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Data-Driven Product Development in Financial Services

Master's Thesis (20 ECTS)

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Data-Driven Product Development in Financial Services

Abstract:

With technological advancements the financial institutions have significantly transformed allowing the financial institutes to use the data for enhancing the products and services. This thesis presents how data helps to enhance the financial products and services for both consumers and providers of such products. Using systematic literature review, it addresses research questions; how can data enhance financial products and services in a way that creates value to the consumers and providers. For customers data enhances credit access and personalization through mechanisms like machine learning and algorithmic advice. For providers it generates value in the form of new revenue sources, operational efficiency, risk reduction, fraud detection and prevention. Banks and financial institutions employ predictive and prescriptive analytics, robo-advisors and cognitive tools to tailor offerings and improve customer experience. Meanwhile, AI systems automate internal processes and enable well-supported decision-making. Next, it tells us how data-driven growth enables inclusive, efficient and strategic growth in retail banking.

Keywords:

Data driven, Data analytics, Financial products, Fintech, Banking.

CERCS: P170 Computer science, numerical analysis, systems, control

Andmepõhine tootearendus finantsteenustes

Lühikokkuvõte:

Tehnoloogiliste edusammudega on finantsasutused oluliselt muutunud, finantsasutustel on avanenud võimalus kasutada andmeid toodete ja teenuste täiustamiseks. See lõputöö tutvustab, kuidas andmed aitavad parandada finantstooteid ja -teenuseid nii tarbijate kui ka toodete pakkujate jaoks. Kasutades süstemaatilist kirjanduse ülevaadet, käsitletakse järgnevat uurimisküsimust; kuidas saavad andmed täiustada finantstooteid ja -teenuseid viisil, mis loob väärtust tarbijatele ja pakkujatele. Klientide jaoks parandavad andmed krediidile juurdepääsu ja toodete isikupärastamist, seda läbi masinõppe ja erinevate algoritmide. Pakkujate jaoks loob see väärtust uute tuluallikate, tegevuse tõhususe, riskide vähendamise, pettuste avastamise ja ennetamise näol. Pangad ja finantsasutused kasutavad pakkumiste kohandamiseks ja kliendikogemuse parandamiseks ennustavat ja ettekirjutavat analüütikat, robot-nõustajaid ja kognitiivseid tööriistu. Samal ajal automatiseerivad AI-süsteemid sisemisi protsesse ja toetavad teadlikumat otsuste langetamist. Lisaks räägib see lõputöö meile, kuidas andmetest lähtuv tegutsemine toetab üleüldiselt jaepanganduses kaasavat, tõhusat ja strateegilist ettevõtete kasvu.

Võtmesõnad:

Andmepõhine, andmeanalüütika, finantstooted, finantstehnoloogia, pangandus.

CERCS: P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine (automaatjuhtimisteooria)

Contents

1. Introduction

Financial institutions offer a wide range of products and services from very basic to complex financial instruments for both individuals and corporate clients. Examples of the product offered by the financial institutes are saving accounts, business accounts, credit cards, debit cards, term deposits, home loans, personal loans etc. for core financial management. In addition to these core offerings, financial institutions also provide specialized services in areas such as wealth management, insurance, and risk management solutions etc.[1]. These financial products and services have been around for more than centuries but in the course of time, the evolution of products and services has been under the heavy influence of technological advancements such as telecommunications, telegraph, application of Automated Teller Machines (ATMs), use of computers, digital applications and fintech's have transformed how financial products are designed, delivered, accessed and consumed [2].

These advancements brought forth a new era characterized by convenience, accessibility and efficiency. For example, electronic banking evolved from the 1960s as the era in which financial institutions started using electronic systems as their means to advance the processing of transactions and improvement of customer service [3]. During the late 1960s to early 1970s Automated Teller Machines were launched which enabled customers to conduct basic functionalities like cash withdrawals and balance inquiries without visiting the branch. During the 1980s telephone banking continued to increase remote banking services like inquire about balances as well as transferring funds through automated voice systems. These paved the way towards increasingly digitalized banking solutions [4].

The real change happened in the 1990s when internet was introduced that enabled banks to offer online banking. With this, customers could into their accounts and balances, make transactions at home with the help of some basic functionalities. As more people began adopting the internet, banks also invested in more secure and feature-rich platforms. The wide use of smartphones and mobile apps made another leap in the 21st century. With the late 2000s and early 2010s came mobile banking applications, which turned the whole customer experience of finance management intuitive, real-time and interactive starting a completely new banking experience [4]. Digitalization of financial services has significantly boosted financial inclusion, especially for those who have been underserved. Mobile banking is playing a crucial role in bringing the essential banking services to people in remote segments [5].

Thus, with the development in technology, financial services began to change from their traditional methods and practices to digital ones. This steady integration of technology has brought not only operational efficiencies but also an increase in scale and scope for financial inclusion and access a new era in the evolution of financial service provisions. This also provided flexibility and a reduction of the costs. With the rapid advancement in technology, the way customers interact with financial services has completely changed. More and more, interactions are happening through online mediums like mobile banking apps and digital payment. In recent years we have been collecting a sea of data with these interactions from different data sources [6].

Financial institutions are using data to create better financial products and services or enhance existing financial products and services. This helps the financial institutions to provide more personalized and efficient products and services for their customers. There has been research

on data-driven transformation in financial institutions, but there are still some challenges. Issues like fragmented data structures, accessibility problems and old legacy systems make it hard to use data effectively. Additionally, integrating various data sources and following compliance and regulatory requirements adds to the complexity.

For instance, Malhotra and Malhotra [7] explain how big data, analytics, and AI are transforming the financial services sector by enhancing risk management, enabling personalized products, and enabling innovations such as open banking and alternative lending. Camilleri explains how data-driven technologies, particularly big data analytics and programmatic advertising are revolutionizing customer-focused marketing and illustrates how firms track and analyze customers' information in real-time in order to create targeted campaigns, and how they address privacy concerns arising from increased data collection [8]. Steven Robbins explains how data-driven insights play an essential role in enhancing fraud identification with in-depth customer conduct and transaction habits' comprehension, thus allowing FinTech companies to accurately identify trends and irregularities which enables proactive decision-making and improves operational efficiency and risk management [9].

However, these studies do not fully explore how financial institutions use data to transform or evolve the products and services particularly in the area of products and services offered to retail customers. So, to fill this gap the thesis focuses specifically on how data is used to enhance financial products and services for retail customers. In turn, this paper seeks to examine how financial institutions can use data to further develop, innovate and expand their offerings.

From the above gap in literature this study aims to address the research question below as financial institutions increasingly adapt data and technology and customers seek financial products and services that are aligned with their goals, behaviors, and needs. Hence there is a need to understand how data drives innovations in financial products and services that meet the retail customer needs and data driven product development effects on consumers and financial institutions which will provide insights into long term viability and strategic growth.

RQ1. How can data enhance financial products and services for those who consume such products and services?

RQ2. How can data enhance financial products and services for those who provide such products and services?

To address the above research questions, we are going to conduct a systematic literature review that includes grey literature. Therefore, the purpose of the thesis is to focus on how financial institutions can utilize data to transform financial products and services for retail customers. It helps identify the value added by the data driven financial products and services to the retail customers. Considering this improvement analysis, the study investigates how data-driven product development affects customer engagement in the context of product adoption. This also includes how data helps optimize the financial product on offer, enhance risk management, and create areas of competitive advantage. The best outcomes of integrating data analytics within financial product development will also be provided through this research.

The remainder of the work is structured as follows. It begins with the background providing essential context. Section 3 describes the Methodology used for research and the procedure of the Methodology. Section 4 presents the Results, while Section 5 discusses these findings and Section 6 concludes the thesis, summarizing the research.

2. Background

This section provides the essential background necessary to understand the main concepts and notions associated with research. This discusses financial products and services provided by financial institutions, data-driven product innovation in financial services and the existing research on the application of data about customers and their behavior to develop and innovate financial services and products.

2.1 Financial products and services

Financial institutions offer an extensive array of products and services to retail customers, SMEs and large corporates. Financial institutions have evolved from branch-based physical transactions to a technology-driven system propelled by economic demands and advancements. The Industrial Revolution institutionalized modern banking through credit bureaus and enhanced access to capital. Checks, wire transfer, and subsequent credit and debit cards have improved transactions by making them safer and more convenient [10]. The digital age has carried this even further by allowing online banking, peer-to-peer lending, and mobile transactions, making financial services more accessible than ever [11]. Post-2008 regulatory changes strengthened credit policies, and fintech innovations and mobile wallets redirected lending and payments [12].

The products offered to individual customers are called retail products. Some of the retail products are deposit accounts, loans, mortgages, credit cards, and other financial products that help individuals to manage their money. They also include investment products such as mutual funds, stocks, and bonds to help customers grow their wealth [13]. In this thesis we are looking at the banking products and services that are offered to retail customers. The categories of products and services that we are looking at in this thesis are Saving, Payments, Loans, and Investments.

Saving products enable people to save and increase their money safely. Financial institutes offer interest in the saving accounts, which motivate their customers to save money today for which they can receive interest for tomorrow. Some of the savings' products offered by the financial institutes are fixed deposits, high-yield savings accounts and recurring deposit accounts.

On the other hand, payment products make transactions more convenient and time efficient. Debit and credit cards, mobile payments, e-wallets, wire transfer, and direct debit are some of the payment products and services provided by financial institutes. Payment products allow consumers to make payments or transactions efficiently. Due to advancements in financial technology contactless payment and real-time online transactions are becoming more popular and are widely utilized.

Loan products provide financial support for various needs of the customers. Some of the loan products offered by the financial institutes include personal loans, auto loans, student loans, and mortgage loans. Personal loans offer unsecured financing for diverse purposes, while auto loans help you buy a car. Student loans cover education expenses, and mortgage loans enable property purchases.

Investment products allow people to grow their wealth using financial products and services. Some of the investment products and services offered by financial institutions are stock broking facilities and products like mutual funds, fixed income products, and structured investment products. They have different products and services for different risk profiles ranging from fixed deposits to high-risk equities.

2.2 Data driven Product Development in Financial services

The recent technological advancements have generated enormous volumes of data [8]. These enormous volumes of data thus generated are processed using data analytics to enhance financial products and services. There are various types of data analytics, each serving distinct purposes. Among these, descriptive, diagnostic, predictive, prescriptive, and cognitive analytics are particularly prominent in data-driven product enhancements [14]. Descriptive analytics facilitate the analysis of historical data, enabling the identification of patterns and trends in customer behavior and transactions. Diagnostic analytics focus on uncovering the root causes of issues such as fraud or transaction errors. Predictive analytics leverage historical data and machine learning to forecast customer behavior and market trends. Prescriptive analytics use advanced algorithms and data analysis to recommend best actions and strategies. Cognitive analytics use artificial intelligence and machine learning to replicate how humans think. These analytics help financial institutions analyze complex data, forecast customer needs and offer customized products and services to the customers. Therefore cognitive analytics improves product features, enable more informed decision-making and improve the overall customer experience [14].

2.2.1 Descriptive analytics

Descriptive analytics uses historical data to describe the past with its trends and patterns and draws out insights from it to answer the question, "What happened?" This data analysis process help make sense of large amounts of information and provides insights into past performance [15].

Descriptive analytics were used in the case of credit card portfolio management of a world's leading credit card to analyze historical spending patterns, transaction frequencies and spending categories across different customer segments. With bar charts, line graphs and heat maps, the bank discovered customer segment spending patterns, including seasonal trends and behavioral differences by card type or wealth type. Descriptive analytics assist banks in recognizing high-value segments, seasonal spending trends which aid them in targeting growth initiatives effectively and improving customer satisfaction.

2.2.2 Diagnostics analytics

Diagnostic analytics goes a bit further to descriptive analytics and finds out the "why" behind a particular trend and this analytics helps to explain the causes of the particular trend [16]. It involves looking at historical data to find out the root causes of specific outcomes or anomalies. Diagnostic analytics investigating past performance and help in understanding the contributing

factors of the past performance so that business can gain insights into how to improve the products and services [15].
For example, a bank notices low customer satisfaction in the feedback surveys from their customers then the bank uses diagnostic analytics to analyze data from feedback surveys, transaction history and service usage patterns. These diagnostic analytics help to find the root causes for the low customer satisfaction like delayed processing times or product defects etc. By understanding the root cause banks can take necessary decisions like to enhance service levels, streamline processes, improve the product defects thereby improving the overall customer experience [17].

2.2.3 Predictive analytics

Predictive analytics uses historical data and statistical algorithms to forecast future events that help to answer the question: "What is likely to happen in the future?" Today artificial intelligence and advanced machine learning algorithms have greatly improved the accuracy of predictive data modelling [14]. Predictive analytics goes a step further to help organizations to forecast some potential scenarios and trends by identifying patterns and relationships from past data and helps the organizations to take necessary actions its advantage.
For example, Banks use predictive analytics to analyze the past data of the customers and identify scenarios and trends like customers at risk of leaving the bank. This analysis helps banks to prevents the customer from leaving the bank and help the banks to retain those customers [18].

2.2.4 Prescriptive analytics

Prescriptive analytics helps to identify the most appropriate steps to achieve the best results that help the organizations to achieve their goals. These suggestions and recommendations are based on the insights that are gained by analyzing historical trends using predictive analytics. Prescriptive analytics answers the question “What should we do next?” [19]. This analytics uses advanced algorithms and decision models to determine the best course of action in different circumstances.
For example, banks prescriptive analytics is used in predicting potential predict loan defaults by analyzing past data like credit history and economic trends. Using advanced algorithms that are used in prescriptive analytics foresees high risk borrowers. This analytics suggests appropriate risk measures. This allows banks to revise the lending policies proactively. These measures help banks to minimize losses and promote financial stability. Ultimately prescriptive offers data-driven decision-making that optimizes profitability and customer trust [20].

2.2.5 Cognitive analytics

Cognitive analytics is relatively new and advanced data analytics that uses artificial intelligence and machine learning to process large amounts of unstructured data like word-processing documents, images, audio files, plain text and social media content to extract insights and make predictions from this valuable information. These enable real-time autonomous decision-

making. As a more advanced form of analytics, it allows companies to gain greater, real-time understanding of complex patterns with insights that might evade traditional analytics. Built to operate autonomously, cognitive analytics solutions can operate in real-time, learning and adapting on the fly. The solutions also operate alongside other analytics software with ease, integrating descriptive, diagnostic, and predictive analytics into a cohesive, intelligent view of the business landscape [14].

For example, a bank uses a chatbot powered by cognitive analytics to handle customer queries. The chatbot deciphers language, tone, and sentiment of the messages sent by customers in a bid to understand if the customer is frustrated, confused, or satisfied. This information allows the bank to identify common pain points in the long term, such as confusion over the eligibility terms of a loan. Using these insights, the bank updates loan products, simplifies processes, and even recommends personalized loan products directly through the chatbot — improving customer experience along with product relevance [21].

The combination of all these analyses-advanced, descriptive, diagnostic, predictive, and cognitive-allows an organization to make informed decisions based on data, optimize processes, and enhance their key strategic initiatives [14]. This enables businesses to create products that better meet customer needs, business objectives and helps the business to stay ahead of competition [22].

2.3 Related work

In this section an overview of the related work is described concerning studies on data driven product development, studies on data driven marketing and studies aimed at improving financial products like loans and payments.

There have been researches on data driven product development by Timm Fichtler, Christian Koldewey, Khoren Grigoryan and Roman Dumitrescu which suggested a systematic data-driven product development, with decision-making in each step of the product life cycle is data-driven. The process starts by establishing goals and objectives, after which data from different sources including transactions, online interactions, and consumer feedback are collected in a structured manner. The data is analyzed in order to derive insights that influence product design, product development, and product testing. By continuously refining products based on real customer data rather than assumptions, this cyclical approach ensures better outcomes. This study explains how data is infused throughout; financial institutions can create products that are more customer-need- and trend-conscious [23]. But this paper explores how Saving, Payments, Loans, and Investments categories of financial products and services can be transformed or evolved using data.

The study by Tony Rizzo examines the ways in which financial institutions can utilize data-driven marketing strategies to aid customer acquisition, retention, and engagement. Through internal and external data, banks are able to segment their customers based on demographics, age, behavior, and preference customer and implement target marketing. Tailored, timely, and relevant communications build trust and long-term relationships. The study highlights the importance of quickly responding to customer behavior, showing how targeted messaging and

content can greatly enhance marketing effectiveness [24]. But this paper focuses on how the financial products and services that are based on data enable personalized product offerings, are advantageous to the financial institution and also highlights how this data-driven approach enables customer engagement, customer experience of financial products and services can be improved.

Studies by Hussain & Robbins explain that before fraud detection in financial institutions relied on rule-based systems that flagged suspicious payments based on predefined rules like large withdrawals or payments from high-risk locations. These systems lacked adaptability and generated a high number of false positives which led to customers. Learning from this customer dissatisfaction financial institutes started integrating Artificial Intelligence and machine learning which leverages vast past fraud case data, customer behavioral data, device data, geolocation data, information to assess risk dynamically, reducing false positives and improving accuracy in detecting the fraudulent payments [9].

On the other hand, this paper discusses how data plays an important part in streamlining fraud and handling transactions. These facilitations make for secure and reliable transactions that greatly increase customer value. Therefore, trust and confidence are built, to increase customer satisfaction and to improve bank performance.

3. Methodology

In this section, we present the research method used beginning with the research questions that guided the research. The research is conducted through a Systematic Literature Review (SLR), a systematic method for searching, evaluating, and synthesizing existing literature on data-driven product development in financial institutions. The chapter introduces the research objective, explains why Systematic Literature Review (SLR) is appropriate for this research, and describes the process followed, about how the Systematic Literature Review (SLR) was performed. By the systematic review of existing work, this research aims to provide an understanding of how banks use data to innovate, create customer value, improve customer experience and financial institutions' performance.

3.1 Planning & Motivation

The objective of the Systematic Literature Review (SLR) of this thesis is to identify in what ways banks and other financial institutions leverage data-driven practices in order to further enhance financial products and services. The two topics on which the SLR investigates are (1) how data-driven banking services and products add value to the consumers and (2) how data-driven banking products and services influence bank performance. SLR methodology is thereafter employed to synthesize available evidence holistically unbiasedly, thus allowing for identification of key trends, and prospects in data-driven product development within financial services. The systematic method allows for better-informed understanding of data-influenced innovation in the sector.

This study sets out a Systematic Literature Review (SLR) a methodical, reproducible, and comprehensive synthesis of existing academic and industry research on data driven product development. In this study reviews of both peer-reviewed scholarly literature and grey literature such as industry reports and working papers are carried out to have a holistic perspective on the topic. This approach follows the guidelines set out by Kitchenham et al. [25] for conducting systematic reviews in business and technology research.

A Systematic Literature Review is applied in this study since it provides for systematic and objective examination of the state of knowledge. As opposed to traditional literature reviews, SLR applies a systematic approach to minimizing bias to have findings based on a reproducible and comprehensive search strategy. This entails systematically identifying, appraising, and synthesizing relevant studies according to pre-specified inclusion and exclusion criteria. By applying a systematic search process, an SLR provides findings that are comprehensive, accurate and evidence-based and paints an objective picture of the research that exists. Since data-driven financial products are emerging at a fast pace, literature on the subject is often fragmented across disciplines, including finance, technology, and customer behavior. A traditional review would be incapable of synthesizing these diverse views, and the resultant knowledge would be incomplete or skewed towards the topic. Conversely, an SLR allows for a systematic synthesis of evidence from different fields, subjecting it to examination, and interpreting the same in an organized way. It also enables one to determine knowledge gaps in literature, opening avenues for research while offering practical lessons to financial institutions that are interested in leveraging data for product development, customer interaction, and business performance.

Systematic Literature Review (SLR) is an approach encompassing systematic identification, evaluation, and synthesis of current studies related to a particular research question. An SLR stands in comparison with narrative or customary reviews because an SLR uses a structured protocol, consisting of a prepared search strategy, eligibility criteria, and quality appraisal methods. Using SLR, academics can capture seminal outcomes, registering literatures gaps, and formulating evidence-based outcomes [26]. With the use of an SLR framework, this study offers a systematic and transparent review of data-driven financial product design, offering conclusions that benefit scholarly and practitioner research and practice alike.

The SLR was executed in compliance with the guidelines proposed by Kitchenham. The stages of SLR comprise three main phases that are planning, conducting, and reporting the review. The planning phase includes identification of the need for a review and formulation of the motivation, specification of the research questions, developing and evaluating the review protocol. The review stage is conducted considering the identification of studies, selection of primary studies, assessment of the study quality, extraction and synthesis of data. The final stage reporting focuses on identifying how findings are developed, shared and assessed. This stage also examines the clarity, impact and usefulness of the information presented and ensures that key takeaways lead to further action and decision-making.

3.2 Research questions

This SLR emphasizes the identification and analysis of the existing publications on data driven product development. The purpose of the research is summarized in a list of more precise research questions. Following objective specified and focus areas, the following research questions (RQ) are formulated.

(1) RQ1: How can data enhance financial products and services for those who consume such products and services?

This question focuses on how data enhanced financial products and services (using data analysis, AI and automation etc) enhance value to customers who consume the products and services like improving customer convenience, providing personalization etc., It assesses how data driven innovations like tailored credit offers, savings suggestions based on forecasting and real-time financial insight provide tangible etc., value to retail-customers.

(2) RQ2: How can data enhance financial products and services for those who provide such products and services?

This question examines the impact of data enhanced financial products and services offered by the financial institutions that led to financial institutes profitability and enhanced operational efficiency etc.

3.3 Search Strategy

The search strategy employed in this Systematic Literature Review (SLR) is the guidelines for conducting systematic reviews that is proposed in "Guidelines for performing Systematic Literature Reviews in Software Engineering," [26] "A Guide to Conducting a Standalone Systematic Literature Review," [27] and "A Systems Approach to Conduct an Effective Literature Review in Support of Information Systems Research," [28]. A systematic search strategy was developed to offer a comprehensive and unbiased collection of relevant studies by formulating search strings and running them on a range of electronic databases.

The aim was to perform a comprehensive search and identify the initial list of primary studies In order to develop the search string, the guidelines suggested by Kitchenham [29] were followed. The range of terms used for the search included the following:

(1) "Data-driven" – This is the main term that indicates the foundation of the research, highlighting the importance of data in financial product development.

(2) "Data analytics" – This term is derived from research questions; this is the analytical approach used to extract insights from financial data.

(3) "Financial products" - This key term ensures that the search includes studies that are focused on the financial products.

(4) "Financial services" - This key term is included so that the search captures studies that are focused on both traditional and non-traditional financial institutions.

   a. Banking
   b. Fintech

Based on the search terms, the following search string was defined:
((“Data – driven” OR “Data analytics”) AND
(“Financial products” OR “Banking” OR “Fintech”)
The above search string was applied in different electronic databases. The databases were selected based on the coverage of computer science journal articles, magazines, and books where data driven product development research is mostly published. The databases also had to be accessed for free using the university domain. The following databases were thus used

(1) IEEE Xplore
(2) Scopus
(3) EBSCO
(4) WoS

Table 1.The total number of papers identified per source.

Source	**Total number of papers identified**
IEEE Xplore	2488
Scopus	828
EBSCO	1629
WoS	3686
Total	8631

The developed search string was executed across all selected databases, with the number of results per source shown in Table 1. The resulting lists were then downloaded and merged into a single dataset that included a total of 8,631 publications.

3.4 Paper selection criteria

The aim of paper selection is to identify papers that are relevant to the study that possess enough information necessary in addressing research questions. The following inclusion and exclusion criteria’s are the aspects for the selection of the papers.
on criteria.
(1) Inclusion criteria (IC):

a. **IC1: Is the paper relevant to the domain of data-driven financial product development?**
   This requirement is to ensure that only data analytics, financial products, banking, or fintech in nature studies are considered and not studies from other fields.
b. **IC2: Does the paper present, review, discuss, or demonstrate a relevant concept of data-driven approach in financial product development?**
   Based on this selection criterion papers that explore, analyze, or apply data analytics, AI or customer insight within the domain of financial services innovation are included or the paper discusses if these enhancements are beneficial for the customers.
c. **IC3: Does the study describe at least one applicable method or approach of using data to enhance financial products, customer experience, or bank profitability?**
   This criteria ensures that the paper chosen offers analysis or case studies on the application of data-driven approaches that influence customer experience, personalization or engagement within financial institutions.

(2) Exclusion criteria (EC):

a. **EC1: Is the full-text version electronically available?**

Articles accessible through the subscribed digital libraries of the university or available online for free are regarded as accessible. Payment articles not accessible through these channels are regarded as inaccessible.

b. **EC2: Language of Study?**

Only studies in the English language were included. Papers that are not written in English were excluded, as reviewer must be able to read the content of the study.

c. **EC3: Duplicate Publications?**

Duplicate studies were excluded based on the following:

Exact duplicates: Papers having the same title, authors, and publication year in different digital libraries. One version was retained.

Version duplicates: Same authors research on related topics. The most recent version was selected.

Conference vs. journal versions: When both exist, the journal version was selected since it is typically deeper and more comprehensive.

d. **EC4: Is the length of the study less than 6 pages?**

Papers less than six pages were not included because they do not have the depth required to effectively discuss data driven product development, which are central to this study.

3.5 Paper selection Procedure

According to the defined paper selection criteria, the selection procedure was executed as follows: first, papers containing fewer than 6 pages were removed, then removing the duplicates, then filtering by paper title, next filtering by paper abstract was performed and finally filtering by reading the full paper was executed. Further, this section describes each of the filtering stages. Table 2 summarizes the data on the number of papers that were processed and filtered.

Table 2. The results of the application of selection criteria per paper filtering stage.

Filtering stage	**Number of identified papers**	**Total number of papers left**
Primary search results	8631	
Filtering by number of pages	3162	5969
Filtering out duplicates	509	5460
Filtering by paper title	4837	623
Filtering by paper abstract	440	183
Filtering by reading the full paper	139	44

(1) **Filtering by number of pages:** In accordance with the exclusion criteria EC4, 3162 papers of fewer than six pages were excluded. 5,969 papers survived to the next filtering stage.
(2) **Filtering out duplicates**: Since a literature search was conducted on four databases, there was a high likelihood of duplication, with the same papers represented in multiple sources. To ensure that there were no duplicates present, a process for removing duplicates was followed. This involved identifying and eliminating 509 duplicate records with identical title, author, and year of publication. After this step 5460 unique papers and was proceeded to the next step of filtering.
(3) **Filtering by paper title:** In this stage, the remaining articles were screened by title for their relevance to the research topic and the inclusion criteria IC1, IC2, IC3. Papers whose titles clearly indicated a lack of relevance to the research topic were excluded. Where the relevance could not be determined from the title, the article was retained for assessment in the next stage. As a result of this filtering process, 4,837 papers were identified as being unrelated and were rejected. The remaining 623 papers entered the next stage of filtering that is filtering by abstract.
(4) **Filtering by paper abstract:** Following the title screening, the abstracts of the remaining papers were assessed to once more judge how related they were to the topic of the research in terms of inclusion criteria IC1, IC2, and IC3. The abstracts of papers that obviously disclosed a research question focus outside the topic of the paper were excluded. Through this process, 440 papers were found to be irrelevant and were excluded from the list. As a result, 183 papers formed the final list of papers relevant to the research study and are eligible for the next stage of filtering, that is filtering by reading full paper.
(5) **Filtering by reading the full paper:** During data extraction, full-text screening of the remaining 183 papers was done for compliance with the inclusion criteria IC1, IC2, IC3 and exclusion EC1, EC2 criteria. Such thorough screening helped in more specific assessment because some exclusion reasons were determinable only after going through the entire paper. Based on this, 139 papers were excluded at this stage. Finally, 44 articles met all the requirements and were included in the data extraction stage.

Following application of the set exclusion and inclusion criteria, 44 articles were selected from an initial total of 8,631 identified using the initial search. These articles were considered eligible for inclusion in this SLR.
In this study, ChatGPT was employed as a supportive AI tool to assist alternative phrasing. No AI-generated text was used; the tool was only used to improve the clarity and quality of writing without serving as a source of original content or data [30].

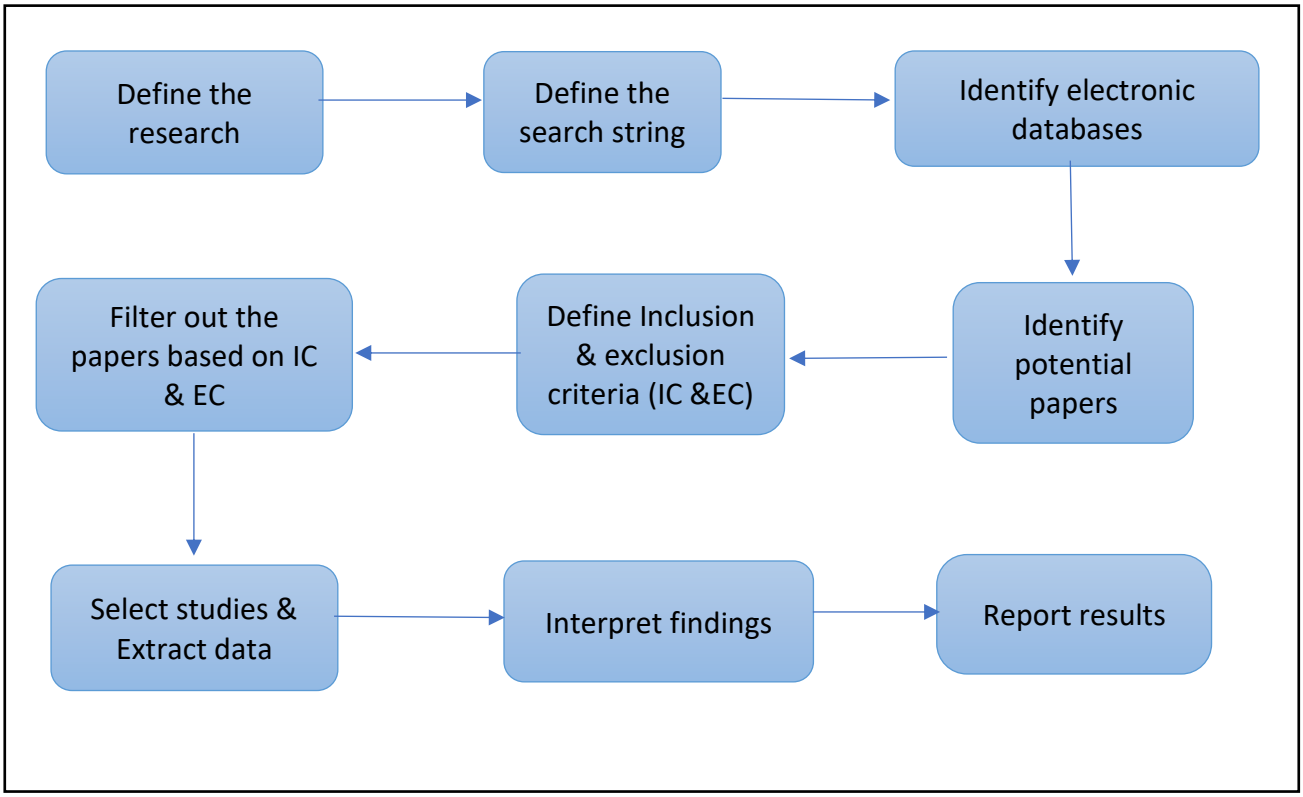

Figure 1. Systematic literature review procedure

3.6 Data Extraction Strategy

In order to proceed with the data extraction phase for analyzing how data-driven strategies enhance financial products and services for retail customers, a structured data extraction form was developed. According to the best practices as outlined in "A Guide to Conducting a Standalone Systematic Literature Review" [27], "Lessons from applying the systematic literature review process within the software engineering domain. J Syst Software engineering domain" [25], and "A Guide to Writing the Dissertation Literature Review" [31], this form allows the collection of data in a organized, without any bias and consistent way.

The extraction form helps organize and gather key findings from the selected literature during the screening process. Based on the formulated research questions RQ1 and RQ2, the form is divided into three categories of data:

(1) Identification Data: Data that helps to identify the paper like paper title, authors of the paper, year of publication.

(2) Context of Study: This data provides the reader with the context of the study describing if the study is related to application of data-driven technology to any financial products and services.

(3) Customer and Business Impact: This data provides the reader with the context of the study describing the impact of data-driven financial products and services on private retail customers and financial institutions.

Table 3. Data extraction form.

Identification Data	
ID	Unique identifier for referencing the paper
Title	Full title of the paper
Authors	Authors of the paper
Year	Year of publication
Data enhancing product and services	
Data Category	Different data categories such as customer transactions, loan records, investment behaviors, credit scores, and insights from social media on public sentiment etc.
Internal/External	The data that is being used from inside the financial institution or from outside it. If the data is created and used within the organization, it's considered internal. If it comes from outside sources, it's external.
Data Source	The origin of the data used in the analysis—whether it is generated within the financial institution through its own operations, such as customer payment transactions, loan records, and internal financial reports, or collected from outside entities and environments, like regulatory bodies, credit rating agencies, social media platforms, or financial markets
Data Type	The data type refers to the nature and format of the data being used—whether it's raw or processed, organized in a clear structure(structured), in free-form like text (unstructured), and whether it's captured as events happen(real-time) or collected from past records (historical).
Data Description	This refers to collecting the information related to the use of data for enhancing financial products and services for private customers focusing on the role of data in creating customer value through personalization, improved service quality etc. Relevant academic literature will be reviewed to extract insights into practical applications, strategic advantages, and measurable impacts within the financial services.
Application Area	This refers to whether the analysis was conducted on the financial products and services offered by institutions.
Application Area – Main product	This refers to the primary products or services that are enhanced using data like payments, investments, savings, loans.
Application Area – Sub-product	This refers to the sub product or services that are enhanced by utilizing data like Custom investment plans, Retirement plans, Cross-border payments, Credit card payments, Personal loans etc.
Processing of the data category	The categories for analyzing data from literature include transaction efficiency and security, personalized financial growth, smarter credit decision making and Investment support. These categories provide a structured framework for data-driven strategies to enhance financial products and services.
Processing data description	This refers to data driven techniques like supervised learning, unsupervised learning, deep learning, behavioral authentication, real-time monitoring etc. to process the data or used to enhance the products and services
Enhancement of Product Service category	This category highlights the advancement of financial products and services by enabling quicker, safer transactions, delivering more customized customer interactions, offering intelligent borrowing and investment solutions, and providing flexible financial planning support.

Enhancement of Product/Service description	This refers to the improvements in financial services like providing timely and customer-focused experiences. It allows institutions to process transactions more securely, assess individual financial behaviors, offer tailored growth opportunities, and provide support aligned with borrowing and wealth-building needs. These insights help deliver faster decisions, smarter financial planning, improving trust, efficiency, and long-term engagement.
Value for Customers	
Value categories	This refers to the Data that boosts security, delivers personalized insights, expands accessibility, and provides proactive guidance to empower customers financially.
Value Description	This refers to the Data that enables financial institutions to deliver greater value to customers by making their experiences safer, smarter, and more supportive. Enhanced security builds trust, personalized insights ensure services are relevant to each individual's financial goals and behaviors. Accessibility allows more people to benefit from financial tools and with proactive guidance, customers receive timely support and recommendations.
Value for Providers	
Value category	Financial institutions can capture value through revenue growth by offering personalized products, achieve operational optimization via automation and real-time analytics, strengthen advanced credit risk management through early detection of risk indicators, and enhance performance by leveraging neural networks for more accurate fraud detection, credit scoring, and customer targeting.
Value Description	This refers to the value that provides get by offering data-enhanced products and services to retail customers like revenue generation that is driven by personalized offerings, Operational efficiency gains are achieved through automation, real-time analytics, and streamlined decision-making processes and proactive credit risk management is enhanced by early detection of risk signals through behavioral and transactional data analysis.

After filtering the primary list, 44 relevant papers were identified. Data was then extracted from these using a structured data extraction form.

4. Results

In this section, the results of the SLR are presented. The results description follows the order of the research questions defined in Section 3.2 of this thesis. Firstly, it addresses the value to the consumers of data enhanced financial products and services. Second, it addresses the value to the providers of such financial products and services.

4.1 Data enhanced financial products and services for consumers:

This chapter presents the results of the investigation into how **data enhancements** are used to improve financial products and services in ways that directly create value for retail banking customers. This analysis addresses the first research question (RQ1), which is to find out how information is utilized to enhance products in the retail banking sector in order to make them more secure, accessible, and user specific. Based on understanding from the review of the studies some key examples of data-driven products and services were identified using keywords and phrase matching methods as discussed in the methodology. The analysis identified two primary areas where data is being harnessed actively for enhanced customer outcomes. The first one is Credit Accessibility where data enables more timely, fair and inclusive lending decisions, and the second one is Personalization where data is used by financial institutions to offer personalized experiences, products and recommendations to the customers that are aligned to their needs. Collectively, these areas depict data as not just a back-end utility but a fundamental driver of value creation for consumers in the digital banking world of today.

4.1.1 Credit Accessibility:

Over the past few years, innovations in credit accessibility have tremendously enhanced the way banks assess customers, making lending faster and fairer. Innovations such as Advance assessment models using machine learning techniques, financial network analysis, and RiskVA allow lenders to go beyond traditional credit scores and consider real-life financial behaviors like repayment consistency, income stability, and spending patterns. These tools help ensure that even customers with non-traditional financial profiles—such as freelancers, students, or those new to credit—are assessed more accurately. As a result, customers benefit from quicker loan approvals, more tailored offers, and expanded access to credit, supporting both financial inclusion and trust in the banking system.

Faster Accessibility to Fundings:
Among the most significant breakthroughs in the past few years for lenders has been increased velocity and equity of credit decisioning. Traditional credit scoring algorithms favor individuals with standardized financial histories, such as contract workers, students, or self-employed individuals. But modern data-intensive technology now allows lenders to assess more consumers' financial behaviors such as timely payments on bills, stable streams of income, and healthy levels of consumption so they make decisions more rapidly and accurately.

Research by Tian et al. [32] reveals that the tools make quicker approvals possible and cut delays for responsible customers.

Importantly, even individuals without a conventional credit history can now be evaluated more equitably. Advanced assessment models like alternative credit scoring, hybrid credit models move beyond static credit scores, allowing borrowers with consistent repayments or stable transaction activity to be recognized as low-risk, despite irregular income or limited credit footprints [33]. By combining multiple sources of information rather than relying on single indicators, the likelihood of unwarranted rejection is significantly reduced. For instance, an individual without a regular salary can still be approved if they have a record of reliable repayments [34].

Also, machine learning techniques such as support vector machines and logistic regression enable lenders to customize interest rates and terms of lending according to the specific customer's consumption behavior [35]. As Hentzen et al. [36] demonstrate such AI-driven models work better compared to traditional scoring models, which results in enhanced matched credit offers and potentially better terms of lending to the customer.

Improved Credit Access through Financial Networks:

A **financial network** represents connections between customers based on tendencies in their behavior when it comes to money. It is a network of nodes, which are single customers, and edges, which are relations such as financial tendency, transaction, or similarity, if you are a first-time credit holder or lack much credit history, your risk level can still be inferred by considering how similar people like you behave around money. For instance, if you're saving and spending pattern is the same as others who have been difficult to repay, then a bank can be cautious. But the opposite is also possible—if you are like good customers, you can be treated as less risky without having a history over the long term.

Imagine you're someone like Anna, who hasn't borrowed before but shares similar, stable behavior with reliable customers. With network-based credit scoring, banks can offer you a fairer assessment—maybe a smaller loan at first, but still a chance to build your history responsibly [37]. By analyzing these financial "networks," banks make more accurate decisions, increasing fairness and inclusivity. This is especially helpful if you don't fit traditional profiles. You benefit by getting access to credit options that may have previously been out of reach [38].

Inclusive Lending Through Context-Aware Insights

Customers are regularly assessed by credit models that ignore key context factors—regional economic conditions in their location, short-term income variations, or switches from one type of employment to another. Such shortcomings can result in unjust rejections or misclassifications, especially for borrowers who behave responsibly but fall outside conventional profiles. Risk Visual Analytics (RiskVA) addresses this issue by incorporating dynamic and contextual data—such as regional economic indicators, product usage patterns, and repayment behavior—into credit assessments.

Although customers do not interact with RiskVA has a direct impact on their lending experience. Through more insightful assessments, RiskVA allows individual customers to be assessed based on their real-life financial behavior as opposed to general risk factors associated

with where they are. For instance, Keim [39] cites an instance in which customers were shielded from being categorized as high risk due to the broader economic challenges of their geographic location. Instead of being unfairly penalized, such customers received credit assessments that accurately reflected their repayment consistency.
This leads to more inclusive and equitable outcomes. Customers benefit from fairer loan approvals, more appropriate interest rates, and increased trust in the credit process. RiskVA helps prevent unjust denials, especially for borrowers in vulnerable or underserved segments, and supports greater financial access for those who might otherwise be excluded due to rigid or decontextualized models [40].
By shifting its strategy from static, generic measurements to more context-sensitive and individual-based evaluation, RiskVA brings tangible value to the customer experience in the sense that it ensures credit decisions are not merely data-driven but also fair and take into account individual situations.

To summarize, lenders and banks are using smarter tools to serve the customer better. It's whether quicker approvals, more accurate evaluations, or access to those with not perfect credit history are at stake. All these innovations are customer centric. You benefit from quicker decisions, tailored products, and better chances to improve your financial life.

4.1.2 Personalization

Personalization in financial services has rapidly evolved from simple product recommendations to sophisticated, data-driven systems that adapt to individual needs in real time. As customers increasingly expect tailored experiences, financial institutions are leveraging technologies such as AI, machine learning, and behavioral analytics to deliver relevant, timely, and meaningful financial guidance. This shift toward intelligent personalization creates substantial value for customers by aligning financial advice, products, and support with each individual's goals, behaviors, and life stage. Platforms based on algorithms and robo-advisors offer customized investment guidance, dynamically modify recommendations, and offer 24/7 assistance—making financial planning more accessible, affordable, and responsive for retail investors or those inexperienced in finances. Such solutions not only diminish bias and increase convenience, but also enable customers to make well-informed, confident decisions, ultimately leading to greater financial control, satisfaction, and long-term well-being.
New technologies are revolutionizing the way banks and financial services help people manage their money. Thanks to data-driven decision making (DDDM), companies can now offer **personalized financial advice** that fits each customer’s unique situation, goals, and preferences. A big part of this change comes from the rise of **robo-advisors**—smart, automated tools that give financial advice using artificial intelligence [41].
Robo-advisors take this a step further. These are online tools that ask you a few questions—like your age, income, and comfort with risk—and then automatically create a **custom investment plan** for you. They can adjust this plan over time as your life changes. One study found that robo-advisors help make professional financial advice more affordable and available

to more people, not just the wealthy. Another study showed that robo-advisors can keep learning about users by behavioral analysis and adjust advice in real-time, helping people stay on track with their financial goals even as their needs change [42].

Interestingly, some customers even prefer robo-advisors over human advisors. Research from Thailand found that many people felt more comfortable using a robot because it seemed more **objective and less judgmental**, especially when talking about sensitive financial issues. People trusted the robo-advisor's suggestions and appreciated how easy and consistent the service [43]. Another study by Hentzen [36] also describes also AI powered robo-advisors platform that analyses market data, assess risk and recommend investments to individual clients. It also describes how it helps to address the concern of investment fraud by reducing the need for human financial advisors. Some banks also use **visual dashboards**—like interactive charts or apps—that show your spending, investments, or savings in a way that's easy to understand. These dashboards help users feel more in control of their money and allow banks to give **better suggestions based on their habits**. Another study by Khanna[44] explains how AI based robo-advisory is a self-assessment tool that assists customers in making decisions about the investments based on the customer goals, financial status and preference. It also explains how this AI based robo advisory offers 24/7 assistance to the customers without human intervention and thus reduces the drawback of human bias that is associated with human advisors. This study also shows that robo-advisory enhances customer convenience.

A study by Pal [45] explains that Robo-advisory is an online automated investment advisory, which employs various AI algorithms to determine the asset allocation and rebalancing of the portfolios of individual investors tends to profile the individual investor by assessing preferences over various aspects such as risk, returns, investment tenure, goals by automated processes and algorithms. Robo-advisory helps individual retail investors in making informed financial decisions efficiently. Robo-advisory are also more suitable to retail investors as it provides the cost advantage due to automated investor profiling and management of investors' life cycle and enhances customer satisfaction.

Looking ahead, even more advanced tools are coming. One study talked about the idea of **"digital twins"**—virtual models of a customer's financial life that can predict what they might need next. Imagine a tool that knows when you're likely to need a tax reminder, a savings boost, or help prepare for retirement—**before you even ask**. That's what digital twin-powered robo-advisors might offer in the near future [46].

However, while all of which is promising in theory, some experts say if robo-advisors take unfair data or don't make their algorithms transparent, then it might result in unfair or even biased decisions in key areas such as approvals for loans. That's why some researchers say companies should use **explainable and transparent AI**, so customers understand why they're being offered certain advice or products.

Building on these technological advancements, one of the most profound shifts in the retail financial services landscape is the move from standardized, one-size-fits-all offerings to hyper-personalized, data-enabled services. Modern financial institutions are leveraging granular data everything from transaction records to behavioral signals to personalize products, experiences, and pricing models for individual customers. This personalization provides daily value in the shape of optimized product recommendations, reduced service fees, dynamically adjusted interest rates, and personalized financial guidance.

To further enhance the value delivered to customers, **Algo-Powered Banking** builds on the foundation of personalization by using advanced algorithms and real-time data to provide highly tailored financial guidance, adapting continuously to each individual's financial goals, behaviors, and life stage.

Algo-Powered Banking can play a pivotal role in improving personalization in financial services, particularly in the areas of savings, pension planning, and investment decision-making. By integrating advanced algorithms and machine learning techniques, the system has processed enormous amounts of data from datasets like social media data, customer data, historical market price data to identify emerging patterns, forecast market trends, and automate trade decisions that are suitable for each customer's unique financial situation, goals, and stage of life.

For example, younger customers who are just beginning their financial journey may be offered personalized suggestions to help them build an emergency fund or start investing in growth-oriented products like equity-based mutual funds. In contrast, someone in their 40s or 50s may receive pension advice that accounts for their income level, retirement goals, and preferred risk exposure perhaps by recommending a balanced portfolio with both growth and income-generating assets. For older individuals approaching retirement, the platform may shift its recommendations toward capital-preserving options, such as government bonds or annuity-based pension products.

What makes Algo-Powered Banking especially valuable is its ability to continuously learn and respond to user behavior and external trends. It combines personal financial data with real-time market indicators and even social sentiment such as reactions to economic news on social media to fine-tune its advice. For instance, if market sentiment suggests rising inflation, the platform might prompt users to consider inflation-protected savings or reallocate assets within their pension portfolio.

Apart from that, system automation makes sure that customers are aligned with their financial goals. Rather than making decisions emotionally about whether the market is rising or falling, users can rely on pre-determined strategies that act according to their risk level and preferences. This makes for consistent saving and investing habits, which is especially important for long-term goals like retirement planning. Overall, the results demonstrate that Algo-Powered Banking supports a more customer centric, data-informed approach to financial planning. It goes beyond the traditional “one-size-fits-all” model by personalized insights and recommendations, enable customers to make more better and informed financial choices throughout their lifetime [47].

In conclusion, data-driven decision making and AI technologies are fundamentally transforming retail financial services. Applications ranging from robo-advisors and interactive dashboards to algorithmic-based platforms, each of which reflects a particular direction towards hyper-personalized, adaptive financial interactions aligned with individual behaviors and needs. As increasingly sophisticated systems like Algo-Powered Banking mature in the future, they have the potential to enable users with context-aware, intelligent financial guidance throughout lifespans. To make that potential a reality responsibly, though, continued vigilance around transparency, fairness, and ethical AI system design must ensure accessible and trustworthy financial innovation.

Table 4.Customer Value insights

Category	General Overview	Subcomponent	Description	Reference
Credit Accessibility	Data-driven credit accessibility improves fairness and speed by evaluating real-life financial behaviors beyond static credit scores. This approach enables banks to serve customers with little or no credit history and promote financial inclusion.	Smarter Tools	Alternative credit scoring, SVM and hybrid models help lenders to assess non-traditional borrowers based on behavior data. It results in faster approvals, personalized terms and reduced rejection rates.	[32], [33], [34], [35], [36]
		Financial Networks	Financial network analysis compares a user to other users with similar financial activity, allowing for unbiased evaluation without credit history. It helps new-to-credit customers gain access and build credit responsibly.	[37], [38]
		Risk Visual Analytics	RiskVA uses regional, behavioral, and product data to assess customers in real-life context. It helps reduce unfair rejections and supports fairer, more inclusive lending decisions.	[39], [40]
Personalization	Personalization uses AI and behavioral data to tailor financial services based on each user's goals and life stage. This enhances affordability, accessibility, and customer satisfaction.	AI-Driven Platforms	Artificial intelligence technology platforms like Algo powered platforms and Robo-advisors provide adaptive, personalized investment advice based on market trends and client behaviors. Digital twins are employed to predict future needs to enhance the accuracy of financial planning.	[36], [41], [42], [43], [44], [45], [46], [47]
		Tailored Financial Services	Platforms analyze behavioral and transactional data to personalize products, rates, and user experiences. Dashboards support informed decisions, automation, and inclusive financial guidance.	[42], [43], [44], [45]

4.2 Role of Data-Enhanced Services in Value Creation for Financial Institutions

In this section the results of how data enhanced financial products and services create value to the financial institutions are described with real-world examples from the literature published in the past few years. From the reviewed literature the value created for financial institutions by the data enhanced products and services are grouped into four areas: generating revenue, driving operational effectiveness, minimizing risk, and enhancing strategic responsiveness.

4.2.1 Strategic Revenue Streams

The study findings point out that strategic revenue sources, supported by data-enhanced financial services, present significant opportunities for value creation for banks. Based on customer-level data provided like spending behavior, income flows, and financial goals, banks are able to create highly personalized products and services, such as customized credit products, dynamic saving plans and customized investment portfolios. This personalization has proven to enhance product take-up and customer satisfaction, driving measurable improvements in revenue per customer. In addition, the integration of AI technologies enables bank personalization efforts to scaleup efficiently, adding a stream of non-interest income and driving higher profitability. Examples from both global implementations and the Saudi Arabian finance technology space support the trend, with evidence of AI-powered recommendation platforms and data enhanced insights leading to greater engagement, higher conversion, and diversified income streams. These findings indicate that strategic models of revenue not only enhance financial profitability but also support banks competitive positioning, decrease dependence on high-risk interest income, and create long-term growth in a digitally driven market environment.

Data-driven banking services help the organizations to tap into new sources of income through the delivery of more relevant, personalized, and timely products to customers. Banks and FinTech firms are designing more tailored credit products, saving services, and investment products depending on customer-specific data inputs like spending habits, income, and objectives. For instance, a digital bank created segmented pricing schemes for personal lending, basing interest rates and repayment terms on customers' individual profiles. This created notable product take-up and customer satisfaction growth particularly enabling product growth and customer monetization [48].

An additional focus is the use of AI to support personalization at scale, which is so crucial in driving new models of revenue. WealthTech platforms currently employ AI-driven recommender systems to analyze customers' past transactions and risk preferences, enabling them to provide very precise investment advice. Personalized products enhance customer engagement and earn higher fee-related revenues, increasing non-interest income and enhancing profitability for each customer [49].

Evidence from Saudi Arabia’s digital finance sector reinforces this dynamic. AI-driven personalization—particularly in product recommendation engines—led to increase in satisfaction. Banks leverage data from mobile apps and digital wallets to identify unmet

customer needs and propose relevant solutions in real time. This not only improved customer lifetime value but also helped diversify income streams beyond traditional interest-based revenue [50].

Literature further reveals that Big Data Analytics (BDA) and Visual Analytics (VA) significantly contribute to revenue gains in banking by enabling data-driven financial innovation, customer personalization, and advanced fraud detection. BDA's value for revenue generation is not derived solely from the technology itself but from the way it is embedded within organizational processes and structures. Using the Affordance Actualization framework, it has been shown that revenue-driving innovation in banks occurs when BDA tools are paired with organizational readiness such as a data-literate workforce, adaptive structures, and collaborative practices across departments. These affordances are actualized through new work routines and strategic shifts that allow banks to develop and deliver timely, customized financial services. This also enhances responsiveness to customer needs, improving customer experience, increasing product adoption, and creating new revenue opportunities [51].

Complementing this strategic view, industry-wide analysis highlights several BDA use cases that directly impact revenue growth. Prescriptive and diagnostic analytics are used to analyze customer data and recommend product personalization. By examining each customer's transaction history, lifestyle information, and web behavior patterns, the bank is able provide tailored loans, investment offerings, and investment advice thus help in higher conversion rates and average revenue per user. Real-world implementations, such as OCBC Bank's use of predictive models to personalize offerings, demonstrate measurable improvements in customer satisfaction by 20% and impacts the revenue growth [52].

In the area of revenue protection, visual analytics tools also deliver value. The EVA platform, which is an analytic solution for visual purposes, supports fraud analysts in identification of suspicious activities through interactive visual interfaces. EVA, unlike rule-based systems, employs visual pattern discovery and temporal data exploration to detect anomalies in transactions. This reduces false positives and speeds up fraud investigations, ultimately lowering investigative costs and protecting customer trust a critical factor in retaining ongoing transactional revenue [53]. Similarly, the VaBank system uses self-organizing maps and topological visualization to detect emerging fraudulent behaviors in large-scale transaction data, reducing losses and improving service continuity [54].

Taken together, these studies provide strong evidence that BDA and VA technologies, when strategically implemented, create measurable financial value for banks. They enable revenue generation through customer-centric innovation and support revenue retention through more effective fraud prevention. To fully unlock this potential, banks must invest in organizational capabilities such as flexible processes, data-driven leadership, and cross-functional collaboration—critical enablers of sustainable, scalable revenue growth [51], [52],[53],[54].

4.2.2 Operational Efficiency

In the context of modern banking, data-driven technologies offer a transformative path to operational efficiency that far surpasses traditional manual processes. The integration of artificial intelligence (AI), machine learning (ML), and automation tools enables banks to streamline routine operations, reduce human error, and accelerate service delivery—outcomes that are increasingly critical in a competitive, real-time financial environment. Unlike conventional approaches that rely heavily on labor-intensive workflows, AI-driven systems automate document processing, customer support, and risk analysis—significantly lowering operational costs while improving service quality. Real-time analytics and intelligent decision-making also empower banks to allocate resources more effectively, improve compliance, and respond faster to customer needs. As a result, these technologies not only enhance internal efficiency but also enable banks to scale securely, reduce costs, and reallocate human expertise toward higher-value strategic functions, making them a superior alternative to traditional models of banking operations.

Efficiency improvements are a critical source of organizational value in data-driven financial services. According to Gul et al. [55] the integration of analytics routine banking activities achieves meaningful productivity improvements, especially for frontline customer interactions and administrative tasks. One of these examples, from their research, is about retail bank application of predictive analytics when managing call-center staff, which increased first-contact resolutions with decreased waiting times. Additionally, the implementation of AI-driven chatbots helped resolve routine customer queries, freeing up human staff to focus on more complex tasks. In another study, Cao et al.[49] describes similar advances in automation through technologies such as natural language processing (NLP) and robotic process automation (RPA). These technologies are now widely used in onboarding and KYC processes, where they can read, verify, and categorize large volumes of documents in seconds. This reduces manual error rates and accelerates the time to service delivery [49], [56] .

Other studies also highlight the role of Artificial Intelligence (AI) and Machine Learning (ML) in improving operational efficiency. These technologies are proving to be game changers by enabling banks to operate smarter, faster, and more effectively. Automation of routine tasks, which were time and resource intensive, is one of the core advantages. Banks now use AI-powered chatbots and virtual assistants to respond to customer queries around the clock, something that previously required large support teams. As Alam et al. [56] explain, this kind of automation not only accelerates service but also reduces human error and allows staff to focus on more complex activities like personalized financial advice or handling non-standard client needs. Kristiana et al. [57] adds that such technologies improve accuracy and consistency in internal processes, especially in data entry and document handling that reduces human error, time for credit proposals and also increase precision of the credit proposals thereby enhances the operational efficiency in the of the financial institutions. AI is also delivering operational gains in fraud detection. Traditional rule-based systems often failed to detect emerging fraud types or triggered excessive false alarms. In contrast, modern AI models can learn from data and identify subtle, previously undetected fraud patterns. Olawale et al.[58] found that deep

learning and graph-based algorithms can now identify complex fraud schemes including synthetic identities and linked accounts with up to 94% accuracy, while also reducing false alerts. These systems analyze thousands of transactions in real time, enabling banks to intercept fraudulent activities as they occur. Sayed underscores the importance of this real-time capability in the context of instant payments, where decisions must be executed within milliseconds [59].

AI is also reshaping credit risk assessment. Rather than relying solely on credit scores, banks are using machine learning to analyze a broader set of data—including transaction histories, spending habits, and bill payment regularity—to assess financial health. Kristiana et al.[57] notes that this approach not only speeds up loan approvals, particularly for retail customers applying online, but also helps reduce defaults. According to Sayed [59] these models enhance risk management by detecting early warning signals in the lending process. Another study by Khanna [44] also explained about AI based robo-advisory has provided tailored recommendation services to the customers and it was proved to reduce the labor cost as there is no human intervention needed for investment advice there by increasing the operational efficiency [50].

All these AI-driven innovations—from process automation and fraud detection to credit evaluation—contribute to improved efficiency, smarter decision-making, and better service delivery. As Alam et al. and Kristiana et al. emphasize, these technologies go beyond mere efficiency; they are transforming customer experience and enabling banks to operate more securely, responsively, and competitively in an increasingly dynamic financial environment [56], [57].

4.2.3 Risk Reduction

Using AI and machine learning for credit risk management is significantly better for banks because it allows them to **move from reactive to proactive and predictive risk handling**. Traditional credit models rely on static data, which can quickly become outdated. Compared to traditional models, AI models examine financial behavior in real time, enabling banks to capture signs of default risk in advance and take remedial actions before losses are incurred. With that comes lower defaults and more robust portfolio performance. AI tools also accelerate decision-making processes, minimize manual errors, and maximize accuracy, incurring lower operational expenses and enhanced customer satisfaction. Also, through the use of a broader range of data, banks can judge creditworthiness more fairly, so they can lend to more people including those with a limited credit record without increased risk. These systems also offer **greater transparency and explainability**, which supports **compliance with regulations** and reduces legal and reputational risk. Overall, AI-powered risk reduction helps banks **minimize losses**, **increase efficiency**, **expand safe lending**, and **strengthen their long-term financial stability and reputation** making it a clearly better approach in today's dynamic environment.

Integration of machine learning frameworks into banking processes offers an efficient method to manage credit risk across the whole customer life cycle, from loan originations to post-loan

surveillance. Forward-looking credit risk management using machine learning and AI is becoming a strategic necessity for modern banks. By embedding predictive analytics across the entire credit lifecycle from loan origination to post-disbursement monitoring and early intervention—financial institutions can significantly reduce default rates, increase credit access, enhance operational efficiency, and improve overall portfolio resilience [60], [61], [62], [63].

The most technically advanced and high-performing solution comes from **Guo et al.** [60] who propose a **credit default prediction system based on customer profile information and time-series behavioral data** using a multi-model ensemble approach. Their framework leverages LightGBM, XGBoost, and local ensemble models to analyze anonymized behavioral records from an industrial-scale dataset provided by the American Express default prediction challenge. The data includes up to 13 months of financial activity for each customer, covering variables related to **delinquency, spending, payments, balances, and risk indicators**. Through **feature engineering techniques** such as multi-step differencing, first/last behavior markers, and aggregation of recent monthly patterns, the model captures nuanced behavioral dynamics that static models cannot detect. The ensemble outputs are integrated using a **score-driven hybrid strategy**, which balances model strengths to enhance generalization. Notably, the solution ranked in the **top 10 out of 4,874 teams**, validating its scalability and performance. **For banks, this approach enables early detection of default risk based on evolving financial behavior, allowing for targeted interventions like repayment reminders, restructured terms, or proactive outreach before defaults occur** that is a major step toward loss prevention and customer experience.

To support real-time credit monitoring, Montiel et al. [63] present a dynamic risk model for predicting over-indebtedness using streaming and batch data. Unlike traditional batch-based systems, their approach employs incremental learning algorithms, particularly Adaptive Random Forests, which continuously update as new behavioral data is received. Their system was tested using both batch and streaming environments and proved effective in identifying borrowers at risk of becoming over-indebted. **For financial institutions, this enables continuous risk surveillance and early flagging of deteriorating borrower conditions, allowing for timely interventions and reduced credit losses**.

At the front end of the credit lifecycle, Dhruv et al**.** [62] develop a two-stage predictive framework that enhances credit decision-making during **loan origination**. In the first stage, the model predicts whether an applicant's income will exceed $50,000 based on features such as **education level, marital status, and employment history**. In the second stage, it forecasts the likelihood of timely loan repayment. The authors used Support Vector Machines and Gradient Boosting to achieve high classification accuracy. Their results show that applicants with stable job histories and at least a high school diploma are significantly more likely to achieve high incomes and repay loans on time. **This model allows banks to screen applicants more precisely and reduce the risk of loan defaults.**

Complementing these technical advances, Sangeetha et al. [61] examine how **AI is transforming customer segmentation and risk assessment** in financial marketing. They observe in their research the role of machine learning models from natural language processing, clustering, and predictive analytics to enhance targeting accuracy and credit scoring performance. Among the significant contributions is leveraging nontraditional data sources, for

example, digital transactional history and social media behavior, to examine customer risk profiles. These inputs offer **hyper-personalized risk assessments**, especially valuable for customers without conventional credit records and also avoid the risk of loan default. Also, it discusses that for banks, the use of transparent and explainable data models offers significant value by reducing regulatory and operational risks. These models allow for greater accountability in decision-making so that institutions stay within data privacy laws and avoid reputational loss. They also enable more accurate credit assessments, allowing banks to expand lending to new customer segments while maintaining portfolio quality. Ultimately, this approach strengthens trust with regulators and customers, and contributes to more stable, risk-aware growth. Further another study by Kakadiya et al.[64] examined how Artificial Neural networks(ANNs) enhanced the creditworthiness assessment of the customers by using the complex, non-linear patterns in customer data like income, age, loan amount, loan duration, credit history, education level, marital status, and employment status. This helped the banks to make more informed lending decisions, lower the default rates and improve the bank's financial stability.

Overall, the contributions of Guo et al., Montiel et al., Dhruv et al., Sangeetha et al. and Kakadiya et al. offer a strategic roadmap for transitioning from **reactive to proactive credit risk management**. **By leveraging predictive analytics and AI throughout the credit lifecycle from origination to monitoring and pre-default intervention, banks can improve the ability to identify early risks, take accurate actions, improve credit access, and build up long-term financial performance in an increasingly dynamic environment.**

4.2.4 Fraud Detection and Prevention

A critical examination of existing literature on financial security identifies how data and intelligent technologies are transforming fraud prevention and fraud detection and contribute great strategic value to banks. Fraud detection enables institutions to identify fraudulent behavior earlier and more accurately, while fraud prevention software pro-actively stops risks before they make an effect. These technologies reduce operational losses, improve decision-making, and enhance customer confidence by offering protective and frictionless digital experiences. Techniques such as Artificial Neural Networks (ANNs), machine learning, and behavioral analytics are helping banks evolve from reactive fraud management to profit-optimizing, strategic fraud response systems [58], [65], [66], [67].

Fraud Detection

One significant insight is that combining multiple fraud detection techniques achieves better results than using a single approach. For example, Faridpour used supervised learning (which relies on historical fraud data) alongside unsupervised learning (which identifies anomalies) to more effectively detect fraudulent activity in bank transactions. This combination enabled more accurate early detection, allowing preventive actions before losses occurred. Similarly, Feng & Kim addressed the issue of data imbalance—where fraud cases are underrepresented—by

using SMOTE (Synthetic Minority Over-sampling Technique) to generate synthetic fraud examples, along with Random Forest and Adaboost for improved classification accuracy. These methods enhanced credit card fraud detection, minimized disruptions such as blocked cards, and improved transaction security. Abbassi et al. also demonstrated how hybrid models using autoencoder deep learning and extended isolation forest techniques on real-life banking transactions with transaction data like Transaction amount, geo location, last login time and reduced false positives and false negatives, offering more precise risk modeling and enhanced fraud identification [65], [66], [67].

Artificial Neural Networks (ANNs) offer banks a very valuable fraud detection technique, especially when combined with business value. Traditional models are likely to concentrate on statistical accuracy, but the examined studies show that profit-optimized ANNs can significantly improve financial outcomes for institutions. Zakaryazad and Duman [68] introduced a novel profit-driven ANN that prioritizes high-impact fraud cases by modifying the error function based on the actual financial cost or benefit of each case. In experiments using real transaction data from two Turkish banks, their model outperformed traditional ANN approaches in total net profit, showing that detection systems optimized for financial significance—not just volume—can maximize value. This shift allows banks to direct investigative efforts toward the most damaging threats, increasing return on fraud management investments.

Faridpour and Moradi [65] expanded on this approach with a multi-layer perceptron (MLP) ANN using adaptive learning rates. It responds quicker when reacting to changing fraud patterns while working in high-dynamics domains like internet and mobile banking. Through momentum-based updating, it addresses one of the most important constraints of the traditional systems like inability to learn early. To banking institutions, it translates into faster action on frauds, minimized loss, and more agile protection of digital channels. In tests against conventional classifiers such as logistic regression and support vector machines, the adaptive MLP consistently delivered superior detection accuracy, making it well-suited for high-transaction environments.

A broader review by Olawale et al.[58] reinforces the strategic value of ANN-based systems in real-world banking operations. Their systematic assessment found that ANNs—especially when integrated with tools like graph neural networks and natural language processing (NLP)—achieved fraud detection rates between 87% and 94% and reduced false positives by 40–60%. This directly improves operational efficiency by cutting down on costly manual investigations and minimizing customer friction. Moreover, their emphasis on **value-driven detection** encourages banks to move beyond raw fraud counts and focus instead on preventing the most financially harmful cases, which is especially important in real-time payment environments where detection windows are extremely narrow.

The review also explains a new regulatory challenge on the rise: the need for model transparency under frameworks like GDPR and AI governance laws. Traditionally, ANN-based models were criticized for their lack of interpretability. However, recent advances in **explainable AI (XAI)** are enabling financial institutions to use powerful neural networks while maintaining regulatory compliance and internal accountability. Banks implementing explainable ANN systems benefit from high-performance fraud detection while ensuring auditors and internal teams can understand the rationale behind automated decisions. This

transparency is crucial not only for legal compliance but also for building stakeholder confidence in automated fraud control systems [58].

Together, these findings illustrate how ANNs—when aligned with business priorities such as profit maximization, adaptability, integration, and explainability—can transform fraud detection from a reactive cost center into a value-generating strategic function. Banks gain through lowered fraud loss, enhanced decision-making, maximized utilization of resources, and increased preparation for changing regulatory and technical environments.

Another key advance is monitoring customers' behavior over time to manage risk proactively, thus making banks adaptive and customer centric. Benchaji et al. [69] applied LSTM (Long Short-Term Memory) models, which are effective at recognizing sequences in data, along with an attention mechanism to identify and prioritize unusual transaction patterns. This helped distinguish between regular and suspicious behavior, reducing false alerts and improving monitoring. Sen et al. [70] research further explored how banks use AI to analyze spending patterns, behavioral authentication, and real-time transaction monitoring. AI techniques such as anomaly detection help identify irregularities such as a customer suddenly making high-value foreign payments and enabling timely fraud interventions.

The speed and responsiveness of AI systems bring additional value to banks. Ezeji showed how AI models can process large procurement datasets and automatically flag unusual patterns that align with known fraud triggers. These instant alerts give customers and banks the ability to act quickly—such as freezing an account reducing the impact of fraud. Odeyemi explained how AI-driven platforms are designed to continuously monitor transactional and behavioral data, identifying threats in real-time with reduced false positives, leading to reduced false alarms and increased service reliability. Mhlanga highlighted how FinTech companies are enhancing fraud detection by combining machine learning, behavioral modeling, and even social media or biometric data, creating comprehensive, real-time protection systems that banks can also adopt to improve their digital services [71], [72], [73].

Fraud Prevention

Fraud prevention involves preventing attacks before losses have been incurred through combining proactive risk modeling and customer verification. Typing speed and scrolling behavior are being employed in behavioral biometrics today in order to authenticate users in real-time to ensure security while not hindering the customer experience. Emmanuel et al. [74] emphasized the effectiveness of combining biometrics and token-based security (e.g., fingerprints, face ID, secure tokens) with AI-driven fraud detection, improving real-time recognition and helping banks maintain both protection and convenience.

Predictive analytics and risk-based authentication have further improved fraud prevention efforts. Kotak Mahindra Bank is applying machine-learning models for catching mule accounts in advance while SBI is implementing AI in all its channels for tightening anti-fraud controls. These help banks step in earlier as well as more accurately and also have strong controls in place while not annoying customers. Banka et al. also presented a logistic regression model built into a web application that analyzes customer data such as transaction amount, age, gender, and location to assess risk in real time. This supports both the bank and the customer in recognizing suspicious activity and strengthens fraud awareness [70], [75].

In today's digital landscape, advanced fraud detection and prevention systems are delivering significant value to banks. Detection methods such as Artificial Neural Networks, adaptive learning, and behavioral modeling help institutions identify and prioritize the most financially damaging fraud cases while reducing false positives and reacting faster to new threats. Preventive methods in the form of biometrics, predictive analytics, and real-time risk scoring stop fraud before it impacts customers or operations. These technologies make fraud management a profit-optimizing process through enhanced operational efficiency, safeguarding high-value assets, meeting compliance requirements, and building trust in customers. By investing in intelligent and value-aligned fraud systems, banks can shift from reactive defense to proactive, strategic fraud control.

Table 5. Provider value insights

Category	**General Overview**	**Sub-component**	**Description**	**Reference**
Strategic Revenue Streams	Data-driven personalization helps banks create targeted products that boost engagement and increase revenue.AI enables these services to scale efficiently and reach more customers. This approach diversifies income streams and strengthens competitive advantage.	AI-Driven Personalization	Banks utilize customer data and AI to personalize credit, saving, and investment products at scale. AI platforms offer risk-aligned guidance, driving product adoption, satisfaction, increasing non-interest income and profitability.	[48], [49], [50]
		Big Data Analytics (BDA) & Visual Analytics (VA) for Innovation	Big Data and Visual Analytics drive innovation and responsiveness through delivering personalized financial services to create new revenue streams and customer experiences.	[51], [52]
		Revenue Protection via Visual Analytics (VA)	Visual analytics tools like EVA and VABank detect fraud using pattern recognition and reduce false alarms. This minimizes the cost of research and helps in customer trust and revenue protection.	[53], [54]
Operational Efficiency	AI and automation streamline processes, reduce human error, and lower costs. Banks can deliver faster, more reliable services while reallocating staff	Workflow Automation	AI chatbots, Natural Language Processing (NLP) facilitate onboarding, and customer support to be automated by reducing manual intervention, accelerating delivery, and enhancing compliance.	[49], [55], [56], [57]
		Cost and Error Reduction	Predictive analytics and smart assistants improve accuracy in internal processes, reduce credit proposal errors, and minimize staff workload.	[56], [57]

	to higher-value activities.	AI in Risk and Credit Ops	Machine learning enhances real-time fraud detection and holistic credit assessment using behavioral data. This boosts approval speed and strengthens risk mitigation.	[44], [50], [57], [58], [59]
Risk Reduction	AI-based credit risk solutions enable banks to actively detect, predict, and manage default risk. These solutions provide more balanced lending decisions and better portfolio performance.	Predictive Credit Risk Models	ML and ensemble models like LightGBM and XGBoost use behavioral and transaction data to predict defaults. This enables early interventions such as payment reminders or restructured loans.	[60]
		Streaming Risk Monitoring	Incremental learning models like Adaptive Random Forests enable real-time monitoring of borrower behavior. They help detect over-indebtedness early through continuous evaluation.	[63]
		Smarter & Fair Lending	AI models such as SVM and Gradient Boosting enhance applicant screening, improving approval precision and reducing default risk. They also promote transparency and fairness by using nontraditional data like social media data for hyper-personalized, inclusive risk scoring while ensuring regulatory compliance.	[61], [62], [64]
Fraud Detection & Prevention	AI enables proactive, precise fraud detection and prevention. These systems lower operational losses and protect customer trust while complying with regulatory standards.	Hybrid Detection Models	Combining supervised and unsupervised models like Random Forest, Adaboost, and Isolation Forest enhances fraud detection accuracy. This approach also reduces false positives in real-time transaction monitoring.	[65], [66], [67]
		Profit-Driven Artificial Neural Networks (ANNs)	Advanced neural networks prioritize high-impact cases, improving detection and reducing losses.	[68]
		Behavior-Based Surveillance	Models like Long short-term memory (LSTM) with attention detect fraud patterns over time, helping banks distinguish abnormal behaviors quickly and reduce disruptions.	[69], [70]
		Real-Time Fraud Response	AI monitors transactions live, flagging suspicious behavior instantly and enabling quick actions like freezing accounts. Behavioral biometrics and predictive models enhance prevention.	[71], [72], [73], [74], [75]

5. Discussion

This chapter presents the research findings against the two research questions. It examines how data is leveraged to improve financial services and products for providers and consumers. The discussion is organized around the main categories that arose from literature, with a presentation of how data-driven technologies are transforming accessibility, decision-making, personalization, and performance within finance. Combined, the findings reveal that data is not only improving processes but redefining what financial services can deliver. These discussion results are organized according to the two research questions.

RQ1: How can data enhance financial products and services for those who consume such products and services?

RQ2: How can data enhance financial products and services for those who provide such products and services?

The research findings were organized into key thematic categories identified consistently across the academic literature. For RQ1, which focuses on consumer value creation, two primary themes emerged. Credit access has been greatly enhanced by data-based credit models that consider customer buying patterns, allowing for faster, more balanced loan approvals—particularly for those in underserved segments. Personalization is a second important aspect, with AI-driven tools such as robo-advisors and interactive dashboards rendering real-time, custom-tailored financial advice that boosts decision-making and customer satisfaction. For RQ2, which explores how financial institutions capture value, four categories were identified. Strategic revenue streams are generated through AI-driven personalization, segmented pricing, and recommendation engines, all of which boost product uptake, customer engagement, and non-interest income. Operational efficiency is achieved through automation technologies such as natural language processing (NLP), robotic process automation (RPA), and chatbots, which streamline workflows, reduce manual labor, and lower costs. Risk reduction is supported by predictive models that monitor dynamic customer behavior to assess credit risk and enable early interventions. Finally, fraud detection and prevention are supported by advanced AI technologies that optimize the accuracy and velocity of detecting high-impact fraud, reducing false positives and raising real-time security.

The results from RQ1 clearly show that data has become a powerful enabler of value creation for retail customers in financial services. The enhancements in credit accessibility that include faster accessibility to Fundings, improved credit access through Financial Networks, inclusive Lending Through Context-Aware Insights and personalization together mark a significant shift toward more inclusive, responsive, and customer-focused financial offerings.
In terms of credit accessibility, data-driven approaches such as machine learning and behavioral analytics allow lenders to go beyond traditional credit scores. These techniques facilitate faster and fairer loan decisions, particularly for customers with limited or non-traditional credit histories, including freelancers, students, or gig economy workers [32], [34]. These tools help reduce bias and support broader, more equitable access to financial services.

Fairer lending is also being driven by network-based models that evaluate a customer's creditworthiness by comparing their financial behavior with that of similar, reliable peers. Even individuals with no formal credit history can now be considered for loans if their patterns match trustworthy customer clusters [37], [38]. This leaves the way open for more precise and representative assessments without compromising risk standards.

Context-aware credit evaluation further personalizes decision-making. Tools like RiskVA combine behavioral data with regional economic metrics, allowing lenders to analyze risk within the customer characteristics, income stability and income consistency, and market conditions [39], [40]. This reduces the chance of unfair rejections due to external economic factors outside the customer's control.

Meanwhile, personalization has been a priority area of enhancement. AI-powered robo-advisors provide personalized investment and savings plans based on customer goals, priorities, and life stage. Real-time dashboards and predictive technologies like digital twins enable active decision-making that helps customers plan proactively rather than reactively [42], [46].

Overall, these developments reshape the customer experience around data-driven relevance, adaptability, and fairness. Financial services are being reshaped from rigid, one-size-fits-all products into dynamic systems that respond to the needs of each individual. But the research also identifies key issues: personalization and inclusion rely heavily on sensitive data, which raises serious questions about privacy, transparency of algorithms, and fairness. Addressing these challenges will be crucial to ensuring that data-enhanced finance remains trustworthy and equitable.

While RQ1 highlights how data enhances financial products and services from the consumer's perspective—focusing on improved accessibility and personalization—RQ2 shifts the focus to how financial institutions capture value through these innovations, particularly in terms of revenue generation, operational efficiency, and risk management. The findings from RQ2 strongly suggest that data is not only reshaping customer experience but also driving measurable value for financial institutions themselves. Across four key domain revenue generation, operational efficiency, risk reduction, and advanced fraud detection—data technologies are enabling providers to become more adaptive, profitable, and resilient.

In revenue generation, data enables providers to move from fixed offerings to highly personalized financial products. By leveraging customer-level information such as spending behavior, financial goals, and income flow banks can deliver tailored credit options, dynamic investment portfolios, and savings tools. AI-based recommendation also further personalize these products resulting in increasing product usage and customer satisfaction [48], [49]. This personalization not only boosts revenue per customer but also expands non-interest income streams. As shown in examples from the Saudi digital finance sector, mobile data and wallet usage allow real-time product suggestions, leading to deeper engagement and better lifetime value [50].

Operational efficiency has also been transformed by data-enabled technologies. AI chatbots, RPA, and NLP systems automate repetitive banking functions—from onboarding and KYC verification to customer service interactions. These tools reduce labor costs, speed up service

delivery, lower error rates, freeing human staff for higher-value roles such as personalized financial advisory [56], [57]. For instance, call center predictive analytics improved resolution ratios and shortened wait times, and automated document processing made back-office operations more efficient [55]. These operational improvements contribute to increased customer satisfaction and brand value in addition to internal cost reductions.

Risk reduction is another domain where data delivers strategic benefits. Modern machine learning models like Gradient Boosting and Support Vector Machines are now used throughout the credit lifecycle—from applicant screening to real-time portfolio monitoring. These systems detect early signs of risk by analyzing income patterns, spending behavior, and financial stability, helping prevent defaults and improve lending outcomes [60], [61], [62]. Institutions can now tailor loan terms dynamically and use explainable models to comply with regulatory standards while expanding lending to previously underserved markets.

In fraud detection, financial institutions are turning to Artificial Neural Networks (ANNs) and hybrid models to enhance both accuracy and financial impact. Rather than detecting fraud only by statistical likelihood, profit-optimized models prioritize high-value fraud cases, increasing return on fraud detection investments [68]. Adaptive MLPs and real-time pattern recognition further improve response time and detection accuracy [65]. The growing use of Explainable AI (XAI) ensures transparency in decision-making—crucial for meeting regulatory standards and sustaining customer trust [58]. This indicates a shift from detecting fraud as a defensive necessity perspective to view it as a proactive strategy to both revenue and customer satisfaction protection.

Together, these changes signal the financial organizations' new value creation and capture strategies that are really powerful. Data is no longer just a support tool—it is a strategic asset embedded across revenue models, operations, risk frameworks, and security systems. However, as data becomes central to value creation, institutions must also manage new risks: including algorithmic bias, regulatory scrutiny, and ethical challenges. Addressing these concerns quickly and openly which will be of prime importance for retaining trust and a competitive edge for the long term.

Beneficiaries, Mechanisms, and Outcomes - RQ1:

Retail banking customers, including those with non-traditional credit histories and underserved populations, are benefiting from AI-driven financial innovations. Credit accessibility has improved, allowing freelancers, students, and others without formal credit histories to access loans. Data-driven credit scoring uses behavioral and transactional data to enable faster, fairer lending decisions [32], [34]. Fairer lending is also supported by financial networks, where individuals with no borrowing history are assessed by comparing them to financially similar peers [37], [38].Context-aware credit evaluation considers external economic conditions and personal behavior, offering fair assessments even during financial instability [39], [40]. Personalization through AI tools and dashboards tailors financial advice and products to individual goals, enhancing decision-making [42], [43], [46].

Together, these advances promote financial inclusion, autonomy, confidence, and greater trust in financial services

Beneficiaries, Mechanisms, and Outcomes – RQ2:

Financial institutions, including banks, fintech firms, and credit providers—are capturing significant value through AI-driven retail financial services. Data enables these organizations to deliver highly personalized, targeted products that boost adoption, cross-selling, and customer retention, shifting revenue models from traditional interest-based structures to value-based offerings [48], [49], [50]. Operational efficiency is enhanced through AI tools such as chatbots, robotic process automation (RPA), and natural language processing (NLP), which automate routine tasks, lower costs, and improve service consistency [55], [56], [57]. Risk reduction is another area of value, with machine learning models like Gradient Boosting and SVM detecting early warning signs of borrower risk and enabling timely interventions [60], [61], [62]. Fraud detection is also significantly improved through adaptive neural networks, which prioritize high-risk cases, increase detection accuracy, and optimize fraud prevention returns. The integration of Explainable AI ensures transparency and compliance with regulations[58], [65], [68].

Overall, all these enhancements lead to higher profitability, reduced risk, and increased agility, enabling institutions to make more effectively informed decisions, all of which helps the institutions strengthen customer relationships and improve their market position while competing in the modern digital environment.

In conclusion, this research highlights that data is no longer merely a support tool within the financial world it has taken on the foundation role of transformation. From broadening the scope of credit availability and providing personalized recommendations to assisting institutions in optimizing their operations and facilitating proactive risk management, data improves every part of the financial system. The institutions that succeed will be those that use data thoughtfully — not only to innovate but to build fairness, trust, and long-term impact. Data-driven finance is not just improving what exists; it is reshaping what financial services mean for both people and providers.

6. Conclusion

This thesis investigated the ways in which data can add value to financial products and services, with special reference to value creation for both providers and consumers. In response to this objective, the research was informed by two research questions: (1) How do data add value to financial products and services for consumers? and (2) How do data add value to financial products and services for providers? To respond to these questions, a systematic literature review (SLR) was carried out, adhering to a reproducible and structured process. The review contained 44 industry and academic sources picked through strict inclusion and exclusion rules. The process allowed for a broad-based and unbiased review of how banks and other financial institutions are utilizing data to improve customer experience, expand accessibility, customize products, and optimize operationally and strategically.

The findings show that for consumers, data-based technology increases access to financial services and allows for a more customized experience.
Powerful capabilities such as machine learning-based credit scoring, financial behavior networks, and context-aware models allow institutions to make more agile, fairer, and more inclusive lending decisions—even to borrowers with no traditional credit history. The use of AI-enabled platforms like robo-advisors, automated financial planning software, as well as real-time dashboards, implies an ability to provide personalized recommendations and investment recommendations. AI helps to enhance convenience and trust from financial advice and planning technologies that ultimately contribute to ongoing financial wellbeing and inclusion efforts.

For financial institutions, data creates measurable value across four main areas: revenue generation, operating efficiency, risk management, and fraud detection and prevention. Real-world applications of the thesis include applying artificial intelligence-based product recommendation systems to improve customer interactions, automation technology that improves customer care and onboarding processes, and predictive analysis that improves credit risk profiling and fraud detection. These examples show how banks can not only leverage data to make internal processes more efficient but also optimize customer relationships as well as continue to stay competitive in an ever-evolving digital landscape.
This thesis contributes to the field of theory and practical knowledge, by providing a structured analysis of data transformation in the production of financial products. The research uses case studies and examples from real-life situations to extend theoretical notions and reminds people that data can continuously be used in an open, ethical, and responsible way.

While the findings provide a strong indication of the way data creates value for providers and consumers both in the financial sector, the limitations of the study must also be taken into account to properly understand the size and context of the findings. The research relies solely on systematic literature review, and therefore, the findings come from published articles rather than first-hand feedback from financial institutions or customers. Therefore, the research will not necessarily reflect the very latest practices or innovations that are constantly emerging in

industry. Second, the thesis focuses exclusively on retail banking products and services, ie., savings, payments, loans, and investments so conclusions reached may not be applicable to other areas like SME banking or insurance. Another limitation is the absence of real-world, experiential perspectives, as no case studies or interviews were conducted to verify or extend conclusions drawn from literature. It is thus the case that while the review identifies trends and uses, it fails to capture internal concerns or customer feedback regarding the use of data-driven products.

Future studies would help bridge these gaps by incorporating empirical studies, e.g., through interviews or surveys, to establish a clearer perspective on the realities of data application in financial product innovation. Long-term, such future studies will need to discuss how financial firms can keep inventing with data and address anticipated risks and burdens. With continuing evolution of regulations such as the GDPR, EU AI Act, and open banking regulations, institutions will need to remain compliant without compromising growth. There is now an ever-strengthening necessity to have data collected and utilized with transparent consent, fairness, and accountability. Further research should also explore the enhancement of customer awareness of data practices and increasing control over user data for users. Moreover, research can explore the ways in which financial institutions can build the proper internal capabilities—like ethical AI models, cross-functional data units, and good governance models—to deal with data in a responsible manner. Last but not least, it is important to monitor how data-driven financial innovations influence various population groups and make sure they foster inclusion instead of feeding digital or financial exclusion.

Finally, this thesis depicts how data possesses huge potential to make financial products and services better for both customers and providers. For customers, it guarantees fairer access to credit and more personalized financial experience. For providers, it offers chances of revenue growth, efficiency gains, reducing risks, and anti-money laundering. By exploring actual cases, the research recognizes how data can drive innovation if utilized to good effect. It also stresses the importance of responsible data practices, customer transparency, and ongoing research to ensure data-driven products benefit all consumers and promote financial inclusion.

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