JOMO KENYATTA UNIVERSITY

OF

AGRICULTURE AND TECHNOLOGY

SCHOOL OF COMPUTING AND INFORMATION TECHNOLOGY

BSC DATA SCIENCE AND ANALYTICS

PROJECT TITLE:

PERSONALIZED FINANCIAL EDUCATION-CLOSING GENDER GAPS WITH RECOMMENDER SYSTEMS

ABBIE PATRICIAH OPENDAH

SCT213-C002-0027/2021

DECLARATION BY STUDENT

THIS PROJECT REPORT IS SUBMITTED TO THE SCHOOL OF COMPUTING AND INFORMATION TECHNOLOGY IN PARTIAL FULFILLMENT OF THE AWARD OF BACHELOR OF SCIENCE IN DATA SCIENCE AND ANALYTICS AT JOMO KENYATTA UNIVERSITY OF AGRICULTURE AND TECHNOLOGY

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SIGN: A.P.O

DATE:11/1/2025

DECLARATION BY UNIVERSITY SUPERVISOR

I DECLARE THAT THIS WORK HAS BEEN SUBMITTED WITH THE APPROVAL OF THE UNIVERSITY SUPERVISOR.

NAME OF SUPERVISOR: DR FANON ANANDA

SIGN:

DATE:

I, **ABBIE PATRICIAH OPENDAH**, HEREBY AFFIRM THAT THIS PROJECT REPORT, BEARING REGISTRATION NUMBER **SCT213-C002-0027/2021**, IS ENTIRELY MY ORIGINAL WORK, WITH ALL EXTERNAL SOURCES DULY CITED AND ACKNOWLEDGED. I FURTHER CONFIRM THAT THIS REPORT HAS NOT BEEN PREVIOUSLY SUBMITTED BY ANY INDIVIDUAL TO ANY OTHER EDUCATIONAL INSTITUTION FOR ACADEMIC PURPOSES.

DEDICATION

This project report is dedicated to my mother, whose unwavering support, encouragement, and understanding have been my constant source of strength throughout this academic journey. Your belief in me made this achievement possible.

ACKNOWLEDGEMENT

I would like to begin by expressing my profound gratitude to Almighty God, whose grace allowed me to bring this project to fruition. I am incredibly thankful to my parents for their unwavering support and for equipping me with the essential tools needed for its completion. Furthermore, I wish to thank the department chairperson, Mr. James Mbao, and my Project Supervisor, Dr. Fanon Ananda, for their expert guidance. May God's blessings be upon you.

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ABSTRACT

Gender disparities in financial literacy hinder women's economic empowerment, driven by limited access to tailored resources and societal constraints. Addressing these gaps requires innovative, personalized educational solutions to enhance financial knowledge and decision-making. This project aims to bridge the gender gap in financial literacy by developing a personalized recommender system that curates financial education content based on users' learning needs, preferences, and goals.

This project leverages machine learning techniques, including collaborative filtering and natural language processing (NLP), to analyze user behavior and identify financial knowledge gaps. By applying tools such as Python, TensorFlow, and NLP libraries (NLTK, spaCy), the system will generate personalized content recommendations.

The proposed system is expected to improve access to relevant financial education, empowering women with personalized learning experiences. By fostering financial inclusion, this project contributes to bridging knowledge gaps and promoting long-term financial independence.

CHAPTER TWO: INTRODUCTION

1.1 Introduction and Background

Financial literacy—the ability to understand and manage financial resources effectively—is a crucial skill in today's rapidly evolving economic landscape (Lusardi & Mitchell, 2014). However, global studies indicate persistent gender disparities in financial literacy, with women generally exhibiting lower levels of financial knowledge compared to men (OECD, 2020). These disparities stem from systemic barriers such as unequal access to financial education, cultural norms, and socioeconomic constraints, which collectively hinder women's ability to make informed financial decisions and achieve economic empowerment (Hung, Yoong, & Brown, 2012).

The significance of financial literacy extends beyond personal financial well-being; it directly influences household financial stability, community development, and national economic growth (Atkinson & Messy, 2013). Research suggests that improving women's financial literacy can lead to positive societal outcomes, including poverty reduction, increased investments in children's education, and enhanced health and well-being (Klapper, Lusardi, & Panos, 2013). Despite these benefits, existing financial education programs often adopt a one-size-fits-all approach that fails to address the diverse needs and learning preferences of women (Fernandes, Lynch, & Netemeyer, 2014). Traditional resources may overlook factors such as cultural sensitivities, time constraints, and differences in financial behaviors, limiting their effectiveness in closing the gender gap in financial literacy.

To address this challenge, this project proposes the development of a personalized recommender system for financial education content, leveraging data science techniques such as machine learning and natural language processing (NLP). By analyzing users' learning patterns, preferences, and financial knowledge gaps, the system will deliver tailored financial education content to enhance engagement and improve learning outcomes. This data-driven approach aims to provide women with relevant, accessible, and practical financial knowledge, empowering them to make informed financial decisions and achieve long-term financial independence.

1.2 Problem Statement

Existing financial education initiatives adopt a generic, one-size-fits-all approach that fails to address the unique needs, preferences, and barriers faced by women, leading to low engagement, ineffective learning outcomes, and persistent gender disparities in financial literacy. Addressing this issue is crucial, as financial literacy is a key driver of gender equality and economic resilience—without targeted, personalized solutions, women will remain financially vulnerable, limiting their independence and perpetuating broader social and economic inequalities.

1.3 Problem Justification

Gender disparities in financial literacy significantly impact women's financial independence, decision-making, and economic opportunities. Traditional financial education methods have not effectively addressed these gaps due to a lack of tailored, accessible content. This project aims to develop personalized recommender systems for financial education, leveraging technology to deliver customized content that meets women's unique needs. By doing so, I hope to empower women with the knowledge and skills necessary to achieve financial security and independence.

1.4. Research Objectives

1.4.0 General Objectives

The primary objective of this project is to bridge the gender gap in financial literacy by developing personalized recommender systems for financial education content. This project aims to empower women with tailored educational resources, enhancing their financial knowledge and decision-making capabilities, and promoting financial independence and security.

1.4.1 Specific Objectives

i. To identify and analyze the financial literacy gaps and unique needs of different genders through data analysis.
ii. To design and implement a personalized recommender system tailored for financial education, considering the unique learning needs and preferences of different genders.
iii. To incorporate machine learning techniques to refine and optimize content recommendations based on user interactions and feedback.
iv. To identify and address potential biases in the recommendation process to ensure equitable access to financial education for all users.

1.5. Research Questions

i. What are the specific financial literacy gaps and unique educational needs of different genders as identified through data analysis?

ii. How can a personalized recommender system be designed and implemented to cater to the distinct financial education needs and learning preferences of different genders?

iii. How can machine learning techniques be utilized to refine and optimize the recommendations of financial education content based on user interactions and feedback?

iv. What strategies can be employed to identify and mitigate potential biases in the recommendation process to ensure equitable access to financial education content for all users?

1.6 Scope of the Study

By defining these boundaries, the study aims to provide a **clear** and **focused** investigation into the development of a personalized recommender system to bridge gender gaps in financial literacy, while managing expectations regarding its scope and limitations.

Boundaries and Limitations:

1. **Focus Area**: This study centers on developing a personalized recommender system specifically for financial education content aimed at bridging gender disparities in financial literacy. It emphasizes creating tailored learning experiences to address the unique needs and challenges faced by different genders.

2. **Data Utilization**: The research will utilize publicly available datasets and user data collected through voluntary participation to identify financial literacy gaps and preferences across genders.

3. **Technological Scope:** The study will focus on integrating machine learning techniques and natural language processing to enhance the personalization and relevance of the recommended content.

Exclusions:

1**. Domains:** The study does not cover other domains such as general education, healthcare, or entertainment recommendations. It is exclusively focused on financial education.

2. **Geographic Scope:** While the study will primarily gather data from a diverse range of users, it may not account for all regional and cultural variations in financial literacy.

3. **Long-term Impact:** The research will not include long-term follow-up studies to measure the sustained impact of the financial education recommender system.

4. **Regulatory and Compliance Issues**: The study will not address specific regulatory or compliance issues related to financial education content across different regions or countries.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

2.1.1 Contextual Background

Financial literacy is a critical skill that enables individuals to make informed financial decisions, impacting their overall well-being and economic stability. Studies have shown that financial literacy influences savings behavior, investment decisions, and retirement planning (Lusardi & Mitchell, 2014). Despite its importance, disparities exist in financial literacy levels across different demographics, particularly between men and women (Hung, Yoong, & Brown, 2012).

2.1.2 Purpose and Relevance

Bridging gender gaps in financial literacy is essential for promoting financial inclusion and economic empowerment. Traditional financial education programs often adopt a one-size-fits-all approach, which may not adequately address the diverse needs of learners, particularly women (Agarwal et al., 2015). The integration of recommender systems presents a promising solution by personalizing financial education content, making it more relevant and accessible (Ricci, Rokach, & Shapira, 2015).

2.1.3 The Gender Gap in Financial Literacy

Research indicates that women generally score lower on financial literacy assessments compared to men (OECD, 2017). This gap has been attributed to various factors, including lower confidence in financial decision-making, cultural and societal norms, and limited access to financial education resources (Bucher-Koenen et al., 2021).

2.1.4 Role of Recommender Systems in Personalized Financial Education

AI-driven recommender systems analyze user behavior and preferences to deliver tailored financial education content (Pazzani & Billsus, 2007). By leveraging machine learning and data analytics, these systems can enhance financial knowledge acquisition and retention.

2.1.5 Purpose of the Literature Review

This literature review explores previous work on gender disparities in financial literacy, the evolution of financial education programs, and the effectiveness of recommender systems in educational settings.

2.2 Historical Overview

2.2.1 Development of Financial Literacy Initiatives

Financial literacy initiatives have evolved from traditional classroom-based programs to interactive digital platforms. Early interventions focused on school curricula and workplace financial wellness programs (Bernheim, Garrett, & Maki, 2001). Recent advancements emphasize digital learning tools, such as mobile apps and online courses (Willis, 2011).

2.2.2 Gender Disparities in Financial Literacy

Studies have consistently shown that men outperform women in financial literacy assessments (Lusardi & Tufano, 2015). Despite efforts to improve accessibility, women continue to face challenges such as financial confidence gaps and societal expectations that limit their engagement with financial matters (Fonseca et al., 2012).

2. 3. Theoretical Frameworks

Introduction to Theoretical Frameworks

This study is grounded in several theoretical frameworks that provide a comprehensive understanding of how adults learn, adopt technology, and make financial decisions. These frameworks guide the development and implementation of personalized financial recommender systems aimed at bridging gender gaps in financial literacy.

Educational Theories

Adult Learning Theories (Knowles, 1980) Adult learning theories emphasize that adults learn best when education is self-directed and problem-centered. According to Knowles, adults are motivated to learn when they perceive the relevance of the education to their personal and professional lives. This theory is particularly relevant for financial literacy **education, as it**

highlights the importance of designing content that is practical, applicable, and tailored to the learners' specific needs and circumstances.

Social Learning Theory (Bandura, 1977) Social learning theory posits that individuals acquire knowledge through observation and interaction with others. Bandura's theory underscores the significance of modeling, imitation, and social reinforcement in the learning process. In the context of financial literacy education, this theory suggests that learners can benefit from observing financial behaviors and practices demonstrated by role models or peers, which can be facilitated through interactive and engaging educational tools.

Technology Acceptance Models

U*nified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)* The Unified Theory of Acceptance and Use of Technology (UTAUT) explains how users adopt and use technology based on four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to the perceived benefits of using the technology, while effort expectancy relates to the ease of use. Social influence considers the impact of others' opinions on the user's decision to adopt the technology, and facilitating conditions involve the availability of resources and support. This model is essential for understanding how users, particularly women, will engage with and adopt the personalized recommender systems for financial education content.

Other Relevant Theories

Human Capital Theory (Becker, 1964) Human capital theory suggests that education and training enhance an individual's ability to make informed and effective decisions, leading to improved economic outcomes. In the context of financial literacy, this theory implies that providing tailored financial education can empower individuals, particularly women, to make better financial decisions, thereby improving their overall economic well-being.

Behavioral Finance Theory (Thaler & Sunstein, 2008) Behavioral finance theory examines how psychological factors, such as overconfidence, risk aversion, and cognitive biases, influence financial decision-making. Understanding these psychological factors is crucial for designing financial education content that addresses the specific challenges and behaviors that women may exhibit in financial decision-making.

Personalized Learning Theory (Kaput, 2018) Personalized learning theory advocates for customizing education to meet the unique needs, preferences, and learning styles of individual learners. Kaput's theory highlights the benefits of personalized learning in enhancing engagement, motivation, and learning outcomes. In the context of this project, personalized learning theory supports the development of recommender systems that provide tailored financial education content to women, thereby addressing their specific financial literacy needs.

2.4. Empirical Review

2.4.1 Gender-Specific Financial Literacy Studies

Key Case Studies

1. ***Lusardi & Mitchell (2011):*** examined gender differences in financial literacy across multiple countries, emphasizing the significant role financial knowledge plays in personal well-being and economic stability. They found that women consistently scored lower on financial literacy tests compared to men, highlighting a global issue. The study concluded that tailored financial literacy programs are necessary to address the specific needs and gaps experienced by women, which aligns with the goals of my project to bridge gender gaps in financial literacy through personal recommender systems.
2. ***Klapper & Panos (2011):*** analyzed financial literacy levels among working women, focusing on the challenges they face in achieving financial independence. The researchers found that working women often have lower levels of financial literacy compared to their male counterparts, which can hinder their economic progress and empowerment. The study emphasized the importance of customized financial education programs targeting working women, aligning with my project's objective of building personal recommender systems for financial education content.
3. ***Van Rooij, Lusardi, & Alessie (2011):*** explored the relationship between financial literacy and investment behavior by gender, highlighting how gender disparities in financial literacy can lead to differences in investment behavior, affecting long-term financial security. They found that women are less likely to invest in stocks and other financial products due to lower financial literacy levels. The study concluded that improving women's financial literacy can enhance their participation in investment

activities, supporting the need for personalized financial education content as proposed in my project.

4. ***OECD (2017)*** report provided a comprehensive overview of global financial literacy disparities, emphasizing the need for targeted financial education initiatives. The findings revealed widespread gender gaps in financial literacy, with women generally scoring lower than men. The report concluded that global efforts are needed to address financial literacy disparities, focusing on gender-specific interventions. This underscores the relevance of my project in addressing this issue through personalized recommender systems for financial education content.

5. ***Agarwal et al. (2015):*** assessed the impact of targeted financial education programs on women, aiming to improve their financial knowledge and decision-making. The study demonstrated significant improvements in women's financial literacy and confidence as a result of the programs, highlighting the effectiveness of targeted financial education initiatives. This case study supports the development of personal recommender systems for financial education content, aligning with the goals of my project to bridge gender gaps in financial literacy.

2.4.2 Recommender Systems in Education

Recommender systems enhance user engagement by providing personalized content based on learner preferences (Resnick & Varian, 1997). Studies have demonstrated their effectiveness in e-learning platforms (Drachsler et al., 2010).

2.4.3 Role of Technology in Financial Education

Digital platforms, such as mobile apps and gamified learning environments, have been shown to improve financial literacy outcomes (Lo, Hsieh, & Chien, 2016).

2.4.4 Case Studies of AI-Driven Financial Education

1. Pazzani & Billsus (2007): evaluated AI-driven personalization in educational tools, exploring the ways in which AI can tailor educational content to individual learners' needs. The study addressed the problem of one-size-fits-all education models that fail to engage diverse learners effectively. Using machine learning algorithms, the authors developed personalized educational tools that adapt to users' learning styles and preferences. The results demonstrated significant improvements in learner engagement and knowledge retention. The key lesson learned was the importance of personalization in enhancing educational outcomes.

2. Ricci, Rokach, & Shapira (2015): analyzed the applications of machine learning in recommender systems, focusing on how these systems can be used to deliver personalized content to users. The problem statement centered on the challenges of accurately predicting users' preferences in dynamic and diverse contexts. The authors employed various machine learning techniques, including collaborative filtering and content-based filtering, to improve the accuracy and effectiveness of the recommender systems. The results showed that machine learning algorithms significantly enhance the performance of recommender systems in providing relevant and personalized recommendations. The lessons learned highlight the critical role of advanced algorithms in achieving high levels of personalization.

3. Willis (2011): reviewed the effectiveness of digital financial education tools, examining how digital platforms can enhance financial literacy among users. The study identified the problem of low financial literacy rates and the limitations of traditional financial education methods. By evaluating various digital financial education tools, the study found that these tools are effective in increasing financial knowledge and improving financial behaviors. The results indicated that interactive and user-friendly digital tools can engage users more effectively than conventional methods. The key lesson learned was the importance of leveraging digital technology to make financial education more accessible and engaging.

4. OECD (2017): assessed the impact of online financial education programs, providing a comprehensive overview of how digital initiatives can address financial literacy

disparities. The problem statement focused on the global challenge of low financial literacy rates and the need for scalable and effective education solutions. The study employed a range of methodologies, including surveys and program evaluations, to measure the impact of online financial education programs. The results showed significant improvements in financial literacy levels among participants, particularly when programs were tailored to specific audiences. The lessons learned emphasized the need for targeted and context-specific financial education programs.

5. Lusardi et al. (2020): investigated AI-driven interventions in financial literacy training, exploring how AI can be used to enhance financial education efforts. The study addressed the problem of persistent financial literacy gaps and the limitations of traditional education methods. By implementing AI-driven interventions, the authors aimed to create personalized and adaptive financial education experiences. The results indicated that AI-driven approaches significantly improve financial knowledge and behaviors among participants. The key lesson learned was the transformative potential of AI in making financial education more effective and accessible.

2.5. Research Gap

Despite advancements in personalized education and recommender systems, significant gaps remain in addressing gender disparities in financial literacy. Existing systems lack a targeted approach to women's unique learning needs and fail to leverage advanced data science techniques such as NLP and adaptive algorithms to address these gaps

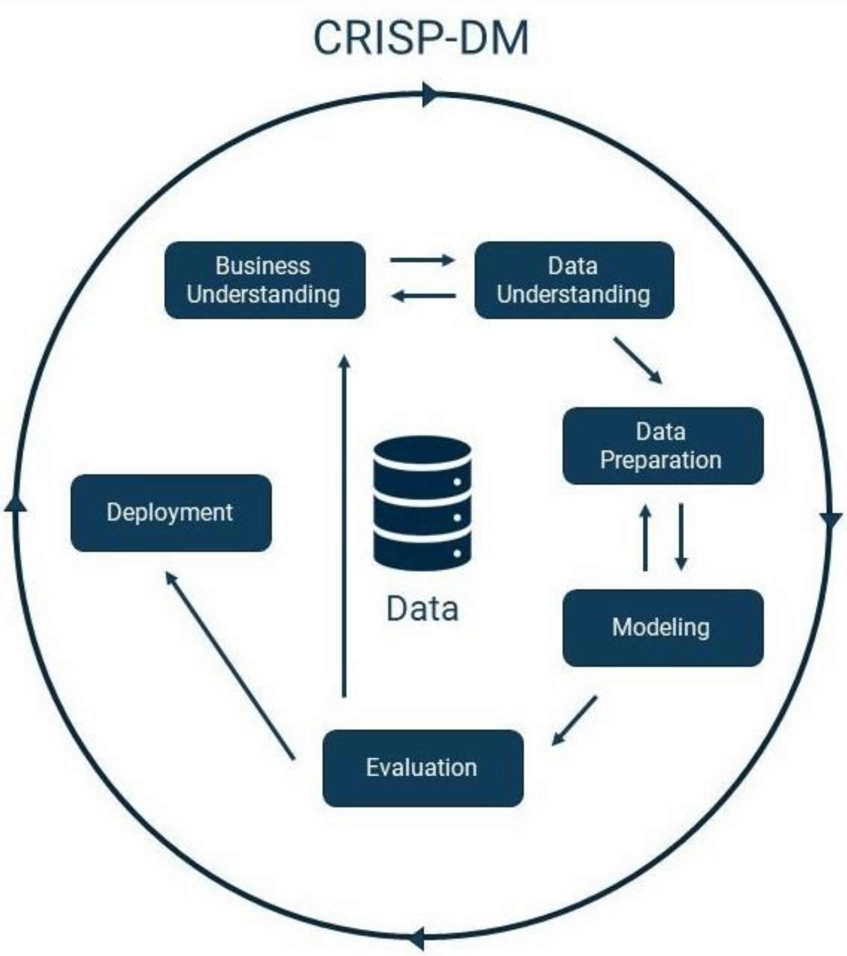
2.6 Conclusion

This literature review underscores the critical need for a targeted, personalized solution to bridge gender gaps in financial literacy. By building on existing methodologies and addressing identified gaps, the proposed project aims to develop a scalable, effective recommender system that empowers women through tailored financial education content

CHAPTER THREE: METHODOLOGY

3.1 Introduction

This chapter outlines the methodology employed to develop a personalized recommender system for financial education content aimed at bridging gender gaps in financial literacy. The CRISP-DM (Cross Industry Standard Process for Data Mining) framework will guide the project, encompassing data understanding, preprocessing, modeling, and evaluation. The approach emphasizes accuracy, and ethical considerations to ensure a robust and impactful solution. The **process diagram below clearly** outlines the key stages of my project.



3.2 Data Description and Collection

3.2.1 Data Sources

The dataset used for developing the personalized financial recommendation system is derived from a Financial Literacy Survey (OECD), designed to assess the financial knowledge, behaviors, and attitudes of individuals across various demographic groups. The primary objective of the dataset is to capture key financial literacy indicators and behavioral traits that influence financial decision-making.

3.2.2 Data Characteristics

The dataset includes the following key features:

Demographic Variables:

- Age Group
- Gender
- Education Level
- Employment Status
- Income Level
- Country or Region

Financial Knowledge and Literacy:

- Financial Literacy Score (overall and by category)
- Digital Financial Literacy Score (general population and internet users

These features are used to:

- Analyze financial literacy levels across genders and identify key factors associated with higher or lower literacy outcomes.
- Build a content-based recommendation engine that suggests personalized action plans or educational content aimed at improving financial literacy and promoting healthier financial behaviors.

- Tailor recommendations especially to underserved or vulnerable groups, such as women or low-income individuals, to help bridge financial literacy gaps.

3.3 Data Preprocessing

3.3.1 Steps in Data Cleaning

Data cleaning was a crucial step to prepare the Financial Literacy Survey dataset for analysis and building the personalized financial education recommender system. The dataset contained a mix of demographic details, behavioral responses, and financial literacy scores across different population groups. The process entailed

- **Handling Missing Data:** Imputation techniques such as mean/mode substitution or predictive modeling.
- **Outlier Detection:** Using statistical methods (e.g., Z-score, IQR) to manage anomalies.
- **Duplicate Removal:** Ensuring data integrity by eliminating redundant entries.

3.3.2 Feature Engineering

- **Feature Selection:** Identifying relevant features such as user learning preferences and engagement metrics.
- **Feature Extraction:** Using techniques like term frequency-inverse document frequency (TF-IDF) for text-based content metadata.

3.3.3 Normalization and Scaling

- Applying Min-Max scaling or StandardScaler from Python’s scikit-learn library to normalize numerical data.

3.4 Modeling and Analysis

The analysis highlights several key factors influencing financial literacy: gender, education level, and geographic location. Gender gaps persist in many countries, emphasizing the need for targeted financial education for women. Higher education is strongly associated with greater financial literacy, and urban populations tend to have higher scores than rural ones. These findings underscore the importance of tailored approaches to financial education and inclusion efforts to address these disparities and promote greater financial well-being globally.

3.4.1 Model Building (Content-Based Recommender System)

This section describes the development of a basic content-based recommender system for financial education products.

- **Loading Data:** Data for the recommender system was loaded from "financial_recommender_dataset.xlsx".
- **Feature Selection:** Features deemed relevant for recommendation, including age, gender, employment status, financial goal, preferred investment, risk tolerance, and literacy level, were selected.
- **One-Hot Encoding:** Categorical features were converted into a numerical format using one-hot encoding with sklearn.preprocessing.OneHotEncoder. This is necessary for calculating similarity using numerical methods.
- **Similarity Matrix Calculation:** The cosine similarity between users based on their encoded features was computed using sklearn.metrics.pairwise.cosine_similarity. The resulting similarity matrix indicated how similar each user is to every other user based on their characteristics.
- **Recommendation Function:** A function recommend_products was defined to provide recommendations for a given user. It identifies users most similar to the target user based on the similarity matrix and recommends the "RecommendedProduct" associated with those similar users.
- **Evaluation (Precision and Recall at k):** The recommender system was evaluated using precision and recall at a specified k (number of recommendations).
  - evaluate_precision_recall_at_k function calculates these metrics for each user and reports the average precision and recall across all users.
  - Precision at k measures the proportion of recommended items that are relevant.
  - Recall at k measures the proportion of relevant items that are recommended.

3.6 Validation and Testing

3.6.1 Cross-Validation

K-fold cross-validation will evaluate model performance across different subsets of the data.

3.6.2 Train-Test Split

The dataset will be split into training (80%) and testing (20%) sets for robust evaluation.

3.7 Tools and Technologies

- **Programming Languages:** Python for data analysis and model development.
- **Libraries:**
    - Data preprocessing: pandas, numpy.
    - Modeling: scikit-learn, TensorFlow.
    - Evaluation: surprise, NLP libraries like spaCy and NLTK.
- **Platforms:** Jupyter Notebook for development and interactive analysis.

3.8 Ethical Considerations

- **Data Privacy:** Ensuring user data is anonymized and securely stored.
- **Bias Mitigation:** Testing the model for potential biases and adjusting algorithms to promote fairness.
- **Fairness:** Evaluating and adjusting the models to prevent any gender or demographic biases in the recommendations.

3.9 Implementation and Deployment

The implementation and deployment phase involves translating the designed system framework into a fully functional recommender system for financial education. This phase includes *coding, integration, testing, and deployment* to ensure the system operates efficiently and meets user needs

3.10 Conclusion

The outlined methodology combines proven data science techniques with innovative modeling approaches to deliver a personalized recommender system tailored to women's financial education needs. By leveraging advanced algorithms and tools and addressing ethical considerations, this methodology aims to produce an impactful solution that bridges gender gaps in financial literacy.

CHAPTER FOUR

4.1 BUDGET

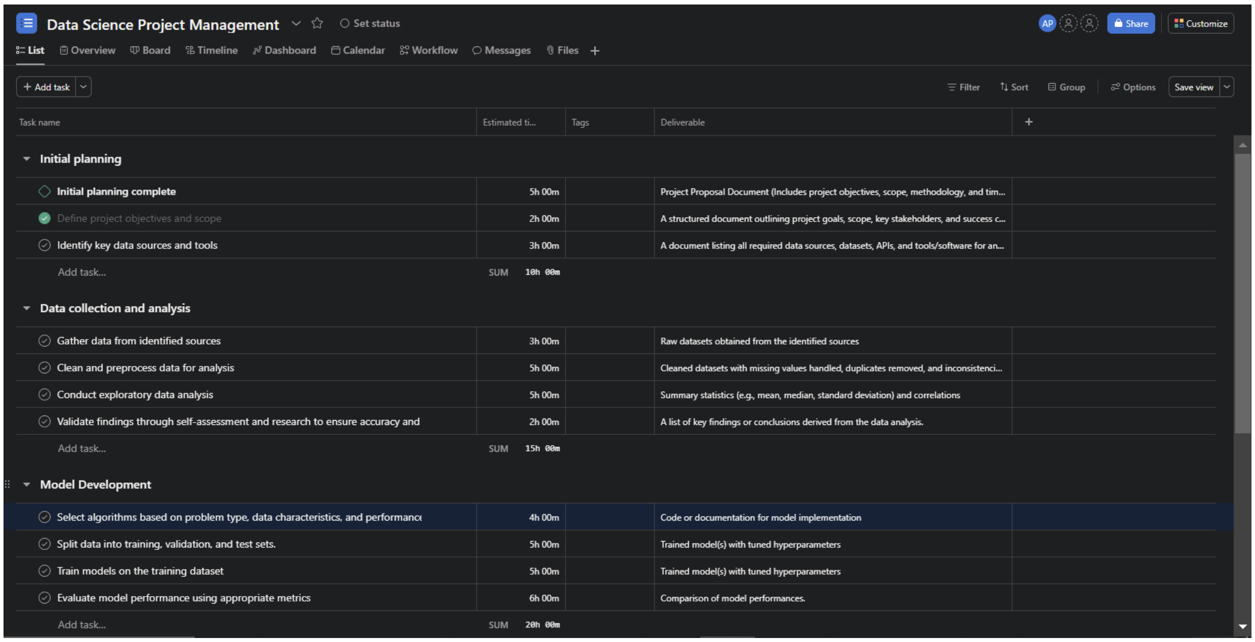
The total cost of the project, **Personalized Financial Education-Closing Gender Gaps with Recommender Systems**, is estimated based on the following components:

Item	Estimated Cost (KES)
Tools subscription	3,500
Internet	8,000
Printing	1,500
Transport	6,000
Airtime for consultation	2,000
TOTAL ESTIMATED BUDGET	21,000

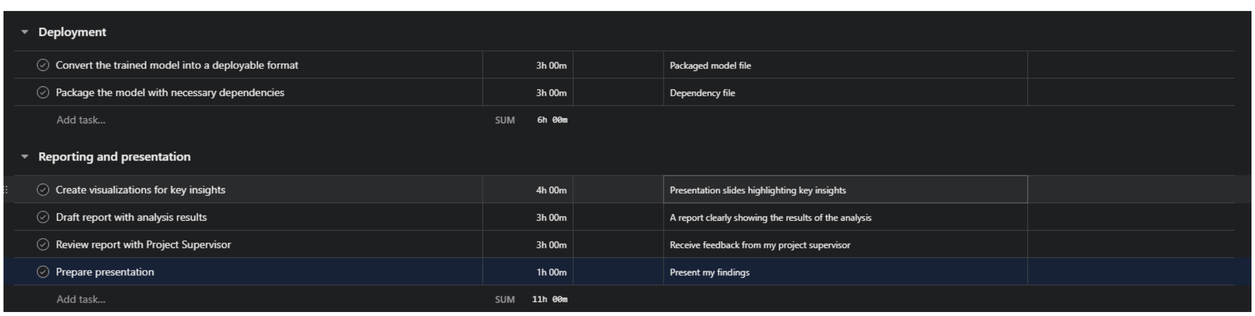
4.2 SCHEDULE

The project flow for developing the personal recommender system is outlined in a Gantt chart, encompassing the following phases:

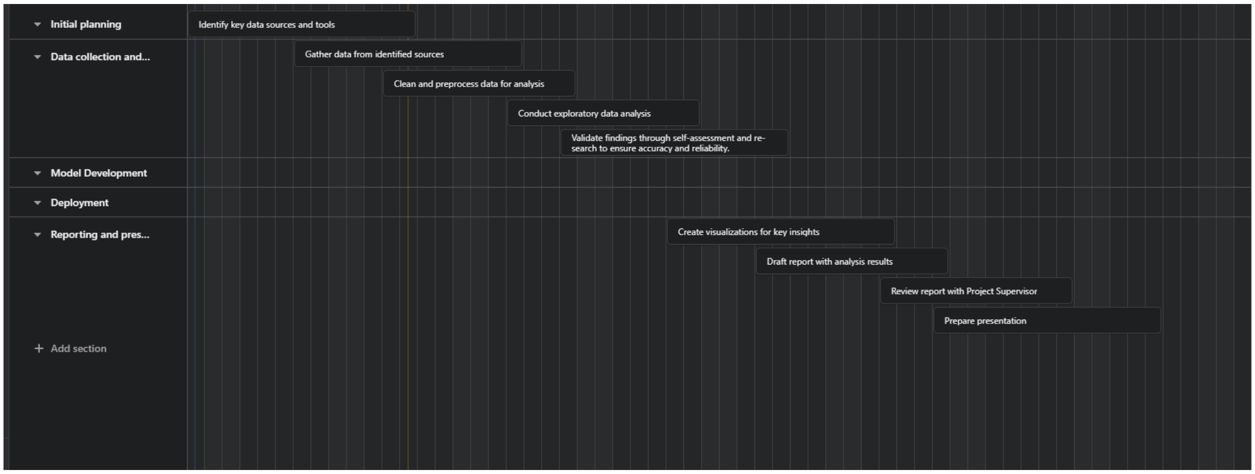
1. **Proposal**: Formulating the research problem and identifying project objectives.
2. **Literature Review**: Exploring existing studies on gender gaps in financial literacy and recommender systems.
3. **Methodology and Modeling**: Designing the system framework, selecting algorithms, and training the model using relevant data.
4. **Evaluation and Analysis**: Testing the recommender system for accuracy and usability, focusing on how well it personalizes financial education content.
5. **Discussion and Results**: Analyzing findings, evaluating the effectiveness of the system in bridging gender gaps, and preparing recommendations.



Task name	Estimated ti...	Tags	Deliverable
Initial planning			
Initial planning complete	5h 00m		Project Proposal Document (Includes project objectives, scope, methodology, and tim...
Define project objectives and scope	2h 00m		A structured document outlining project goals, scope, key stakeholders, and success c...
Identify key data sources and tools	3h 00m		A document listing all required data sources, datasets, APIs, and tools/software for an...
Add task...	SUM 10h 00m		
Data collection and analysis			
Gather data from identified sources	3h 00m		Raw datasets obtained from the identified sources
Clean and preprocess data for analysis	5h 00m		Cleaned datasets with missing values handled, duplicates removed, and inconsistenci...
Conduct exploratory data analysis	5h 00m		Summary statistics (e.g., mean, median, standard deviation) and correlations
Validate findings through self-assessment and research to ensure accuracy and	2h 00m		A list of key findings or conclusions derived from the data analysis.
Add task...	SUM 15h 00m		
Model Development			
Select algorithms based on problem type, data characteristics, and performance	4h 00m		Code or documentation for model implementation
Split data into training, validation, and test sets.	5h 00m		Trained model(s) with tuned hyperparameters
Train models on the training dataset	5h 00m		Trained model(s) with tuned hyperparameters
Evaluate model performance using appropriate metrics	6h 00m		Comparison of model performances.
Add task...	SUM 20h 00m		



Task name	Estimated time	Tags	Deliverable
Deployment			
Convert the trained model into a deployable format	3h 00m		Packaged model file
Package the model with necessary dependencies	3h 00m		Dependency file
Add task...	SUM 6h 00m		
Reporting and presentation			
Create visualizations for key insights	4h 00m		Presentation slides highlighting key insights
Draft report with analysis results	3h 00m		A report clearly showing the results of the analysis
Review report with Project Supervisor	3h 00m		Receive feedback from my project supervisor
Prepare presentation	1h 00m		Present my findings
Add task...	SUM 11h 00m		


Initial planning
Identify key data sources and tools
Data collection and...
Gather data from identified sources
Clean and preprocess data for analysis
Conduct exploratory data analysis
Validate findings through self-assessment and re-search to ensure accuracy and reliability.
Model Development
Deployment
Reporting and pres...
Create visualizations for key insights
Draft report with analysis results
Review report with Project Supervisor
Prepare presentation
Add section

CHAPTER FIVE

SYSTEM DEVELOPMENT AND DEPLOYMENT.

5.1 Introduction and Overview

This section details the deployment strategy and implementation considerations for a ***personalized financial education content recommender system***. The system, developed with Lovable AI and leveraging web technologies (HTML, CSS, JavaScript), aims to empower users through tailored financial learning. The website is ***clean, professional, inviting, and accessible***, utilizing soft, inclusive colors and a friendly tone, focusing on responsiveness across devices.

5.2 Design Considerations

The core design philosophy revolves around user experience and accessibility.

- **Clean and Professional, Inviting and Accessible:** The layout prioritizes clarity and ease of navigation. Inviting elements include engaging imagery, clear call-to-action buttons, and a consistent, friendly tone throughout the website.
- **Responsive Design:** A mobile-first approach will be adopted for development, ensuring the website functions seamlessly on smartphones, tablets, and desktops. Media queries in CSS will be extensively used to adjust layouts, font sizes, and image scaling for optimal viewing on various screen sizes.
- **Friendly Tone:** The language used across the website will be encouraging, empathetic, and easy to understand, avoiding financial jargon where possible. The aim is to encourage continued engagement.

5.3 Core Components and Implementation Details

5.3.1. Homepage (Landing Page)

- **Header:**
    - **Title/Logo:** A prominent, well-designed logo (Fin Path) is displayed on the top left. The title is clear and concise.
    - **Navigation Menu:** A clean, responsive navigation menu, i.e, ("Home," "About Us," "Content Library," "Contact," "Get Started ") is located on the top. On mobile, this will collapse into a hamburger menu.
- **Tagline:** A concise and impactful mission statement, "Empowering You Through Personalized Financial Learning," is prominently displayed below the header, immediately communicating the website's value proposition.

- **Call to Action (CTA):** A visually distinct and strategically placed button, "Get Your Personalized Plan," serves as the primary CTA, directing users to the onboarding form. This button uses an action-oriented verb and a contrasting color to draw attention.

5.3.2. User Onboarding / Input Form

This critical section focuses on **collecting user data** to power personalized recommendations. The form prioritizes **interactivity and ease of use**.

It starts with **Basic Information** (Age, Gender, Location, Education Level) and then moves to **Digital Access**, which includes **Internet Access** (radio buttons: "Reliable," "Occasional," "Limited") and a **Digital Confidence Slider (1-5)**.

Users then answer a few **Financial Knowledge quiz-like questions** (e.g., "How would you rate your financial knowledge?").

Finally, the **Preferences section** lets users choose their **Preferred Learning Style** (checkboxes: "Video," "Reading," "Interactive Tools," "Social"), indicate **how much time they can dedicate**, and select **preferred content types**.

Progress indicators (e.g., "Step 1 of 4") guide users through the interactive process.

5.3.3. Recommendation Dashboard

This will be the central hub for users to access their personalized content.

- **Personalized Action Plan Cards:**
    - Each recommendation is presented as a visually appealing "card" with a clear title, content type (e.g., "Video," "Quiz"), estimated completion time, and a brief description, e.g., "Watch this intro to budgeting (Video) - 10 min"
    - Each card has a "View Resource" button.
- **Progress Tracker:** A clear visual progress bar shows the user's progress. This aligns with gamification.
- **Categories/Filters:** Users can filter recommendations by category (e.g., "Budgeting," "Saving," "Investing") or content type. This allows for focused learning.
- **Lovable AI Integration:** This is where the core of the Lovable AI model comes into play. Upon user input, the collected data will be sent to the backend (where Lovable Ai's model or a similar recommendation algorithm will be integrated). The model will then process this data against the available content library to generate personalized recommendations displayed on this dashboard.

5.3.4. Content Library

A browsable and searchable collection of all available resources, categorized and tagged.

- **Tag-based Filtering:** Users can filter content by various tags (e.g., "beginner," "advanced," "video," "article," "credit score," "mortgage").
- **"Featured Resources" Section:** Even within the general content library, a prominent section will display content recommended specifically for the logged-in user, reinforcing the personalization aspect.

5.3.5. User Profile Page

- **Store User Info:** If user login is implemented, this page will display their registered information (Name, Email Address, Phone Number, Location, etc.). Users are be able to edit this information.

5.3.6. About Page

- **Mission Statement:** Reiterates the core mission of empowering users through financial literacy.
- **"How it Works":** A simplified explanation of the recommender system's mechanics. This builds trust by transparently explaining how user data is used to generate recommendations (e.g., "Our smart algorithm analyzes your preferences to suggest content that's just right for you.").

5.3.7. Contact / Feedback Page

- **Contact Form:** A standard contact form for users to send messages, ask questions, or report issues. This will include fields for name, email, subject, and message.
- **Contact Information:** An email address and phone number for direct communication.
- **FAQ section:** to provide quick and easy access to answers to common inquiries

5.3.8. Footer

- **Quick Links:** Essential links such as "Privacy Policy," "Terms of Service," "About Us," and "Contact Us."
- **Social media/External Resources:** Links to social media profiles .
- **Copyright Information:** Standard copyright notice.

5.4. Technology Stack

The recommender system website is created as a functional prototype using Lovable A.I., with a focus on simplicity, interactivity, and accessibility. The technology stack was intentionally kept lightweight to enable easy demonstration of the system's capabilities without requiring a complex backend infrastructure.

Frontend: HTML, CSS, and JavaScript

- **HTML**: Forms the structural foundation of the website, including the layout, user input fields, and display areas for recommendations.
- **CSS**: Used to style the interface, ensuring a visually appealing, user-friendly design that aligns with a light and welcoming color scheme.
- **JavaScript**: Powers the core logic of the recommender system. It captures user input from the form, processes it through a rule-based or data-driven logic module, and dynamically displays personalized action plans or financial education recommendations.

Recommender System Logic (Embedded in JavaScript)

- The recommendation engine is embedded directly in the client-side JavaScript. It uses predefined mappings between user inputs (such as selected topics or user needs) and corresponding educational content or action plans.
- This approach simulates the behavior of a more complex model without needing a server or live data processing, making it ideal for prototyping and demonstration.

No Backend or Database (Prototype Focus)

- As a prototype, the website does **not include a backend server** or **database**. All data processing is done in the browser using JavaScript.
- This decision was made to reduce complexity while still enabling the demonstration of key functionalities of the recommender system.

This technology stack is optimized for showcasing the **core concept** of a personalized financial literacy recommender system. It allows users to interact with the system, explore recommended learning content, and understand how such a system can support financial education — all in a lightweight, browser-based environment.

Here is the link to the website: https://preview--finpal-wealth-pathways.lovable.app/

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