

# Marion Lyaka

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# MAKERERE UNIVERSITY BUSINESS SCHOOL



## DEVELOPMENT OF A MACHINE LEARNING AGGREGATOR FOR A PERSONALISED FINANCIAL PRODUCT RECOMMENDATIONS AT OLD MUTUAL UGANDA

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November 2025

## DECLARATION

We, the undersigned, declare that to the best of our knowledge, this proposal  
Is our piece of work, and has never been published and/or submitted  
For any other University or Higher Institution of Learning.

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## APPROVAL

This project proposal has been submitted with my approval as supervisor my signature is here appended:

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## INTRODUCTION

### 1.1 Project Background

The global services industry is undergoing a significant transformation driven by data analytics and artificial intelligence. Machine learning has emerged as a suitable technology for enabling hyper- personalization, allowing financial institutions to move beyond one size fits all products to tailored solutions that meet individual customer needs 'According to the world Bank (2022). In East Africa, adoption of FinTech and data driven services is accelerating with institutions seeking to leverage customer data for competitive advantage and improved service delivery. Personalised recommendations are no longer a luxury, but an expectation as seen in e-commerce and streaming services and the financial sector is rapidly catching up.

Old mutual Uganda, as a leading financial service provider offers a wide range of products which include life insurance, unit trust, savings, family life protector also known as FLPs. Old Mutual operates across several African markets, including South Africa, Kenya, Tanzania, Rwanda and Uganda and offers products such as life insurance, unit trust savings plans and life protector policies. However, the current process of matching customers to the most suitable products often relies on broad segmentation or manual financial advisor assessments which may not fully optimize for individual customer circumstances, risk profiles and long-term goals. Our project proposes the development of a Machine learning Aggregator.

The importance of this system is that it will act as a central platform that aggregates customer data from various touchpoint within old mutual and utilizes machine learning algorithms to analyse this data. The outcome will be a system that generates highly personalised financial product recommendations for existing and potential customers, hence enhancing customer engagement, satisfaction and financial inclusion.

Our team has identified an opportunity to design and develop a Machine Learning aggregator for Old Mutual Uganda. This initiative aims to address the need for improved



client engagement by enabling customers to more easily and compare the company's products and services leading to quicker claims processing, enhanced responsiveness and an overall better customer experience.

## 1.2 Statement of the Problem

Ideal financial services provision involves offering every customer a uniquely tailored suite of products that aligns perfectly with their financial goals, risk tolerance and life stage and therefore maximizing customer value and long-term loyalty (Deloitte 2023). Currently however, Old mutual Uganda primarily relies on generalized marketing and advisor led sales which may not efficiently match the vast array of available products to the specific needs of each customer, potentially leading to sub – optimal product uptake and missed opportunities for deeper customer relationships. This approach risks customer dissatisfaction due to irrelevant product offers, lower cross-selling efficiency and an inability to proactively identify customers who would benefit from various or specific financial solutions.

A machine learning based aggregator and recommendation system has the potential to analyse complex customer, customer data, identify hidden patterns and provide accurate, personalised product recommendation hence enhancing customer experience, increasing sales conversion rates and fostering greater financial literacy and inclusion among Old Mutual's Clientele.

## 1.3 Project Goal and Objectives

### 1.3.1) Project Goal.

This project seeks to design and develop a Machine Learning Aggregator prototype for Old Mutual Uganda in Kampala District to provide personalised financial product Recommendations and improve customer engagement.

### 1.3.2) Project Objectives

- To analyse the current customer product matching and recommendations processes at old mutual
- To study the functional, data and technical requirements for developing a Machine Learning Aggregator for Financial product recommendations

- To design and develop a working prototype of the Machine Learning Aggregator.
- To test and evaluate the performance and usability of the developed prototype.

### 1.3.3) Project Scope Summary

The project will focus on designing a Machine Learning based Aggregator prototype that integrates sample customer data. The prototype will use synthetic or anonymised customer data and will not access, process or expose any real customer records from Old Mutual Systems. The scope includes the design of the system architecture, the development of a core recommendation engine using a selected Machine Learning algorithm for example collaborative filtering or content-based filtering and the creation of a basic user interface for displaying recommendations. The project will not involve a full-scale integration with all Old Mutual's live production Systems nor a full company- wide implementation.

### 1.4) Anticipated Significance of the Project.

The project will provide Old Mutual Uganda with a blueprint for a modern, data driven customer engagement tool, potentially leading to increased customer satisfaction and product uptake,

For the team, it signifies the practical application of skills in Machine Learning, software development, and systems analysis, providing invaluable experience in developing a cutting-edge IT Solution for the financial Sector.

### 1.5) Project Assumptions

The team assumes that sample or anonymised customer data schemas will be available for design and testing purposes or that suitable synthetic data can be generated.

The team assumes that necessary software for example relevant Machine Learning like Scikit learn, python, a web framework etc and adequate computing power will be accessible for the duration of the project.

The team assumes that the project supervisor will be available for guidance and that the team can access sufficient public domain important information about financial product recommendation systems for literature and design inspiration.

The team assumes that the core objectives and scope of the project will remain stable once approved with my major changes requiring formal review.

## REVIEW OF LITERATURE

### 2.0 Introduction

This literature review covers five key domains relevant to the project objectives which are Machine Learning Recommender Systems, Financial Services Personalisation, Data aggregation and personalisation, Machine Learning ethics in finance and the Ugandan digital finance ecosystem. By exploring these areas, this review establishes the foundational concepts, current technologies and critical considerations that inform the design and development of the proposed machine learning aggregator.

The financial services industry is undergoing a significant transformation, driven by the adoption of machine learning (ML) and artificial intelligence (AI) to shift from product centric models (Deloitte,2023). A core application of this shift is the use of recommender systems which leverage algorithms to provide personalised financial product suggestions, therefore improving customer engagement and satisfaction (Jannach et al.2022) .This literature review will establish the foundation knowledge for developing such a system by synthesizing research across five key domains ,Machine learning recommender systems, financial services personalisation, data aggregation and preprocessing, Machine Learning ethics in finance and the Ugandan digital finance ecosystem. By examining these areas, the review will highlight both the transformative potential of Machine Learning in finance and the specific implementation gaps that often exist in developing economies.

### 2.1 Machine Learning in the Financial Services Sector.

Machine Learning (ML) has transitioned from a niche technology to a core driver of innovation and efficiency in the global financial services industry. Early Application focused on back-office automation and fraud detection, using algorithms to identify anomalous transaction patterns at a scale impossible for human analysts (Buchanan, 2021) says. The scope of Machine Learning (ML) has since expanded dramatically.

Today Machine Learning power sophisticated credit scoring models that incorporate nontraditional data, enhancing predictive accuracy and enabling financial inclusion for populations with limited credit histories (Chen and Li, 2021). Furthermore, algorithmic trading systems execute complex strategies in milliseconds, and natural language processing (NLP) analyses market sentiment from news articles and social media to inform investment decisions (Huang et al., 2022). In customer facing functions, Machine Learning driven chatbots and virtual assistants handle routine inquiries, improving operational efficiency and freeing human agents for more complex tasks (Deloitte, 2023). This widespread adoption underscores a clear industry trend towards data driven decision making, which directly justifies exploring a Machine Learning based solution for enhancing product recommendation and customer engagement in the financial sector.

## 2.2 Recommendation Systems (Algorithms and Techniques)

At the heart of any personalization engine lies a recommender system, which are, information filtering systems that predict a user's preference of an item (Ricci, Rokach and Shapira, 2022). The Literature identifies several dominant algorithmic approaches each with distinct strengths and weaknesses relevant to financial services. on the principle of "Wisdom of the crowd", recommending products that same or similar users have liked. For example, if user A and User B have similar investment histories, a product held by User B but not User A would recommend to User Marion (Aggarwal, 2016). A significant advantage of CF is its ability to discover complex, latent relationship between the users and products without needing detailed knowledge of the product attributes themselves (Jannach et al., 2022). However, a key challenge with this method is the "cold start" problem where the algorithm is ineffective for new users or products with no historical interaction data. In contrast, Content Based Filtering recommends items based on their similarity to items a user has liked in the past, using the items' inherent attributes (Ricci et al., 2022). for instance, if a customer has consistently invested in a low-risk income focused unit trusts, the system would recommend other products with attributes like "low-risk" and "income fund". This method avoids the cold start problem for new products but can lead to lack of serendipity. Therefore, to overcome the limitations of individual methods, Hybrid Models have gained prominence. These combine collaborative and content-based techniques and potentially

others to produce more accurate and robust recommendations (Ricci et al., 2021). For a financial Context where both User behaviour and product attributes are crucial, a hybrid approach is often considered the most effective.

### **2.3 Data Aggregation and Preprocessing for Financial Machine Learning.**

The performance of any Machine Learning system is fundamentally constrained by the quality and structure of its data. A Machine Learning Aggregator must integrate data from disparate sources which in a financial institution like Old Mutual could include CRM Systems, transaction histories, demographic data and web analytics. This process presents significant challenges including dealing with inconsistent formats, missing values and data silos (Muller and Guido, 2020). Before this aggregated data can be used for model training, it must undergo rigorous pre-processing pipeline. This involves cleaning that is, handling missing values through techniques like imputation (using mean/median for numerical data) or deletion, and correcting errors. Transformation therefore this is normalizing numerical values for example using (MinMaxScaler or StandardScaler) to ensure features contribute equally to the model categorical variables such as 'occupation 'or 'branch location' must be converted into a numerical format through encoding techniques like one hot encoding (Geron,2019) . categorical variables and lastly Integration (combining data from different sources into a unified dataset, often using a unique customer identifier as a key). For financial Machine Learning features engineering is particularly important- creating new predictive variable from raw data such as deriving a "savings to income ratio" or a "risk tolerance score" from transaction history and demographic information. Therefore, this entire pipeline from aggregating disparate data sources to the meticulous engineering of informative features constitutes a critical, critical, non-negotiable precursor to training an effective and reliable recommendation model for Old Mutual's clients in Uganda.

### **2.4) Personalization in Financial Products**

Beyond the technical mechanics of recommender systems, personalization represents a powerful business strategy in modern finance . The industry shifts from generic mass marketing to dynamic one-to-one customer engagement has demonstrated significant measurable benefits to a McKinsey and company(2022) report, financial institutions

that leverage advanced personalization techniques can increase revenue by 10-30% and increase customer retention and acquisition efficiency by 10-25%. This is achieved by delivering the right channel, which dramatically enhance customer lifetime value and reduces acquisition costs (Deloitte, 2023). In practical, personalised finance product recommendations help customers achieve their financial goals more effectively, whether it is saving for education, planning for retirement or managing risks. This tailored guidance builds trust and fosters deeper loyalty. A study by (Gartner 2023) found that implementations of AI driven personalisation engines in banking led to a 15.20% increase in product cross selling efficiency. For Old Mutual Uganda with its portfolio spanning life insurance, unit trusts, savings plans and retirement products. this strategic approach is crucial. Personalization enables a move beyond simply presenting a generic list of all available unit trusts to proactively suggesting a specific, tailored mix to investments that aligns with a customer's age, financial obligations and long-term aspirations thereby deepening the customer relationship. By connecting customer data to product attributes, a Machine Learning aggregator can cut through the complexity for the customer, demonstrating a clear understanding of their needs and therefore increasing product uptake and satisfaction (Kumar et al., 2019).

## 2.5 The FinTech Landscape in Uganda.

The feasibility and potential impact of the proposed aggregator must be understood within the Specific context of Uganda's digital ecosystem. Uganda's FinTech landscape is rapidly evolving, primarily driven by high mobile phone penetration rate of over 70% and governmental initiatives promoting a digital economy (Bank of Uganda 2023). The foundational Success of mobile money services, with over 65% of the adult population using platforms for example MTN Mobile Money and Airtel Money has acclimated a significant portion of the population to digital financial transactions (GSMA, 2023). This has created a growing, digital savvy customer base with increasing expectations for convenient and accessible financial services. However, the adoption of advanced data driven personalisation by traditional insurers and asset managers remains nascent stages (2023). While the market is competitive with several providers, the focus has largely been on product availability rather than hyper personalised customer engagement. This gap represents a significant strategic opportunity for an established institution for example Old Mutual. By leveraging its

vast repository of customer data, Old Mutual can bridge the gap between traditional financial services and the digital expectations of the modern Ugandan consumer. This approach would mirror innovations seen in more mature markets like Kenya and south Africa but would be critically customized to local Ugandan consumers behaviours, regulatory frameworks and market dynamics.

## 2.6 Ethical Considerations in Financial AI

The deployment of AI in finance is not without its risks, and a responsible project must proactively address them. A primary concern is algorithms bias. If a Machine Learning model is trained on historical data that reflects societal or internal biases, it may perpetuate or even amplify them, for example by systematically offering poorer product terms to certain demographics groups (Floridi et al, 2021). This necessitates techniques for bias detection and mitigation, Secondly, data privacy and security are paramount, especially under regulations like Uganda's Data protection and Privacy Act, 2019. The aggregator must be designed with robust data governance and encryption. Finally, the "black box" nature of some complex Machine Learning models can lead to a lack of transparency and explainability. A customer is more likely to trust a recommendation if the advisor can explain the reasoning for example "we are recommending this retirement fund or plan because of your age and stated risk issue". The field of Explainable AI is dedicated to humans, a feature that should be considered in the system design.

## 2.7 Conclusion.

The literature review has synthesized knowledge across key domains to establish a robust foundation for the development of a machine aggregator in the Ugandan Financial Context. The analysis confirms that Machine Learning powered recommender systems, particularly hybrid models that mitigate cold-start problems (Jannach et al.,2022), represent a significant advancement in delivering personalized financial services. The documented benefits of personalization including increased customer acquisition, retention, and cross- selling efficiency (McKinsey,2022;



Gartner,2023) provide a compelling business rationale. Furthermore, the evolving Ugandan FinTech landscape, characterized by high mobile money penetration (GSMA, 2023) but nascent adoption of advanced personalisation by traditional institutions (IRAU,2023), presents a strategic opportunity for implementation.

Critically, this review directly informs the subsequent design and development of the prototype. The technical approach will be guided by the synthesis of literature, leading to the following project specific decisions: **Machine Learning Approach**, a hybrid recommender system will be developed, justified by its ability to leverage both content-based filtering for new users/products and collaborative filtering as data accumulates. **Data strategy:** The data aggregation and preprocessing pipeline will be designed with techniques for handling missing values, normalization and feature engineering, specifically creating features like risk tolerance scores from variable data. **Ethical Framework:** The system architecture will incorporate principles of Machine Learning ethics, prioritizing data anonymization in the prototype and considering Explainable AI(XAI) techniques to ensure transparency and mitigate bias. This comprehensive scholarly foundation justifies the project's feasibility and outlines a clear, literature driven path for the system's architecture, implantation and evaluation which will be detained in the subsequent Research Methods chapter.

## RESEARCH METHODS

### 3.0 PROJECT METHODS

#### 3.1 Research Design or Research Approach

The project team will adopt a Design Science Research Approach (DSR). DSR is a well-established paradigm in information systems that focuses on the creation and evaluation of innovative artifacts to solve identified organisational problems(Hevner et al.,2004) This approach is particularly appropriate for the developing digital innovations like the proposed Machine Learning Aggregator, as it provides a structured framework for building and evaluating a practical solution to the problem of low customer engagement at Old Mutual(Rai and Tang 2023).. The Design Science Research Approach or Process involves iterative cycles of problem identification, objective definition, design and development, demonstration, evaluation and communication.

#### THE DESIGN SCIENCE RESEARCH PROCESS OF THIS PROJECT IS AS ILLUSTRATED IN THE TABLE BELOW

This project adopts a Design Science Research (DSR) approach, which is uniquely suited for building and evaluating a practical IT artifact like the Machine Learning aggregator. This methodology's iterative cycles of design and evaluation ensure the prototype is systematically developed and refined to effectively solve the specific problems of improving customer engagement for Old Mutual.

DSR STAGE	RESEARCH OBJECTIVE ADDRESSED	PROPOSED METHODS	EXPECTED RESULTS
Problem identification	To analyse the current product matching and recommendations processes at old mutual.	<ul style="list-style-type: none"><li>i. Interviews with finance advisors simulated.</li><li>ii. Review of company documents by the public.</li><li>iii. Literature Review</li></ul>	A Detailed report on the limitations of the current product matching system

<b>Definition of objectives</b>	To study the functional, data and technical requirements for developing a Machine Learning Aggregator for Financial product recommendations.	<ul style="list-style-type: none"> <li>i. Brainstorming sessions</li> <li>ii. Requirement workshops within the team</li> <li>iii. Feasibility analysis.</li> </ul>	A Finalized list of functional requirements for the aggregator
<b>Design and development</b>	To design and develop a working prototype of the Machine Learning Aggregator.	Use of python, scikit learn, Flask framework, UML diagrams for design, database design (SQLite).	A Working prototype of the ML Aggregator with a core recommendation engine and a simple UI
<b>Demonstration</b>	To test and evaluate and usability of the developed prototype.	<ul style="list-style-type: none"> <li>i. Unit testing</li> <li>ii. Integration testing</li> <li>iii. Acceptance Testing with a small group of peers.</li> </ul>	A tested, functional prototype and a report system performance for example accuracy, speed.
<b>Evaluation</b>	To test and evaluate the performance and usability of the developed prototype	<b>Analysis</b> of testing results against predefined success criteria for example recommendation relevance.	<b>An</b> evaluation report detailing the prototype's effectiveness, usability and limitations.
<b>Communication</b>	All	<b>Compilation</b> of the final project report and presentation to supervisors and faculty.	<b>The</b> project proposal and the final project report and defence

### 3.2 Project Organisation (client)

The project is being undertaken by Old Mutual Uganda, a financial services institution with a significant customers base and a network of over 50 financial advisors in the Kampala region. The primary users of the envisaged system are Old Mutual Marketing team and its financial advisors. These stakeholders are critical to the prototype's success, as advisors are directly responsible for product matching and customer profiling, while the marketing team relies on customer insights for targeted campaigns. The end beneficiaries are the customers of the organisation, who will receive more personalized service. This project's team will engage with these stakeholders throughout the design process to ensure the solution meets both business and user needs.

### 3.3 Sources of Project Data

The project will utilize data from two distinct categories to fulfil different project needs and these include qualitative data for system requirements and quantitative data for model development.

#### i) Qualitative Data for Requirements Elicitation

Primary qualitative data will be gathered to understand the current business processes and user needs at Old Mutual. This will be conducted through semi-structured interviews with financial advisors and focus group discussions with the marketing team. These methods are essential for eliciting the functional requirements and understanding the challenges in the current product recommendation and customer profiling workflows.

#### ii) Quantitative Data for Model Training and Evaluation

For the development and testing of the machine learning model, a synthetic customer dataset will be generated. This approach is necessary because access to real, sensitive customer data is restricted due to privacy regulations and ethical concerns. The synthetic dataset will mimic the structure and statistical properties of real customer data, including attributes like age, income, risk profile and product interaction history in Machine Learning prototyping to enable model training without compromising customer privacy (Jordon et al.,2022). The analysis of this dataset constitutes the quantitative aspect of the project.

### 3.4 System Analysis and Design Approaches

The project will employ an OBJECT-ORIENTED ANALYSIS AND DESIGN(OOAD) approach to model the system's architecture. This method is chosen for its architecture. This method is chosen for its effectiveness in structuring complex systems using modular components like classes and objects which align perfectly with the data entities and interactions in a Machine Learning Aggregator. Key OOAD artifacts will include use case diagrams to capture interactions between users (advisors, customers) and the system, class diagrams to define the structure of core entities for example customer, Financial Product, Recommendation and system architecture diagrams to outline the overall software components and data flow.

The development process will be guided by the Agile methodology. This approach is particularly suited for this DRS project as it supports rapid prototyping and allows for iterative cycles of development and testing. This project will be broken down into two-week sprints, enabling the team to frequently validate functionalities for example the performance of a recommendation algorithm with stakeholders and incorporate feedback promptly. This iterative nature is crucial for refining the Machine Learning model and ensuring the final artifact is both functional and relevant.

### 3.5) Anticipated Project Constraints.

#### i) *Technical Skill Gap:*

The team's proficiency in advanced Machine Learning Concepts and specific python libraries like Scikit -learn, TensorFlow is developing skill. This will be mitigated through dedicated upskilling on platforms like Coursera and by working through practical tutorials on Kaggle. The team will prioritise mastering Scikit learn for the core recommendation algorithms and will schedule biweekly consultation meetings with the project supervisor to review code and conceptual understanding.

#### ii) *Data Access:*

Access to real, sensitive customers data from Old Mutual will not be possible due to privacy regulations. The team will instead use synthetic data generated based on public data schemas and anonymised market research to build and validate the prototype. Public datasets from sources like the UCI Machine Learning Repository may also be adapted to simulate financial product preferences.

#### iii) Time Limitation:

The academic timeline is fixed 12 weeks academic timeline. To manage this, the team will employ rigorous project management using an Agile-based Jira board for task tracking and a detailed Gantt chart to ensure timely delivery of milestones. The scope will be strictly controlled to ensure core functionalities are delivered by the deadline with advanced features being stretch goals.

### 3.6) Timeline and Milestones

The project will follow a 12-week timeline, structured around the core phases of the Design Science Research (DSR) methodology. The Gantt chart in the Appendices below illustrates the schedule, clearly aligning each major project activity with its corresponding DSR stage to ensure a logical and rigorous development process.

### 3.7) Ethical Considerations

For a machine learning project in the financial sector, ethical rigor is paramount. The project team commits to the following. (1) **privacy and Data protection**, as access to the real customer data is not feasible, the project will use synthetically generated data. This approach completely avoids the risk of exposing personally identifiable information (PII) and adheres to data protection regulations like Uganda's Data protection and Privacy Act. (2) **Fairness and Algorithmics Bias**, we recognise that Machine Learning models can perpetuate or even amplify existing societal biases. The synthesis dataset will be carefully designed to represent a diverse customer base. The model's recommendations will be routinely tested for fairness across different demographics segments to prevent discriminatory outcomes. (3) **Transparency and Explainability**, the black box nature of some Machine Learning models is a significant concern in finance where possible, the project will prioritise interpretable models and incorporate Explainable AI(XAI) techniques hence this will allow the system to provide clear reasons for its recommendations, building trust with both advisors and customers.(4) **Use of Synthetic Data**, The use of synthetic data is not just a practical constraints but an ethical choice for this prototype phase. It allows for innovation while completely mitigating risks associated with handling sensitive financial information. This limitations of this approach will be explicitly acknowledged in the final evaluation.

*Disclosure and Declaration Statement:*

The project team intends to use Generative AI tools for example ChatGPT and GitHub Copilot, strictly under the guidance of our supervisor. These tools will be used for brainstorming initial code structures, debugging assistance, and improving report writing clarity. All AI generated content will be critically reviewed and validated by the team. We declare that the core work including problem solving, algorithm selection, coding and analysis will be our own.

## REFERENCES

Aggarwal, c. c (2016). *Recommender System: The textbook*. Springer International publishing.

Bank of Uganda. (2023). *Annual Report 2022/2023*. Retrieved from <http://www.bou.or.ug>

Baskerville, R., Baiyere, A., Gregor, S., Hevner, A., & Rossi, M. (2023). Design Science Research: A unified Framework for impactful Research. *Journal of information technology*, 38(2), 131-150.

Buchanan, B. (2021). *Artificial intelligence in finance*. The Alan Turing Institute.

Deloitte. (2023). *The future of personalisation In financial services*. Deloitte insights.

Drechsler, A., Hevner, A., & Vom Brocke (2021). A Design Science Research Primer: An Introduction to the DSR Paradigm. *In Design Science Research. Cases* (pp. 1-14) Springer, cham.

Florid, L., Cows, J., Beltrametti, M., Chatila, R., Chaze Rand. p., Dignum, V., & Vayena, E. (2021). *In Ethics, Governance, and policies in Artificial Intelligence* (pp. 19-39) Springer, Cham.

Gartner. (2023). *Market guide for personalization*



*Engines in banking.* Gartner, Inc.

GSMA. (2023). The mobile economy:

*Sub Saharan Africa 2023.* GSMA

Intelligence.

Insurance Regulatory Authority of Uganda

(IRAU). (2023). *Annual insurance industry report*

*For the year ended 31<sup>st</sup> December 2022.*

McKinsey & Company. (2022). *The new imperative*

*For personalization in financial services.*

Ricci, F., Rokach, L., & Shapira. (2022).

*Recommender systems: Techniques, applications,*

*And challenges. In F. Ricci, L. Rokach, & B. Shapira (Eds)*

*Recommender systems Handbook* (pp. 1-35). Springer.

## APPENDICES

### APPENDIX I: Proposed project Budget

Item	Description	Quantity	Unit Cost (UGX)	Total Cost (UGX)
Software and development	Google Colab pro for enhanced GPU access	3 months	50000	150000
Hardware	Portable External Hard Drive (Data Backup)	1	150000	150000
Communication	Internet Data Bundles	5 members	40000	200000
Stationery and printing	Report Printing and Binding (2 copies)	2 sets	50000	100000
Contingency	Unforeseen costs for example software subscriptions, transport.	1	100000	100000
TOTAL				800000

### APPENDIX II: Data Collection Tools Intended to Use

This appendix serves as evidence of our preparedness for the primary data collection phases of your project. It contains the actual instruments we will use to gather information from people and documents. For a project like the Machine Learning Aggregator, this is crucial for the initial stages of the Design Science Research Process which are Problem Identification and Requirements Elicitation).

**Purpose**

To Demonstrate Rigor. This shows that you have thoughtfully designed your data collection process.

To Ensure Validity. This allows the supervisor to review and approve the tools, ensuring they will effectively gather the information needed to meet our objectives.

**i) *Semi structured interview Guide***

Target participants: Simulated old mutual Financial Advisor and Branch Manager

Introduction: “Good morning/afternoon/evening.

We are Bachelors of Business Computing students from Makerere University Business School. We are developing a Machine Learning recommendations. Your participation in this interview will help us understand the current process and challenges and this will take approximately 15-20 minutes, All information will be used solely for academic purposes”.

**Section A: *Current process and challenges***

1. Can you describe the step-by-step process you use to recommend a saving or investment product to a new client?
2. What Customer information is of high critical for your recommendation decision? for example in terms of Age, income, existing portfolio and risk appetite).
3. What are the main difficulties you encounter when trying to match a client with the most suitable product from old mutual's portfolio?
4. How do you currently stay updated on the details and changes of all the product offered by old mutual?

**Section B: *Technology and solution Orientation***

5. In your own words, what is the biggest weakness of the current manual or semi-automated recommendations process?
6. If a software tool could assist you, what would be the most important feature it should have?
7. How would you want this system to present its recommendations to you for it to be trustworthy and actionable?

**Conclusion:** “Thank you for your valuable time and insights. This information will be very helpful for our project. if there anything else you want to add on, we are always available.

ii) ***Focus Group Discussion Guide.***

**Objectives:** To brainstorm and prioritize functional requirements for Machine Learning Aggregator prototype

**Participants:** Project Team Members and simulated product owners.

Moderator’s Script:

**Introduction** (6 minutes): Welcome, state the goal: “Today, we will define what our Machine Learning Aggregator must do, let us now brainstorm features”.

***Brainstorming Round (20 minutes):***

“Based on the interview findings, what features should our system have? Think about the data input, processing and output.” Hence moderator lists all ideas on whiteboard or even any board.

***Discussion and prioritization*** (15 minutes): “let us review this list. Using Moscow method, which features are Must haves for our prototype? Which are should haves or could haves?”

***Wrap-up (4 minutes):*** Summarize the agreed upon “Must Have “features.

iii) ***User Acceptance Testing Questionnaire***

**Instructions:** Please use the provided prototype to complete the task below, afterwards, answer the following questions.

Task Scenario:” A new client Marion is 35 years old earns 4.5 million UGX monthly has a high-risk appetite and wants to invest for long term growth. Use the Machine Learning Aggregator prototype to get a product recommendation for her.

## Part A: Usability and Effectiveness

No	statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	The user interface was intuitive and easy to navigate	1	2	3	4	5
2	The system's recommendation was relevant to the client's profile	1	2	3	4	5
3	The information presented product details, reasons for recommendation was clear.	1	2	3	4	5
4	I would be confident using this system in a real-world scenario.	1	2	3	4	5

## Part B: Qualitative Feedback

1. What was the most positive aspects of your experience with the prototype
2. What was the most confusing part?
3. What single improvement would have the greatest impact on this system?

### APPENDIX III: Schedule of Activities/ Gantt Chart

#### PROJECT TIMELINE MACHINE LEARNING AGGREGATOR FOR OLD MUTUAL UGANDA.

WEEK	DSR PHASE	KEY TASKS & DELIVERABLES
1	PROBLEM IDENTIFICATION	<ul style="list-style-type: none"> <li>Literature Review Completion</li> <li>Finalize problem statement</li> <li>Draft project objectives</li> </ul>
2	OBJECTIVES DEFINITION	<ul style="list-style-type: none"> <li>Define project Scope</li> <li>Develop Research Questions</li> <li>Create initial project plan</li> </ul>
3	DESIGN AND DEVELOPMENT (phase 1)	<ul style="list-style-type: none"> <li>Conduct Stakeholder Interviews</li> <li>Finalize system Requirements</li> <li>Create use case Diagrams.</li> </ul>
4	DESIGN AND DEVELOPMENT (phase 2)	<ul style="list-style-type: none"> <li>Design System Architecture</li> <li>Create class Diagrams and wireframes</li> <li>Develop Data Models</li> </ul>
5	DESIGN AND DEVELOPMENT (phase 3)	<ul style="list-style-type: none"> <li>Set up Development Environment</li> <li>Generate Synthetic Dataset</li> <li>Begin Core ML Algorithm Development</li> </ul>
6	DESIGN AND DEVELOPMENT (phase 4)	<ul style="list-style-type: none"> <li>Implement Recommendation Engine</li> </ul>

		<ul style="list-style-type: none"> <li>• Develop Basic UI Components</li> <li>• Initial Data Preprocessing Pipeline</li> </ul>
7	DESIGN AND DEVELOPMENT (phase 5)	<ul style="list-style-type: none"> <li>• Complete ML Model Integration</li> <li>• Develop User Interface</li> <li>• Internal Alpha Testing</li> </ul>
8	DESIGN AND DEVELOPMENT (phase 6)	<ul style="list-style-type: none"> <li>• Prototype feature completion</li> <li>• Code optimization and debugging</li> <li>• Documentation update</li> </ul>
9	DEMONSTRATION	<ul style="list-style-type: none"> <li>• Internal prototype Demonstration</li> <li>• Stakeholder Feedback Session</li> <li>• Collect User Acceptance Test Input</li> </ul>
10	EVALUATION (phase 1)	<ul style="list-style-type: none"> <li>• System Integration Testing</li> <li>• ML Model performance Evaluation</li> <li>• Bug fixing and Refinements</li> </ul>
11	EVALUATION (phase 2)	<ul style="list-style-type: none"> <li>• User Acceptance Testing</li> <li>• Final Performance Optimization</li> <li>• Prepare Evaluation Report</li> </ul>
12	COMMUNICATION	<ul style="list-style-type: none"> <li>• Final Report Compilation</li> <li>• Project Documentation completion</li> </ul>

		<ul style="list-style-type: none"><li>• Défense Presentation Preparation</li></ul>
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