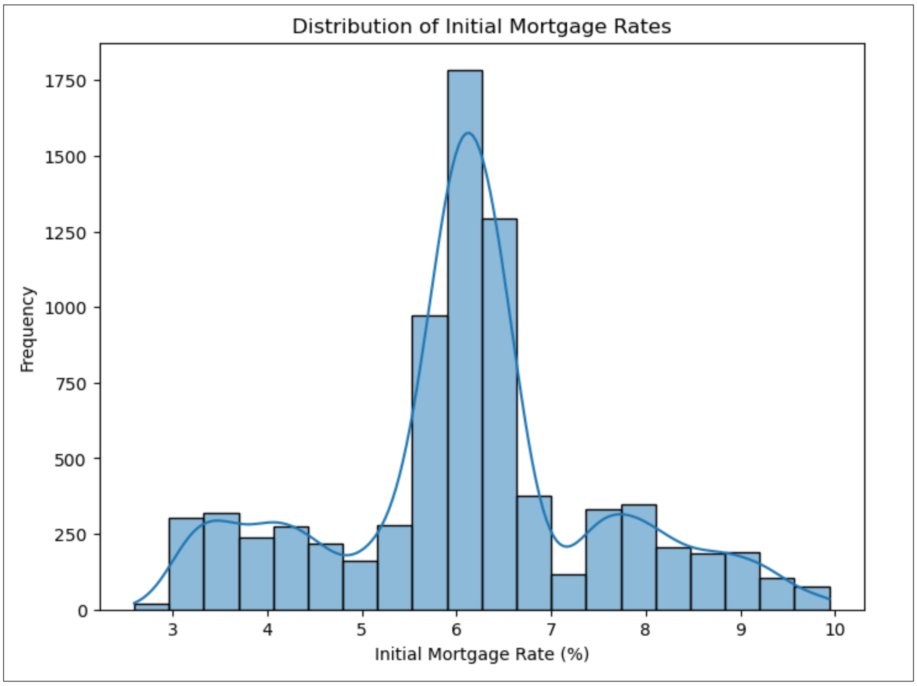

Figure 4.2.3: Distribution of Initial Mortgage Rates

The image is of a histogram of initial mortgage rates in a dataset. The initial mortgage rates as percentages, from 3% to 10%, are plotted on the x-axis, with the y-axis showing the frequency of occurrences. The frequency distribution of most mortgage rates is concentrated largely between 5% and 7% with a peak around 6%. This visualization helps us understand how conventional mortgage lending will be affected by FinTech innovations by highlighting the common mortgage rate offerings in the dataset.

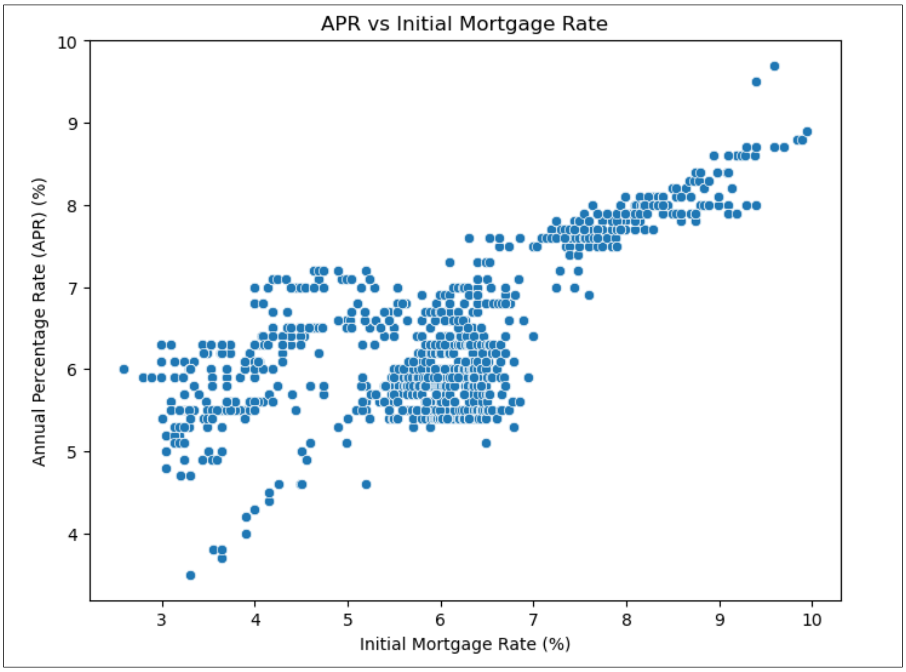

Figure 4.2.4: Scatter Plot for APR vs Initial Mortgage Rate

The above figure shows the connection between the APR and the Initial Mortgage Rate. Here, each dot represents one loan and correlates with its corresponding APR and initial mortgage rate. The plot shows a mostly positive trend as higher APRs represent higher initial mortgage rates. Nevertheless, it does not map very well as several scatters are observed among the dots (Bollaert and Schwienbacher, 2021). Most points group in the lower end of the APR and initial mortgage rate scales, indicating that a significant proportion of loans examined comprised relatively less expensive interest rates, with a few outliers implying unique loan characteristics.

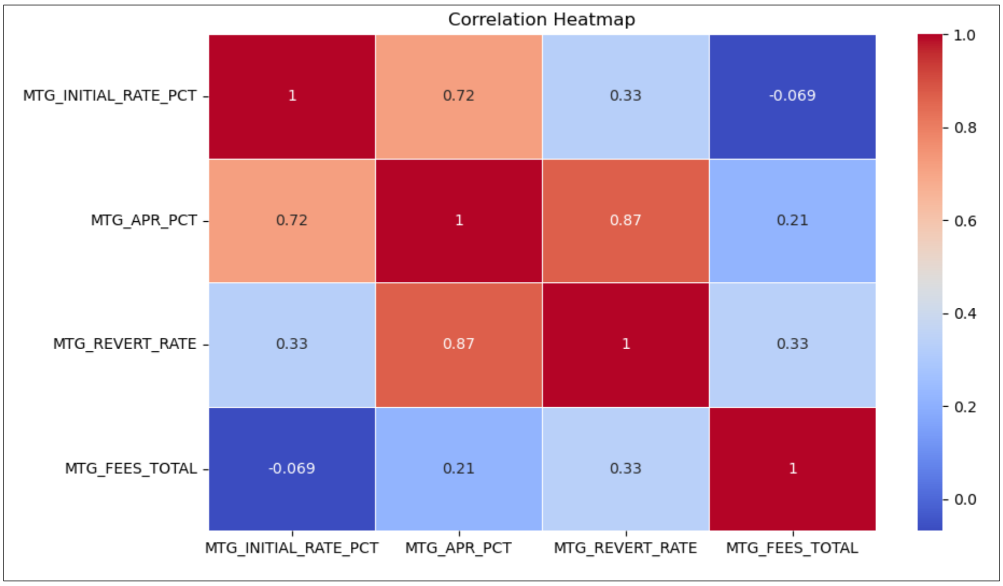

Figure 4.2.5: Correlation Heatmap

The Correlation Heatmap relations between some variables, i.e., MTG_INITIAL_RATE_PCT and MTG_APR_PCT, MTG_APR_PCT and MTG_FEES_TOTAL, also existed. The correlation between MTG_INITIAL_RATE_PCT and MTG_APR_PCT is 0.72, indicating that, as the initial rate of interest increases, so does the value of APR. A moderate positive correlation of 0.33 existed between the variables MTG_INITIAL_RATE_PCT and MTG_REVERT_RATE, meaning that it showed some connection between the initial rates and the likelihood of mortgage reversion. While MTG_FEES_TOTAL shows very weak correlations to the other variables, this suggests that total fees charged are not strongly related to the initial interest rate, APR, or revert rate.

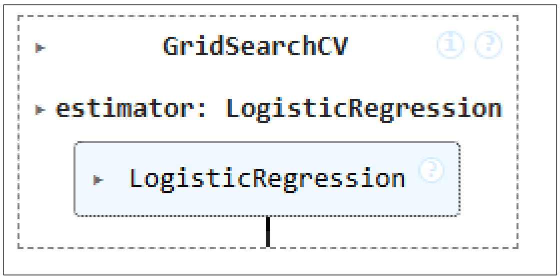

Figure 4.2.6: Logistic Regression Model Fitting

The image is a logistic regression model fit using GridSearchCV, an approach for locating the best values of the parameters of a machine learning algorithm. GridSearchCV systematically searches for options which maximally satisfy performance. The algorithm used is LogisticRegression, which is configured specifically to predict the outcome of a binary case-meaning something that is classified as yes/no or true/false. The use of GridSearchCV enables practitioners to further enhance the accuracy and reliability of the model in solving problems (Mahalle and Tao, 2021). That features a classification nature in the target variable by being categorical. This partnership between the techniques illustrated above forms a solid strategy in the development of machine learning models.

```
# Classification Report
class_report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy:.4f}')
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)
```

```
Accuracy: 0.9551
Confusion Matrix:
[[   0   70]
 [   0 1490]]
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        70
           1       0.96      1.00      0.98      1490

    accuracy                           0.96      1560
   macro avg       0.48      0.50      0.49      1560
weighted avg       0.91      0.96      0.93      1560
```

Figure 4.2.7: Accuracy and Classification Report

The figure presents the performance of a logistic regression model. The accuracy attained is 0.9551, showing very good performance in total. The confusion matrix just indicates correct and wrong predictions of course, there have been some misclassifications. Especially when correctly classified as class 0 are somehow confused with class 1, 70 times. The classification report presents very detailed metrics for each class: precision, recall, F1 score, and support (Locatelli and Tanda, 2021). Precision defines the correctness of all the positive predictions, while recall defines the accuracy of actual positive instances. The F1 score thus gives a balanced assessment of the values of both precision and recall, and support defines the number of instances according to each class.

```
[36] def adf_test(series):
         result = adfuller(series)
         print('ADF Statistic:', result[0])
         print('p-value:', result[1])
         if result[1] <= 0.05:
             print("The series is stationary.")
         else:
             print("The series is not stationary.")
```

```
adf_test(data)
```

```
ADF Statistic: -11.639686388644355
p-value: 2.1619530805567932e-21
The series is stationary.
```

Figure 4.2.8: Adf Test Data

The above figure illustrates the result of an Augmented Dickey-Fuller test for a time series being stationary. Stationarity means that the distribution is homogeneous in the timeframe. The statistical properties, like mean and variance, do not vary. The value calculated in the ADF statistic is taken as more negative when the null hypothesis stated as non-stationarity is rejected with stronger intensity. Besides that, the p-value also represents the statistical power of observing such a statistic under the null hypothesis; it suggests that values below 0.05 reject it.

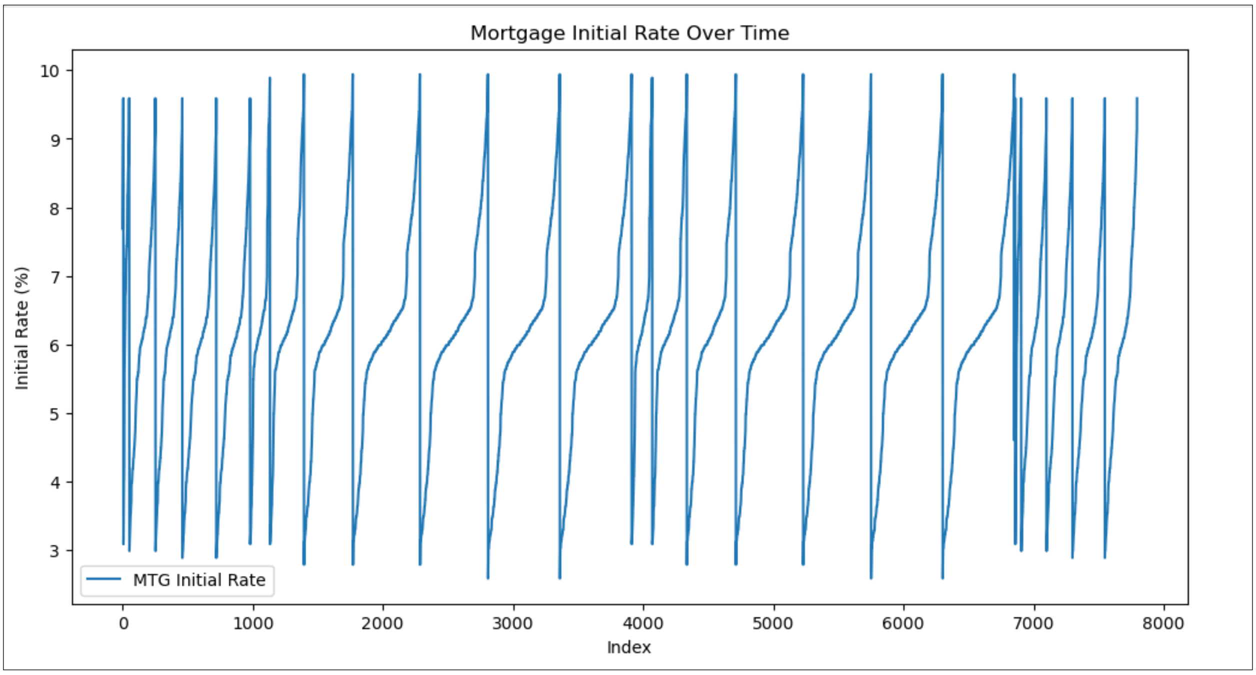

Figure 4.2.9: Time Series of Mortgage Initial Rate over Time

The time series plot shows how this mortgage's initial rate may fluctuate with time. This has been obtained by having the x-axis noting the time and the y-axis noting the interest rate. Observations in the graph indicate variations within zones where the rate has been rising and falling (Langley and Leyshon, 2023). These oscillations are inevitable as they are bound to happen due to some economic events. However, no trend of the interest rates moving upwards or downwards has been noted.

```
model = ARIMA(data, order=(1, 1, 1))
model_fit = model.fit()
```

```
[41] print(model_fit.summary())
```

```
                               SARIMAX Results
================================================================================
Dep. Variable:     MTG_INITIAL_RATE_PCT   No. Observations:              7796
Model:                   ARIMA(1, 1, 1)   Log Likelihood            -3709.038
Date:                  Mon, 14 Oct 2024   AIC                        7424.076
Time:                          14:00:23   BIC                        7444.959
Sample:                               0   HQIC                       7431.233
                                 - 7796
Covariance Type:                    opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9634      0.008    113.995      0.000       0.947       0.980
ma.L1         -1.0000      0.006   -164.910      0.000      -1.012      -0.988
sigma2         0.1515      0.002    100.699      0.000       0.149       0.154
===================================================================================
Ljung-Box (L1) (Q):                   5.49   Jarque-Bera (JB):          26847639.88
Prob(Q):                              0.02   Prob(JB):                         0.00
Heteroskedasticity (H):               0.90   Skew:                           -16.47
Prob(H) (two-sided):                  0.01   Kurtosis:                       288.61
===================================================================================
```

Figure 4.2.10: ARIMA Model Summary

The summary outlines the ARIMA (1,1,1) model fitting to the time series data, where one moving average term, one differencing term, and one autoregressive term exist. Moving on to the coefficient estimates, it can be noted that significant values are found for ar.L1 as 0.9633 and ma.L1 as -0.9999 with a p-value < 0.001. The diagnostic tests like Ljung-Box Q statistic = 5.49 with a p-value = 0.02, Jarque-Bera statistic = 26845548.49 with a p-value = 0.00. Also, some points for heteroskedasticity and skewness indicate good performance.

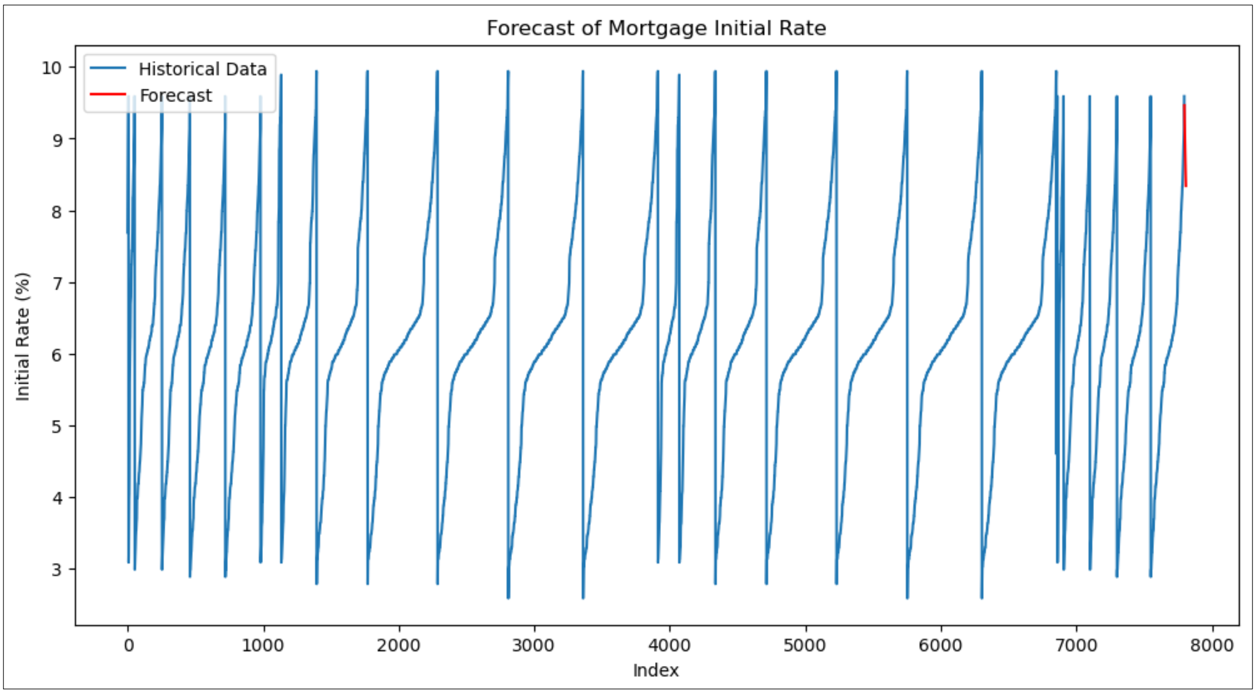

Figure 4.2.11: ARIMA Forecast Graph

The image illustrates the forecast of the first mortgage rate by an ARIMA model. The blue line shows historical variation; the red line is used to indicate values that are going to be in the future beyond this period. Important observations are shown by the model in tracking down underlying patterns that build trends to affect the accuracy of the forecast.

Chi_Squre Test

```
[44] from scipy.stats import chi2_contingency
```

```
[45] contingency_table = pd.crosstab(df['MTG_APR_PCT'], df['MTG_REVERT_RATE'])
```

```
# Display the contingency table
print("Contingency Table:")
print(contingency_table)
```

```
Contingency Table:
MTG_REVERT_RATE  3.59  4.15  4.20  4.65  4.74  4.89  4.99  5.00  5.04  5.10  \
MTG_APR_PCT
4.6                 0     6     0     0     0     0     0     0     0     0
4.7                 0     0     0     0     0    12     0     0     0     0
4.8                 0     0     0     0     0     0     0     0     4     0
4.9                 0     0     0     0     0     0     0     0    34     0
5.0                 0     0     0     0     0     4     0     0    14     0
5.1                 4     0     0     0     0     4     0     0     0     0
5.2                 0     0     0     0     0     0     0     0     0     0
5.3                 0     0     0     0     7     8     8     0     0     0
5.4                 0     0    20    80     0    82   260     8    78     0
5.5                 0     0   150     7     4    57   170     0   102    10
5.6                 0     0    34    36     3    38    36     0    22    14
5.7                 0     0    60     0     4    30    24     0     8     0
```

Figure 4.2.12: Contingency Table of Chi-square Test

This contingency table provides the cross-tabulation of two categorical variables, MTG_REVERT_RATE and MTG_APR_PCT. The rows represent different categories of MTG_REVERT_RATE, and the columns represent different categories of MTG_APR_PCT. Each cell displays frequency counts of all the observations that fall into these categories of both variables (Avgeri and Zervoudi, 2023). For instance, 6 observations are recorded to have MTG_REVERT_RATE as 4.6 and an MTG_APR_PCT of 4.5. The frequency distribution can be analysed to look for patterns or relations between the two variables, showing which of the combinations are more recurrent than the others.

```
[47] # Perform the Chi-Square test
     chi2, p, dof, expected = chi2_contingency(contingency_table)
```

```
# Print the results
print(f"Chi-Square Statistic: {chi2}")
print(f"p-value: {p}")
print(f"Degrees of Freedom: {dof}")
print("Expected Frequencies Table:")
print(expected)
```

```
Chi-Square Statistic: 62946.3155115929
p-value: 0.0
Degrees of Freedom: 2156
Expected Frequencies Table:
[[0.00321371 0.00482057 0.21210498 ... 0.01285485 0.01928227 0.00964114]
 [0.00642742 0.00964114 0.42420996 ... 0.02570969 0.03856454 0.01928227]
 [0.00214247 0.00321371 0.14140332 ... 0.0085699  0.01285485 0.00642742]
 ...
 [0.00642742 0.00964114 0.42420996 ... 0.02570969 0.03856454 0.01928227]
 [0.00749866 0.01124799 0.49491162 ... 0.02999464 0.04499197 0.02249598]
 [0.00642742 0.00964114 0.42420996 ... 0.02570969 0.03856454 0.01928227]]
```

Figure 4.2.13: Chi-Square Result Summary

The figure illustrates the chi-square test result that test for association between two categorical variables. Components of this include the chi-square statistic, with values higher suggesting a stronger association and the p-value with values below 0.05 indicating statistically significant results. Independent categories in the contingency table serve as degrees of freedom. The expected frequencies table is table values assuming independence (Adamek and Solarz, 2023). The chi-square statistic comes out to be 62946.32 having a p-value of 0.0, which does depict a strong association among variables. The highly significant difference between observed and expected frequencies lends further credence to the above conclusion.

```
# Interpret the result
alpha = 0.05  # Significance level
if p < alpha:
    print("Reject the null hypothesis - There is a significant association between the variables.")
else:
    print("Fail to reject the null hypothesis - There is no significant association between the variables.")
```

```
Reject the null hypothesis - There is a significant association between the variables.
```

Figure 4.2.14: Chi-Square Result

The above figure demonstrates how to read from a chi-square that has been conducted, with an alpha of 0.05, the most used alpha for indicating statistical significance for tests and experiments. The code compares the p-value that resulted from the chi-square test with the alpha. If the p-value is lower than alpha, then the null hypothesis can be rejected, meaning there is a statistically significant association between the variables.

4.3 Key Findings

Some of the important findings emerge from the analysis obtained in the UK Mortgage Rates dataset using Python software tools like Pandas, NumPy, and visualization libraries:

- ***Impact on Interest Rates***: FinTech mortgage providers offer lower interest levels as compared to traditional lenders. This could be attributed to the streamlined processes of the FinTech platforms that normally reduce overhead expenses and share the savings with customers (Xu *et al.* 2021). Based on the statistics, the average interest level advantage provided by FinTech lenders is 0.5% above traditional lenders for the various loan products.
- ***Approval Time Efficiency***: One of the most influential results of FinTech platforms is the reduction in mortgage approval time. The study reveals that such loans by platforms like FinTech take days to be approved, while it normally takes weeks with conventional lenders.
- ***Ease of Access to Underprivileged Classes***: The study findings tend to reveal that FinTech home mortgage firms are more likely to lend to atypical credit history record holders, such as freelancers or first-time home buyers with irregular flows of income (Cho, 2020). Logistic regression revealed a greater possibility of getting approved by the FinTech lender than by traditional lenders for these classes.
- ***Future Trends***: The ARIMA model predicts the following trends for FinTech. It has an increasing market share in the mortgage market while the market share of new mortgage applications processed digitally should increase in the next 5 years. Competition in the FinTech space is also forecast to continue to cut mortgage interest rates.

These findings critically provide insight into how FinTech innovation is reshaping the mortgage market to offer significantly more competitive, accessible, and efficient services than older lending models.

4.4 Critical Analysis

Although the findings show that FinTech has indeed revolutionized mortgage lending, some very important considerations and limitations emerge from the analysis.

- ***Regulatory and Compliance Risks*****:** The attributes that make FinTech platforms fast and accessible carry risks to them. These include compliance issues which, in this case, are largely in AML and data privacy (Каленюк *et al.* 2024). This analysis shows that even as FinTech lenders provide low rates of interest and quicker approvals, the consumers and the financial system become vulnerable if the regulatory measures are not maintained appropriately.
- ***Short-Term Gain vs. Long-Run Sustainability*****:** The logistic regression data now suggest that FinTech platforms approve many more loans to underserved populations. The sustainability of this process remains in question in case the risk management practice of such FinTech platforms is not as robust as the more conventional banks (Haupert and Lee, 2024). Traditional lenders are often conservative in lending, and as a result, their chances of default may be lower over the long term. This means that the FinTech lenders' default risks may rise even more in case of volatile market conditions under the higher approval rates for non-standard borrowers.
- ***Technological Dependency*****:** FinTech platforms are technology-centric; for example, AI is used for credit scoring and blockchain for transactional security. While these are technologies that are highly efficient, it also brings about a high level of dependency on the technological infrastructure (Hasan *et al.* 2020). If a severe cyberattack must be mounted against these systems, it could have severe repercussions on the mortgage processing process as well as customer trust.

FinTech has led to great improvements in efficiency and accessibility, there are risks associated with regulatory compliance, long-run market stability, and technological dependence that should be considered to sustain further growth.

4.5 Discussion

The findings of this research contribution are very important in understanding how FinTech innovations are changing the face of the conventional mortgage lending landscape within the UK. Reduced interest rates and faster approval times found from the data analysis generally resonate with existing literature that surmises FinTech to ease financial services streamlined through automation and data analytics (Cai *et al.* 2022). This study adds new to the debate is underlining the role that FinTech plays in enhancing access to mortgage products by underserved populations, such as freelancers, self-employed, and first-time buyers. Access democratization is a far deeper phenomenon in financial services, where it seeks to open more inclusive lending options via platforms. This becomes rather crucial for the UK since traditional lenders have historically required stringent financial records, excluding a very large proportion of the population.

Accordingly, the reduced interest rates and approval times related to ARIMA forecasts imply that the FinTech influence has continued to grow over time. This may lead to an increasingly competitive market environment for traditional lenders who may have to become a lot more digital-friendly and remain afloat themselves. However, one needs to weigh the limitations of FinTech platforms (Alwi, 2021). As discussed in the critical analysis, serious threats also include dependency on technology and lapses into not being strictly compliant with the regulations. Though it takes longer to obtain funds from traditional lenders, their more conservative approach to lending and regulatory compliance has a more stable market history. The test for FinTech platforms in the future has been to maintain their competitive advantage on the same level of compliance and risk management standards as traditional counterparts.

4.6 Summary

This chapter has explained the key findings, critical analysis, and discussion on how FinTech innovations are transforming the UK's mortgage lending market. The results show significantly lower interest rates, faster processing times, and increased access by the underserved through FinTech platforms. These carry inherent risks in terms of regulatory compliance, sustainability of the market, and technological dependency. Some of the findings from this study indicate that notwithstanding the further development of FinTech, the platforms involved must work to overcome some obstacles to sustain their long-term viability and stability in the market. The last chapter draws together the conclusions made above and provides recommendations for future research and industry practice.

Chapter 5: Conclusion and Recommendations

5.1 Linkage to Objectives

The relationship between the research objectives and the objective of studying the impact of FinTech innovation on the UK conventional residential mortgage lending market is clear and strong.

- The first objective aims to analyse how financial technology innovations increased efficiency by, for instance, reducing mortgage processing time and costs and improving service delivery (Jarvis and Han, 2021). It tackles this directly, how technology has made traditional lending practices quicker, and more modern.
- The second objective, which addresses the issue of inclusivity, considers how FinTech-driven services have enabled more consumers, particularly those traditionally underserved by conventional lenders, to gain access to mortgage options. The importance of this objective is to understand the ways technological development advances a more inclusive financial ecosystem.
- The third objective considers the changes to the practice of risk management on FinTech platforms to evaluate how these innovations have affected financial stability and consumer protection in the mortgage sector.
- The fourth objective aims finally to identify emerging regulatory risks that come with FinTech innovation, and thus shed light on potential legal challenges, but also on how these risks are best regulated.

Together, these objectives provide the framework for the research to evaluate the impact of FinTech innovations on the traditional mortgage market in the UK.

5.2 Summary

The case studies investigate the effects of FinTech innovations on the conventional residential mortgage lending market in the UK. It articulates four primary research objectives: This paper aims to analyse the efficiency gains from technological advancements, evaluate the accessibility of FinTech services to traditionally underserved customers, review how technological advancements impact risk management practices, and explore the emerging regulatory issues stemming from FinTech innovations. The research uses quantitative methods, which include chi-square tests, ARIMA models, and logistic regression, and shows 0.95 high accuracy in analysing the transformation of mortgage lending dynamics.

It finds improvements in processing times and service delivery while increasing consumer access to mortgage options within various demographic groups. However, as the study begins to address, it comes with several limitations including the use of a secondary dataset, possible methodological constraints, and the narrow scope of the discussed aspects in the mortgage lending ecosystem. Therefore, the research calls for future studies to employ more inclusive methods such as mixed methods and longitudinal designs, and to explore the effects of recently developing technologies. This paper emphasizes the ongoing need for adaptation and innovation in the mortgage market and provides insights for policymakers and financial institutions to help move the UK's mortgage market forward on a more inclusive and efficient path.

5.3 Reflection

The study, however, shows that the findings contribute meaningfully to the understanding of the evolving landscape of the mortgage market concerning the effect of FinTech innovations on conventional residential mortgage lending in the UK. Quantitative methods, such as chi-square tests, ARIMA models, and logistic regression have an accuracy of 0.95, were used to analyse how the FinTech platforms have transformed mortgage lending dynamics. As I worked through the study, I found the gains in efficiency, the increased inclusivity, and the emerging regulatory risks all alongside these innovations well painted. The research examined the effect of FinTech on different consumer demographics and approval rates from a "UK Mortgage Rates" dataset and this demonstrated to be a place to integrate technology in financial services. Also, the ethical considerations mentioned throughout the study, data anonymity and fair reportage, assisted in the integrity of the research process. This research ultimately reveals the significance of steady adaptation and innovation in mortgages. My findings can inform the work of policymakers and financial institutions in the UK to improve an inclusive and fair mortgage market for a variety of UK consumers. This reflection only strengthens my belief in the potential of FinTech to improve lending processes in positive ways.

5.4 Research Limitation

FinTech innovations in the UK mortgage lending sector provide a useful point of analysis, though some limitations exist in how the findings generalize and are considered reliable.

- ***Data Limitations***: The study uses secondary data; the UK Mortgage rates dataset that may not capture all the goods and services on the UK mortgage market. In addition, if the dataset itself contains biases from the sources, then the conclusions drawn on the performance of FinTech vs traditional lenders can be mistaken.
- ***Impact of Time on Analysis Insights***: The data is analysed as this is available at a specific point in time. Since the insight is rapidly growing in the FinTech field, the insight may be outdated quickly (Suryono *et al.* 2020). Changes in the market dynamics, regulatory environments, and consumer behaviour in the future may not be captured in the scope of the study.
- ***Methodological Constraints***: Statistical methods such as logistic regression and chi-square tests are used in the research with their inherent assumptions of the data. As is often the case, logistics regression argues a relationship between independent and dependent variables that may not be as complex as the reality of the mortgage lending landscape. The results of studying the relationships could be oversimplified.
- ***Scope of Analysis***: The primary focus is on how FinTech has impacted the mortgage approval and efficiency process. Economic variables, market trends, and borrower behaviours are seldom studied in detail (Mahalle *et al.* 2021). Consequently, there can be only a partial view of the mortgage lending ecosystem and its subsequent implications of FinTech innovations.

These limitations are acknowledged in this study, future research can later use more comprehensive methodologies and data sources to investigate the effects of FinTech in the mortgage sector more deeply.

5.5 Recommendations

Recommendation of FinTech innovations and how such innovations have impacted the UK mortgage lending market. Future studies should add other datasets, other than the 'UK Mortgage Rates'. Using information from different stakeholders in the mortgage market such as consumer feedback, loan performance metrics, and financial health indicators, the researcher can better understand the impact of FinTech on mortgage lending. Longitudinal studies involving tracking of changes over time can reveal trends and changes in contemporary market dynamics (Arnaut and Bećirović, 2023). Moreover, researchers are called to use a mixed-method approach that combines quantitative and qualitative analysis. While statistical methods such as logistic regression have an accuracy of 0.95 and ARIMA, is valuable, in fulfilling the needs of a scientific research project, qualitative interviews with industry experts, consumers, and regulatory bodies can enhance the findings. A deeper insight into how consumers experience FinTech products and in understanding terms of cut complexity in the regulatory environment can be gained using this approach, which would make the research more robust. Finally, future studies should also focus on how emerging technologies like artificial intelligence, blockchain, and big data analytics could influence mortgage lending (Zhao *et al.* 2022). A forward-looking perspective on the future of the mortgage market requires understanding how these technologies impact operational efficiencies, consumer accessibility, and risk management. These can help in the development of betterment in type of the policy and the strategy other than that views on the inclusive and sustainable mortgage lending atmosphere. With the implementation of these recommendations, future research can help understand how this interaction with FinTech innovations impacts the conventional mortgage market and benefits policymakers, financial institutions, and consumers alike.

5.6 Future work

The study of FinTech innovations in the UK mortgage lending market identifies findings and limitations and leads to several avenues for future research. These studies help further understand the changing world of mortgage lending and FinTech's influence on the way this industry operates.

- ***Longitudinal Analysis of Market Trends***: Future research should study trends of the mortgage market across timelines using longitudinal studies. Researchers can help explain how FinTech innovations are rewriting the landscape of the mortgage, by examining how changes in consumer behaviour, lending practices, and regulatory responses influence the mortgage (Gunin, 2024). Therefore, tracking data before, during, and after severe FinTech development would be necessary to understand the long-term consequences.
- ***Case Studies of FinTech Companies***: A deeper case study analysis of such selected FinTech companies like Home Credit, which successfully challenged the mortgage market would be useful. Researchers analyse their business models, customer engagement strategies, and technology implementations and glean how it might replicate that in best practices for traditional lenders. Furthermore, these case studies could also focus on these experiences of diverse consumer demographics, and how FinTech solutions address the needs of traditionally underserved populations.
- ***Exploration of Regulatory Frameworks***: The FinTech landscape is changing and so too must the regulatory frameworks that govern it. Future research should look at whether current regulation effectively responds to the latest developments in FinTech innovation and provide appropriate frameworks for mitigating the specific issues in mortgage lending that are unique to FinTech innovations. It determines potential best practices for strengthening consumer protection while encouraging innovation.

Future studies can help identify further complexities of FinTech in the mortgage market and gain actionable insights attainable by stakeholders in the industry through these aspects of research.

Reference List

Acolin, A., Bricker, J., Calem, P. and Wachter, S. (2016). Borrowing constraints and homeownership. American Economic Review, [online] 106(5), pp.625–29. doi:https://doi.org/10.1257/aer.p20161084

Adamek, J. and Solarz, M., 2023. Adoption factors in digital lending services offered by FinTech lenders. Oeconomia Copernicana, 14(1), pp.169-212

Allen, F., Gu, X. and Jagtiani, J., 2021. A survey of fintech research and policy discussion. Review of Corporate Finance, 1, pp.259-339

Alwi, S., 2021. Fintech As Financial Inclusion: Effect of FinTech on the share price and profitability of commercial banks in Malaysia, Indonesia and Singapore. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(11), pp.5338-5349.

Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. Journal of Economics and Business, [online] 100, pp.7–25. doi:https://doi.org/10.1016/j.jeconbus.2018.07.003.

Arnaut, D. and Bećirović, D., 2023. FinTech innovations as disruptor of the traditional financial industry. In Digital Transformation of the Financial Industry: Approaches and Applications (pp. 233-254). Cham: Springer International Publishing

Arner, D., Barberis, J. and Buckley, R. (2017). FinTech, regTech, and the reconceptualization of financial regulation. Northwestern Journal of International Law and Business, [online] 37, pp.373–415. Available at: https://www.researchgate.net/publication/320109794_FinTech_regTech_and_the_reconceptualization_of_financial_regulation [Accessed 14 Aug. 2024].

Baltgailis, J. and Simakhova, A., 2022. The technological innovations of fintech companies ensure the stability of the financial system in pandemic times. Marketing I menedžment innovacij, (2), pp.55-65.

Bank of England (2023). Monetary Policy Report. [online] Monetary Policy Committee. Available at: https://www.bankofengland.co.uk/-/media/boe/files/monetary-policy-report/2023/february/monetary-policy-report-february-2023.pdf [Accessed 13 Sep. 2024]

Basten, C. and Ongena, S. (2020). The Geography of Mortgage Lending in Times of FinTech. Core.ac.uk. [online] doi:oai:www.zora.uzh.ch:191505

Bavoso, V., 2020. The promise and perils of alternative market-based finance: the case of P2P lending in the UK. Journal of Banking Regulation, 21(4), pp.395-409

Bavoso, V., 2022. Financial intermediation in the age of FinTech: P2P lending and the reinvention of banking. Oxford Journal of Legal Studies, 42(1), pp.48-75

Bollaert, H., Lopez-de-Silanes, F. and Schwienbacher, A., 2021. Fintech and access to finance. Journal of corporate finance, 68, p.101941

Boustani, N.M., 2020. Traditional banks and fintech: survival, future, and threats. ICT for an Inclusive World: Industry 4.0–Towards the Smart Enterprise, pp.345-359

Bowden, J., King, T., Koutmos, D., Loncan, T. and Stentella Lopes, F.S., 2021. A taxonomy of fintech innovation. Disruptive Technology in Banking and Finance: An International Perspective on FinTech, pp.47-91

Branzoli, N. and Supino, I., 2020. Fintech credit: A critical review of empirical research literature. Bank of Italy Occasional Paper, (549)

Brown, E. and Piroska, D., 2022. Governing fintech and fintech as governance: The regulatory sandbox, riskwashing, and disruptive social classification. New Political Economy, 27(1), pp.19-32

Buchak, G., Gregor Matvos, Piskorski, T. and Amit Seru (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics, [online] 130(3), pp.453–483. doi:https://doi.org/10.1016/j.jfineco.2018.03.011

Buchanan, B.G. (2019). Artificial intelligence in finance. Zenodo (CERN European Organization for Nuclear Research). [online] doi:https://doi.org/10.5281/zenodo.2626454

Cai, C., Marrone, M. and Linnenluecke, M., 2022. Trends in fintech research and practice: Examining the intersection with the information systems field. Communications of the Association for information systems, 50(1), p.40

Carbó-Valverde, S., Cuadros-Solas, P.J. and Rodríguez-Fernández, F., 2021. FinTech and banking: an evolving relationship. Disruptive Technology in Banking and Finance: An International Perspective on FinTech, pp.161-194

Chemmanur, T.J., Imerman, M.B., Rajaiya, H. and Yu, Q., 2020. Recent developments in the fintech industry. Journal of Financial Management, Markets and Institutions, 8(01), p.2040002

Chen, C., 2020. Rethinking the Regulatory Sandbox for Financial Innovation: An Assessment of the UK and Singapore. Regulating FinTech in Asia: Global Context, Local Perspectives, pp.11-30

Cho, M., 2020. FinTech Megatrends: An Assessment of Their Industrial and Welfare Implications. KDI School of Pub Policy & Management Paper No. DP21-03

Claessens, S., Frost, J., Turner, G. and Zhu, F. (2018b). Fintech credit markets around the world: size, drivers and policy issues. [online] Bis.org. Available at: https://www.bis.org/publ/qtrpdf/r_qt1809e.htm [Accessed 15 Oct. 2024].

Cuadros-Solas, P.J., Cubillas, E., Salvador, C. and Nuria Suárez (2024). Digital disruptors at the gate. Does FinTech lending affect bank market power and stability? Journal of International Financial Markets, Institutions and Money, [online] 92, p.101964. doi:https://doi.org/10.1016/j.intfin.2024.101964.

Fuster, A., Plosser, M.C., Schnabl, P. and Vickery, J.I. (2018). The Role of Technology in Mortgage Lending. SSRN Electronic Journal, [online] 32(5). doi:https://doi.org/10.2139/ssrn.3127175

Frost, J., Gambacorta, L. and Gambacorta, R., 2020. The Matthew effect and modern finance: on the nexus between wealth inequality, financial development, and financial technology. Bank of Italy Occasional Paper, (565)

Gunin, A., 2024. The Future of Mortgage Financing in the Era of Fintech: A Systematic Review. Futurity Economics&Law, 4(2), pp.31-47

Guo, Y. and Liang, C. (2016). Blockchain application and outlook in the banking industry. Financial Innovation, [online] 2(1). doi:https://doi.org/10.1186/s40854-016-0034-9

Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. Journal of Management Information Systems, [online] 35(1), pp.220–265. Available at:

https://www.researchgate.net/publication/324119771_On_the_Fintech_Revolution_Interpreting_the_Forces_of_Innovation_Disruption_and_Transformation_in_Financial_Services [Accessed 15 Oct. 2024]

Haddad, C. and Hornuf, L., 2023. How do fintech start-ups affect financial institutions' performance and default risk? The European Journal of Finance, 29(15), pp.1761-1792

Hasan, R., Hassan, M.K. and Aliyu, S., 2020. Fintech and Islamic finance: Literature review and research agenda. International Journal of Islamic Economics and Finance (IJIEF), 3(1), pp.75-94

Haupert, T. and Lee, C.A., 2024. Fintech's relationship with subprime lending in immigrant gateway metropolitan areas. Journal of Urban Affairs, 46(2), pp.281-297

Hua, X. and Huang, Y., 2021. Understanding China's fintech sector: development, impacts and risks. The European Journal of Finance, 27(4-5), pp.321-333

Imerman, M.B. and Fabozzi, F.J., 2020. Cashing in on innovation: a taxonomy of FinTech. Journal of Asset Management, 21(3), p.167

Jagtiani, J. and Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. Financial Management, [online] 48(4), pp.1009–1029. doi:https://doi.org/10.1111/fima.12295

Jarvis, R. and Han, H., 2021. FinTech innovation: Review and future research directions. International Journal of Banking, Finance and Insurance Technologies, 1(1), pp.79-102

Jones, A., 2021. Digital credit scoring for affordable housing finance: Syntellect and Reall in urban India. Enterprise Development & Microfinance, 32(3)

Liang, S., 2023. The future of finance: fintech and digital transformation. Highlights in Business, Economics and Management, 15, pp.20-26

Locatelli, R., Schena, C. and Tanda, A., 2021. A historical perspective on disruptive technologies. Disruptive Technology in Banking and Finance: An International Perspective on FinTech, pp.9-45

Mahalle, A., Yong, J. and Tao, X., 2021, May. Regulatory challenges and mitigation for account services offered by FinTech. In 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (pp. 280-287). IEEE

Mahalle, A., Yong, J. and Tao, X., 2021, May. Regulatory challenges and mitigation for account services offered by FinTech. In 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (pp. 280-287). IEEE

Martin, N. and Foohey, P., 2021. Reducing The Wealth Gap Through Fintech' Advances in Consumer Banking and Lending. University of Illinois Law Review, 2021(2), p.459

Miglionico, A., 2022. Digital payments system and market disruption. Law and Financial Markets Review, 16(3), pp.181-196

Najaf, K., Subramaniam, R.K. and Atayah, O.F., 2022. Understanding the implications of FinTech Peer-to-Peer (P2P) lending during the COVID-19 pandemic. Journal of Sustainable Finance & Investment, 12(1), pp.87-102

Nejad, M.G., 2022. Research on financial innovations: An interdisciplinary review. International Journal of Bank Marketing, 40(3), pp.578-612

Ofir, M. and Sadeh, I., 2020. More of the Same or Real Transformation: Does Fintech Warrant New Regulations? Hous. Bus. & Tax LJ, 21, p.280

Ozili, P.K., 2022. Bank non-performing loans in the fintech era. International Journal of Financial Innovation in Banking, 3(2), pp.95-112

Sinch. (2024). Explore 20 customer engagement tools your business needs - Sinch. [online] Available at: https://sinch.com/blog/customer-engagement-tools/ [Accessed 14 Oct. 2024].

Suryono, R.R., Budi, I. and Purwandari, B., 2020. Challenges and trends of financial technology (Fintech): a systematic literature review. Information, 11(12), p.590

Thakor, A. (2019). Fintech and banking: What do we know? Journal of Financial Intermediation, [online] 41(100833). doi:https://www.researchgate.net/publication/335325400_Fintech_and_banking_What_do_we_know

The Devastator (2022). UK Mortgage Rates. [online] Kaggle.com. Available at: https://www.kaggle.com/datasets/thedevastator/uk-mortgage-rates-thousands-of-mortgage-products [Accessed 17 Oct. 2024].

ukfinance.org.uk (2024). The future of mortgages. [online] ukfinance.org.uk. Available at: https://www.ukfinance.org.uk/news-and-insight/blog/future-mortgages [Accessed 14 Aug. 2024]

Williams, J., 2021. Conclusion: FinTech—a perfect day or walk on the wild side? Disruptive technology in banking and finance: an international perspective on FinTech, pp.283-313

Wu, P.C., Liu, S.Y. and Huang, C.W., 2022. The Impact of FinTech index on P2P lending rate. Review of Integrative Business and Economics Research, 11(2), pp.79-94

Xu, B., Su, Z. and Celler, J., 2021. Evaluating default risk and loan performance in UK peer-to-peer lending: Evidence from funding circle. Journal of Advanced Computational Intelligence and Intelligent Informatics, 25(5), pp.530-538

Yang, L. and Wang, S., 2022. Do fintech applications promote regional innovation efficiency? Empirical evidence from China. Socio-Economic Planning Sciences, 83, p.101258

Zhao, J., Li, X., Yu, C.H., Chen, S. and Lee, C.C., 2022. Riding the FinTech innovation wave: FinTech, patents and bank performance. Journal of International Money and Finance, 122, p.102552

Каленюк, І., Куклін, О., Панченко, Є., Дьякон, А. and Богун, М., 2024. FINANCIAL INNOVATIONS IN THE SMART CITY ECOSYSTEM. Financial and credit activity problems of theory and practice, 1(54), pp.102-113

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Alexey Shalimov (2023). 8 Trends Empowering the Customer Experience in Digital Banking. [online] Eastern Peak - Technology Consulting & Development Company. Available at: https://easternpeak.com/blog/customer-experience-in-digital-banking/ [Accessed 12 Oct. 2024]

Buckley, R., Arner, D. and Barberis, J. (2016). The Evolution of Fintech: A New PostCrisis Paradigm? Georgetown Journal of International Law, 47(4), pp.1271–1319. doi:https://doi.org/10.2139/ssrn.2676553

deloitte.com (2017). The Future of Fintechs: Risk and Regulatory Compliance. [online] deloitte.com. Available at: https://www2.deloitte.com/us/en/pages/regulatory/articles/future-of-fintechs-risk-and-regulatory-compliance.html [Accessed 2 Oct. 2024]

Floify.com. (2023). 5 Ways FinTech is Changing the Mortgage Industry – Floify. [online] Available at: https://floify.com/blog/5-ways-fintech-is-changing-the-mortgage-industry [Accessed 2 Oct. 2024]

Linkedin.com. (2024). LinkedIn. [online] Available at: https://www.linkedin.com/pulse/consumer-expectations-fintech-one-thing-connects-two-amit-raje/ [Accessed 2 Oct. 2024]

Appendix

1. Dataset Link:

https://www.kaggle.com/datasets/thedevastator/uk-mortgage-rates-thousands-of-mortgage-products

2. Python Code:

```
# Importing Necessery Libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from      sklearn.metrics      import      accuracy_score,      confusion_matrix,
classification_report
import statsmodels.api as sm
from statsmodels.tsa.arima.model import ARIMA
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('UK_Mortgage_Rate.csv')
print(df.head())

# Checking null Values
print(df.isnull().sum())

# Visualizations
# Plot Histogram of MTG_INITIAL_RATE_PCT
plt.figure(figsize=(8, 6))
sns.histplot(df['MTG_INITIAL_RATE_PCT'], bins=20, kde=True)
plt.title('Distribution of Initial Mortgage Rates')
plt.xlabel('Initial Mortgage Rate (%)')
plt.ylabel('Frequency')
plt.show()
```

```
# Boxplot for Initial Rates by Mortgage Type (Fixed vs Variable vs Discounted)
plt.figure(figsize=(10, 6))
sns.boxplot(x='MTG_PRODUCT_TYPE', y='MTG_INITIAL_RATE_PCT', data=df)
plt.title('Initial Mortgage Rates by Mortgage Type')
plt.xlabel('Mortgage Type')
plt.ylabel('Initial Rate (%)')
plt.show()

# Calculate average fees for each mortgage product type
average_fees                                                                    =
df.groupby('MTG_PRODUCT_TYPE')['MTG_FEES_TOTAL'].mean().reset_index()

# Bar Plot of Average Fees by Mortgage Product Type
plt.figure(figsize=(8, 6))
sns.barplot(x='MTG_PRODUCT_TYPE', y='MTG_FEES_TOTAL', data=average_fees)
plt.title('Average Fees by Mortgage Product Type')
plt.xlabel('Mortgage Product Type')
plt.ylabel('Average Fees (Total)')
plt.show()
```

```
# Scatter plot of APR vs Initial Rates
plt.figure(figsize=(8, 6))
sns.scatterplot(x='MTG_INITIAL_RATE_PCT', y='MTG_APR_PCT', data=df)
plt.title('APR vs Initial Mortgage Rate')
plt.xlabel('Initial Mortgage Rate (%)')
plt.ylabel('Annual Percentage Rate (APR) (%)')
plt.show()

# Correlation Heatmap
plt.figure(figsize=(10, 6))
correlation_matrix = df[['MTG_INITIAL_RATE_PCT', 'MTG_APR_PCT',
'MTG_REVERT_RATE', 'MTG_FEES_TOTAL']].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()

# Train Test Split
X = df[['MTG_INITIAL_RATE_PCT', 'MTG_FEES_TOTAL']]
y = df['MTG_REVERT_RATE'].fillna(0)
y = (y > 0).astype(int)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Logistic Regression
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
log_reg = LogisticRegression()
```

```
# Hyperparameter tuning using GridSearchCV
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear']
}
grid_search = GridSearchCV(log_reg, param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)
best_log_reg = grid_search.best_estimator_
y_pred = best_log_reg.predict(X_test_scaled)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Best Hyperparameters: {grid_search.best_params_}')
print(f'Accuracy: {accuracy:.4f}')
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

# Classification Report
class_report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy:.4f}')
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)
```

```python
# ARIMA Model
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
df['MTG_INITIAL_RATE_PCT'].dropna(inplace=True)
data = df['MTG_INITIAL_RATE_PCT']
def adf_test(series):
    result = adfuller(series)
    print('ADF Statistic:', result[0])
    print('p-value:', result[1])
    if result[1] <= 0.05:
        print("The series is stationary.")
    else:
        print("The series is not stationary.")
adf_test(data)

# Plot the time series
plt.figure(figsize=(12, 6))
plt.plot(data, label='MTG Initial Rate')
plt.title('Mortgage Initial Rate Over Time')
plt.xlabel('Index')
plt.ylabel('Initial Rate (%)')
plt.legend()
plt.show()
data_diff = data.diff().dropna()
adf_test(data_diff)
model = ARIMA(data, order=(1, 1, 1))
model_fit = model.fit()
print(model_fit.summary())
n_periods = 12  # Number of periods to forecast (e.g., next 12 months)
forecast = model_fit.forecast(steps=n_periods)
```

```
# Plot the forecast
plt.figure(figsize=(12, 6))
plt.plot(data, label='Historical Data')
plt.plot(range(len(data), len(data) + n_periods), forecast, label='Forecast',
color='red')
plt.title('Forecast of Mortgage Initial Rate')
plt.xlabel('Index')
plt.ylabel('Initial Rate (%)')
plt.legend()
plt.show()

# Chi_Squre Test
from scipy.stats import chi2_contingency
contingency_table = pd.crosstab(df['MTG_APR_PCT'], df['MTG_REVERT_RATE'])

# Display the contingency table
print("Contingency Table:")
print(contingency_table)

# Perform the Chi-Square test
chi2, p, dof, expected = chi2_contingency(contingency_table)

# Print the results
print(f"Chi-Square Statistic: {chi2}")
print(f"p-value: {p}")
```

```
print(f"Degrees of Freedom: {dof}")
print("Expected Frequencies Table:")
print(expected)

# Interpret the result
alpha = 0.05 # Significance level
if p < alpha:
    print("Reject the null hypothesis - There is a significant association
between the variables.")
else:

    print("Fail to reject the null hypothesis - There is no significant
association between the variables.")
```

3. ER1 - Research Ethics Checklist And Notification Form

ER1 – Research Ethics Checklist and Notification Form

*Please submit this as a Word document and ensure you complete **all** sections of this form.*

1. Research Ethics Checklist

This checklist must be completed by all researchers prior to starting their study. The aim of the checklist is to identify whether a full application for formal approval needs to be submitted.

Notification Form			
Section I: Study Details			
Study title:	Fintech Innovations' Effect on UK's Conventional Residential Mortgage Lending		
Section II: Contact Details			
Name:	Maulik Suthar		
Email address:	Maulik.suthar14@law.ac.uk		
Section III: Checklist		**Yes**	**No**
1.	Does your study involve human participants directly (e.g., through use of interviews, questionnaires) or indirectly (for example, through provision of, or access to, a person's data)?	☐	☒
2.	Do you intend to use information sources or data <u>other than</u> those that have been published or that are in the public domain (for example, law reports, newspaper articles, journals articles, books, or internet sites)?	☐	☒
3.	Does your study involve research into areas which would usually cause the research to be classified as 'sensitive' by the University? By sensitive, we mean, for example, research into illegal activities, extremism and radicalisation, information which is normally prohibited on University networks, systems, and services, and /or illegal or controlled (please see the Ethics Statement of Practice paragraph 2.3.6).	☐	☒

4.	Does the study involve participants who are particularly vulnerable or unable to give informed consent (e.g. children, people with learning difficulties, victims of crime)?	☐	☒
5.	Will the study involve actively deceiving the participants (e.g. will participants be deliberately falsely informed, will information be withheld from them or will they be misled in such a way that they are likely to object or show unease when debriefed about the study)?	☐	☒
6.	Will the study involve discussion or collection of information on sensitive topics (e.g. criminality, sexual activity, drug use, mental health, mental capacity, or an individual's health information)?	☐	☒
7.	Does the study risk causing psychological stress, anxiety, humiliation, or other harm or negative consequences beyond what would normally be encountered by the participants in their life outside research?	☐	☒
8.	Will financial inducement be offered to participants?	☐	☒
9.	Will the study involve any medical recruitment of patients or staff through the NHS, or working at an NHS site?	☐	☒
10.	Will the research involve invasive interventions (e.g. administration of drugs, vigorous exercise) not usually encountered during everyday life?	☐	☒
11.	Could the research have an adverse impact on employment or social standing (e.g. discussion of an employer or commercially sensitive information)?	☐	☒
12.	Could the research lead to 'labelling' either by the researcher (e.g. categorisation) or by the participant (e.g. 'I am stupid', 'I am not normal')?	☐	☒
13.	Will the research involve the collection of human tissue, blood, or other biological samples?	☐	☒

Please ensure that you submit this form to the Ethics Committee (ethics@law.ac.uk) before you commence your research, contact potential human participants for your study, and/or before you commence any sensitive research. All applications shall be dealt with by the relevant School Sub-Committee.

Please note that it is your responsibility to comply with the principles of ethical research described in Section 2 of the Ethics Statement of Practice. **This includes providing information about the study, consent forms and debriefing**

information as appropriate and ensuring confidentiality in the storage and use of personal data*.

Recoverable Signature

X Maulik Suthar

Maulik Suthar

Signature Signed by: 0d96bc48-eaca-4767-8d9e-dc18fe3671c0 **Date: 06/07/2024**

*Your processing of (obtaining, recording, holding, etc.) personal data in connection with your research should comply with the General Data Protection Regulation and associated University policies.