BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE

DEPARTMENT OF COMPUTER SCIENCE

Evaluation of a machine learning-based career guidance information system on enhancing career guidance practices in secondary schools.

Submitted by Isaac T. Rongoti

Reg Number: B211211B

Supervisor: Mr. C Zano

Year : 2025

A research project is submitted to Bindura University Of Science Education in partial fulfilment of the requirements of a bachelor of Science honors degree in computer science.

Dedication

Special thanks to my beloved parents and my family, whose unwavering love and support have shaped my journey. Your sacrifices and guidance inspire me every day.

Acknowledgement

Firstly, I would like to thank the Lord Almighty God for protecting me and giving me such a wonderful opportunity to be here through his unmerited favour and grace. It's all because of God that I reached this far.

I would love to express my deepest gratitude to my parents, whose unwavering support and encouragement have been the foundation of my academic journey. Their sacrifices and belief in my potential have inspired me to pursue my dreams with determination and resilience. They have instilled in me the values of hard work and perseverance, which have guided me through the challenges of my research. This research paper is a statement of their love and support, and I am forever grateful of their presence in life.

I would also like to extend my heartfelt appreciation to my supervisor, Mr C Zano, whose guidance and expertise have been invaluable throughout this research process. His insightful feedback, constructive criticism and unwavering support have not only enhanced the quality of my work but have also fostered my growth as a researcher. I would also want to thank him for believing in my abilities and for encouraging me to push the boundaries of my knowledge. His mentorship has been instrumental in shaping my academic career, and I am truly grateful for his dedication and encouragement.

Finally, I would like to acknowledge Bindura University of Science Education for providing an enriching academic environment that has nurtured my intellectual curiosity. The resources, facilities, and collaborative spirit have greatly contributed to the success of my research. I am thankful for the opportunities I have had to engage with fellow students and faculty members, which have broadened my perspectives and deepened my understanding of the field.

DECLARATION

I, Isaac Takudzwa Rongoti, hereby declare that the research project titled '**Evaluation of a machine learning-based career guidance information system on enhancing career guidance practices in secondary schools.**

' is my original work. This research project is being submitted to Bindura University of Science Education.

I declare that:

1. The research project has been developed by me, and any contributions from other sources have been appropriately acknowledged.
2. The research project has not been submitted for funding or approval to any other institution or organization.
3. The research project was conducted under ethical principles and standards, and all necessary ethical approvals will be sought up and obtained.
4. Any potential conflicts of interest have been identified and disclosed in the research project.
5. I understand that any falsification of information, plagiarism, or other unethical behavior concerning this research project will result in disciplinary action, including revocation of funding and/or termination of the research project.

I hereby affirm that to the best of my knowledge, the information presented in this research project is accurate and truthful.

Signature(Student)………… ……………Date:20/06/25

Signature(Supervisor)…… ……………Date: 20/06/25

Signature (Chairman)…… …………………Date : 20/06/25

Abstract

Access to structured career counselling remains a significant issue for many secondary school students in Zimbabwe, particularly in less-privileged areas. Traditional guidance methods like career days and one-on-one counselling are mostly unavailable due to financial constraints, poor infrastructure, and a lack of trained counsellors. In order to bridge this gap, this study proposes and develops a machine learning-based mobile career guidance information system that provides personalised career path forecasts and mentor recommendations. The system uses a random forest classification model, which was trained on student profiles that include interests, hobbies, and subject strengths, to predict suitable career fields.

Additionally, based on profile similarities, a cosine similarity-based content-based filtering method pairs students with suitable career mentors. The system's front end was constructed with Flutter, and the backend authentication was handled by Supabase. A research science methodology was used for this study since the research involved developing, designing and evaluating a technological solution. A purposive random sampling technique was used to select respondents in Bindura District of Zimbabwe, and a mixed-methods approach was the research design that was employed. Structured questionnaires were used to collect quantitative data in order to evaluate students' access to career counselling and validate prediction results. Descriptive statistics were used to gain a comprehensive evaluation of students responds . To assess the system's usefulness and relevance, qualitative data was gathered from open-ended comments provided by teachers and system users.

Metrics like accuracy, precision, recall, F1-score and confusion matrix were used to evaluate model performance for system evaluation, while Supabase logs and in-app user interactions enabled formative assessment of system engagement. The proposed system can significantly expand students' access to career counselling in remote and underserved areas, according to the results. It also shows promise in providing customised recommendations that enhance students' academic preferences and abilities. The results of the study show that when machine learning technologies are mobile-accessible and locally contextualized, they offer a feasible means of enhancing career counseling practices in low-resource settings like Zimbabwe.

Contents

Table Of Figures

Chapter 1: Problem Identification

1.1 Introduction

A crucial part of secondary education is career counseling, which gives students the information, resources, and guidance they need to make wise decisions about their future. Many students, especially those in resource-constrained environments, are at a serious disadvantage in the increasingly complex global job market due to the lack of inclusive and effective career guidance strategies. The reach and impact of traditional career guidance methods, like career fairs, counseling sessions, and printed career brochures, are limited, particularly in Zimbabwe, where underfunded and rural schools encounter financial and logistical obstacles when attempting to implement such programs. Because of this, a large number of students graduate knowing very little about career paths that fit their interests, abilities, and goals.

The emergence of machine learning (ML) and artificial intelligence (AI) offers a chance to revolutionise the way career counselling is provided. Large data sets can be processed by these technologies to provide tailored recommendations, replicate real-world work settings, and link students with experts in related fields. In this regard, career counselling programs based on machine learning show promise as intelligent and scalable instruments that close the educational accessibility gap. By predicting students' strengths, matching them with mentors or resources in real time, and offering personalised career recommendations, these systems can overcome many of the drawbacks of traditional approaches.

This study investigates the creation and assessment of a machine learning-powered career counseling information system designed for secondary schools in Zimbabwe. Based on students' stated interests, pastimes, and academic strengths, the system uses a Random Forest algorithm to forecast suitable career paths for them. Furthermore, the system integrates human support and predictive analytics by recommending relevant mentors through content-based filtering based on cosine similarity. Increasing student exposure to career opportunities and guidance in spite of financial and structural obstacles is the aim.

This study tests the viability, efficacy, and usability of the suggested solution in addition to examining the current status of career counseling in Zimbabwe using a combination of quantitative and qualitative research methodologies. It is anticipated that the results will advance the fields of education technology, guidance and counseling, and machine learning applications in developing nations both practically and academically.

1.2 Background of the problem

A career constitutes a continuous and evolving process that signifies advancement along a professional trajectory (Baruch, 2015). A career decision represents a significant milestone in the career-planning process, necessitating alignment with individual suitability (Lent & Brown, 2020). An appropriate career decision significantly influences an individual's life (Haneef et al., 2020). Career guidance includes a range of services aimed at aligning an individual's expectations, interests, qualifications, and skills with societal or global standards (European Center for the Development of Vocational Training (CEDEFOP) et al., 2019). Furthermore, prior studies emphasize the significance of career counseling in facilitating individuals' access to information regarding available occupations and opportunities (Gati & Levin, 2015), particularly for students who may encounter challenges in making career decisions due to a lack of adequate knowledge (Ashari et al., 2019; Haneef et al., 2020).

The job market in Zimbabwe, like many other countries is rapidly evolving due to technological advancements and economic shifts. High school students often face challenges in making informed career choices due to lack of access to up-to-date information on job market demands and industry trends (Mtemeri, 2017) . Traditional career guidance methods may not be sufficient to address these dynamic changes leading to a gap between student career aspirations and actual job market (Westman et al, 2021). For Zimbabwe to fill the gaps in the different sectors of the economy there is a need to develop school pupils' knowledge and positive attitudes towards the different manpower need (Mutungwe et al, 2011). School pupils need guidance in career opportunities as they progress in their learning. Guidance may be limited in Zimbabwe secondary schools as shown by students proceeding to 'A' level who show problems in selecting subject combinations that match specific career paths (Mutungwe et al, 2011). Students applying to enroll at university have had problems selecting appropriate programs related to their 'A' level combinations (Mutungwe et al, 2011). Effective career guidance requires collaborative efforts among schools, universities, employers, and career counselors, as indicated in a report by Chimbiri in the Financial Gazette dated 10 April 2009 (Mutungwe et al, 2011). Fitzkenny (2013) noted that while numerous career paths exist, individuals lacking guidance and counseling in making future career choices may face limitations in their options. This is particularly true for those unprepared for workplace requirements, who underestimate their abilities, or who are unaware of the diverse opportunities available that could expand their career possibilities. The Zimbabwean education system aims to deliver quality education but encounters substantial obstacles in preparing students with the essential skills and knowledge required for the dynamic job market (Mtemeri, 2017). The challenge is exacerbated by the nation's economic landscape, characterized by instability and elevated unemployment rates. Numerous universities in Zimbabwe face challenges in offering programs that correspond with contemporary market needs. This gap frequently leads to graduates possessing insufficient skills that employers desire, thereby worsening unemployment gap. The extensive integration of information technology and communication systems has significantly enhanced the delivery of student career guidance services (Pordelan & Hosseinian, 2022; Supriyanto et al., 2019). Online career services and career information systems are being created to assist students in the career decision-making process. These technological tools fulfill various functions, such as facilitating career decision-making, intervention, and planning (Zainudin et al., 2020). The primary role of career counsellors is to facilitate guidance activities that assist students in making informed choices, decisions, and preparations regarding their future occupations and careers (Yeşilyaprak, 2019). This service aims to assist students in their transition to higher education institutions, considering their abilities, interests, needs, personality traits, and living conditions (Atay et al, 2024). The services offered in this context are documented and managed within the e-Guidance System (Atay et al, 2024). Students should obtain career guidance services to choose a department and university that align with their preferences and competencies, representing a significant step in their career development. The diversification of career choices has increased the complexity for individuals in determining their own paths. Furthermore, the selection of an appropriate university and department plays a crucial role in shaping an individual's career and job satisfaction, subsequently affecting the overall productivity of society (Turan & Kayıkçı, 2019). This situation underscores the necessity for customized and effective guidance services that facilitate informed career decisions and assist students in evaluating their career options and competencies (Atay et al, 2024).

This research aims to explore the potential of a machine learning-based career guidance information systems in enhancing career guidance for high school students in Zimbabwe, focusing on how it can bridge the gap between education and employment.

1.3 Problem statement

Several secondary schools in Bindura District, Zimbabwe lack the financial means to provide organized and easily accessible career counselling, regardless the fact that career assistance plays an important role in shaping students' future goals. For students from schools which are limited financially, traditional methods like career fairs(career days) and in-person mentoring may still be unaffordable, leading to gaps in access to career information. Furthermore, when they do exist, the guidance systems that are in place now are primarily generic and do not account for the unique interests and academic abilities of students. This study suggests a mobile-based system for career guidance information that makes use of machine learning—more especially, a Random Forest model—to predict suitable career paths for students according to their academic aspirations and interest and a content-based filtering using cosine similarity to network students with career mentors.

1.4 Research Objectives.

1.To determine the current state of career guidance practices in Zimbabwean secondary schools.

2. To develop a machine learning based career guidance Information system.

3. To evaluate the career guidance Information system.

1.5 Research Questions

1. What career guidance services are being offered to secondary school learners in Zimbabwe ?
2. Can a machine learning based career guidance Information system be developed and integrated into Career guidance for improved accessibility?
3. How to evaluate the effectiveness of the machine learning based career guidance information system?

1.7 Justification/Significance of the Research

Historically, careers in the workplace were secure and straightforward, enabling individuals to follow a lifelong profession. However, recent changes and trends in the work environment have created a landscape of continual shifts, leading to unpredictable and diverse career trajectories(Ehindero et al, 2023).This has resulted in an increase in temporary positions, prompting employees to transition between various jobs that align with their skills and expertise (González et al., 2020).The changing job market creates difficulties in securing and retaining jobs, highlighting the importance for individuals to stay employable by embracing creativity and innovation (Ehindero et al, 2023).

Zimbabwe faces high unemployment rate, by early 2024, unemployment rate was about 21.8%, with nearly 37% of adults searching for work. Over 2.5 million of Zimbabweans aged 15-34 are not in education, employment or training (ZIMSTAT, 2024).Without Systematic guidance students may choose subjects and careers that do not match labor-market trends, resulting in high youth unemployment and skills mismatch(OECD,2024). High use of mobile devices(13.88 million active SIM connections) by 2024, means that a mobile system can reach many learners even in remote areas (DataReportal, 2024). Improved guidance is critical to help Zimbabwe's youth make informed choices that enhance employability(Afrobaromrter, 2025; OECD, 2024)

The traditional career counselling often employs a one-size-fits-all approach, failing to account for individual interests, strengths, and unique circumstances. In some circumstances it is normally coupled with socioeconomic and cultural bias. Formal career guidance programs exist only in a minority of schools and are often are often inconsistent. A recent study in Manicaland found that although basic emotional support is given, student career planning, exploration and development are minimal. Many high school students lack the resources and guidance to make informed decisions about their education. The research aims to empower them with insights and support, helping them identify their strengths and align them with promising career options.

Furthermore, new guidance practices provide considerable advantages for individuals and societal well-being (Barnes et al., 2020).As countries strive to promote evidence-based career guidance, the expanding use of data analytics and digital technologies for monitoring and evaluating the effectiveness of career guidance services becomes increasingly prevalent (Harrison et al., 2022). Ifan (2015) stated that, the manual career guidance system is quite tedious, time consuming, less efficient, more prone to error and inaccurate in comparison to computerized systems According to Atay et al. (2024), career information systems should make it possible for career development interventions that are based on evidence to work. To make professional choices, people need to know how to connect information about the job market with specific professions or higher education programs. It's important to remember that going to college is a big part of getting a job. Jamiu et al. (2023) contend that modern young adults participate in learning and interaction that extends beyond conventional school environments, viewing communication over digital platforms as a literacy practice that enhances their learning experience. Digital technology especially mobile apps with Machine learning can overcome traditional practices gaps by providing scalable, personalized guidance. Nearly all Zimbabweans have some mobile and improving data speeds so a well-designed mobile application could reach diverse regions (DataReportal, 2024). Machine learning and recommender algorithms can tailor advice to each student's grades, interests and backgrounds. (Trujillo, Pozo & Suntaxi, 2025) contended that ML-driven guidance can change career counselling by providing more accurate, personalized and, scalable recommendations. ML-Models that consider academic performance and personal interests often outperform traditional counselling, improving the match between students , skills and suitable career paths and thereby reducing dropouts(Gouda & Bhavani, 2025). Recommender systems are already used in education and career tools elsewhere to simplify choice overload(OECD, 2024).

1.8 Assumptions

1.Student Engagement - It is assumed that students will be willing to use a mobile-based platform for career guidance and will actively engage with the resources provided.

2. Technology Access- It is assumed that students have access to smartphones or other mobile devices with internet connectivity, which is crucial for the platform's usability.

3. Availability of Counselors-It is assumed that career counselors and professionals will be available and willing to participate in the platform, providing guidance and support to students.

4. Market Relevance -It is assumed that the career guidance provided through the platform will align with current job market demands and opportunities in Zimbabwe.

1.9 Limitations

1. Geographical Disparities- The research may not fully represent the experiences of students in extremely remote areas where access to mobile technology is limited.

2. Sample Size- The initial implementation may involve a limited number of schools, which could affect the generalizability of the findings.

3. Technological Barriers- Some students may face challenges related to digital literacy, which could hinder their ability to effectively use the platform.

4. Sustainability - The long-term sustainability of the platform is uncertain, depending on continuous funding, maintenance, and the engagement of counselors.

5. Variability in Career Choices-The diverse interests and aspirations of students may make it challenging to provide tailored guidance that meets everyone's needs.

1.10 Scope of Research

The scope of the research for the development of the career guidance information system mobile app includes analyzing the following areas.

1. **Career day landscapes**: It will include a review on existing career day programs, assessing its impact on students.

2. **Target Audience**: Conduct surveys and interviews with high school students, educators and industry professionals to understand their needs, preferences, and challenges in career planning.

Chapter2: Literature Review

2.1 Introduction

This chapter compiles all the literature that will be used throughout the research project. It contains the definition of the project title, historical background of the development of career guidance in Zimbabwe, career guidance and counselling, the roles of guidance and counselling, the roles of counsellors in secondary schools, training and supervision, data and information systems. It also explores the challenges faced by developing countries like Zimbabwe, and the potential of mobile application social platform to address these challenges. It examines existing research on career development theories, the role of technology in career guidance and the successful implementation of AI driven solutions. This system will employ Random Forest machine learning algorithm, random forests or decision trees can detect key patterns accounting for multiple strengths, weaknesses, interests, and external factors human advisors cannot match. The algorithms can ingest diverse student data points to determine optimal career and development suggestions tailored to the individual.

2.2 Theoretical Frameworks

2.2.1 Holland's Theory of Vocational choice

Holland's theory of vocational choice proposes that individuals select careers that align with their personality types. It categorizes individuals into six personality types: Realistic, Investigative, Artistic, social Enterprising and conventional (RIASEC). These types, when matched with suitable occupational environments, can lead to greater job satisfaction and success.

2.3 Career guidance practices in Zimbabwe

Secondary education is the connecting link between primary and higher education where a student has to decide what profession he wants to pursue or what profession should be the best for him (Subhrajyoti,2023).According to super's 1957 development theory and supported by (Subhrajyoti ,2023), 15-24 age is considered as the exploration phase of individual career development where the student is categorized by formatting the self-concept and occupational concept. Traditional career guidance approaches often rely on individual counseling, workshops, and career fairs (Herr & Cramer, 1996). The Zimbabwean culture is deeply rooted in communal values, (Ringson, 2017) argued that children are not individually raised rather in a collective manner (community responsibility) in this case this has an impact to their life choices as children in Zimbabwe do not generally have the autonomy to choose a career that they are not socialized into. Another study by (Mtemeri, 2019) aimed to examine the influence of family on career choices for their children. The study drew conclusions with the use of descriptive statistics, in contrast to the father (46%), the family company (28%), the dominant profession in the family (27.7%), and the extended family members, who had varying but lesser effects, the mother (47.3%) and the siblings (51%) had a significant influence on children's career choices. The professional choices of their children were similarly perceived to be influenced by the parents' careers (59.8% and 51.9%, respectively). The results of this study show that parents, siblings, and moms have the most say on the jobs their kids choose. That being said, it was thought that the mother had the most power over the father and the siblings. More and more students are going to career advise teachers for help because they are having trouble picking a job in school (Rosli and Suib, 2020). According to a research by Mtemeri (2022), the students claimed that their courses and the school's screening process had a big effect on their job choices, making some jobs more interesting to them than others. The report also said that teachers who give job guidance think that schools may help students with their careers by giving them career help. They say that career counseling helps students make better choices regarding their jobs and clears up any confusion. It was also shown that students' job choices were affected by their contacts with peers (Goya and Perdhana, 2024). According to a study by Mtemeri (2020) on how peers affect students' career choices, the study's findings showed that students' job choices were affected by the professional knowledge they got from friends and peers. Students talk to their peers and classmates about important job possibilities. Teachers who help students with their careers agreed with them when they said that friends' suggestions for employment were very important in making decisions. The study also found that other students affected the job choices of pupils.

. According to the observations made by Mutungwe(2011) showed that in Zimbabwe there is a career day session that are organized by the ministry of Public Service. .

2.4 Technology in Career Guidance.

According to Hooley and Staunton (2020), digital technologies give people access to a wealth of information that they can utilize to guide their career decisions. People can act and interact in ways that were previously impossible thanks to digital technology. These tools can help people live better lives by, for instance, enhancing information access, facilitating communication, opening up new avenues for teaching and learning, or enabling people to communicate across distances (Hooley & Staunton, 2020). The primary indicator of high-quality career counseling is the final destination of graduates (Alim, 2019). For students and job seekers, online career resources, virtual career fairs, and career planning tools have become indispensable resources (Sampson et al., 2020). Technology integration in career counseling can improve accessibility, offer tailored suggestions, and support ongoing education (Noe, 2008). However, issues like affordability, internet access, and digital literacy can make it difficult for developing nations to successfully implement technology-based solutions (ILO, 2018).

The Use of Technology in Counseling In addition to increasing the range of services available, digital tools can give people new ways to get help at any time or location. Improved accessibility, greater access to information, assessments, and networks, as well as reduced overall costs and enhanced cost-effectiveness, are some possible advantages of utilizing technology in career counseling (Sampson et al., 2020). According to Hooley et al. (2015), guidance staff have historically employed technology in three ways: 1) to provide learning and career information that supports career building; 2) to facilitate automated interaction such as career assessments, simulations, or games; and 3) to offer communication options. Guidance professionals and service designers must plan which technologies to use and how in order to develop integrated or blended guidance, or guidance through digital means (Bakke et al., 2018).

The willingness of guidance organizations and professionals to adapt is just as important as the technical solutions or user skills when it comes to integrating new and emerging technologies into guidance services (Kettunen & Sampson, 2019). Staff members' technological aptitude and orientation determine how much technology is incorporated into guidance procedures (Kettunen et al., 2013). With the promise of greater accessibility and individualized support, digital technologies are being utilized more and more in career counseling globally. According to the OECD (2024), counselors can work more closely with students by using digital tools to automate routine guidance tasks. To assist students in exploring careers and training, national portals (such as Ireland's Careers Portal) and platforms (such as the UK's CiCi) curate labor market data, self-assessment tools, and employer connections.

. Beyond "test-and-tell" questionnaires, computer-assisted career guidance (CACGS) systems now incorporate social connectivity, big-data analytics, and adaptive assessments. According to a systematic review, when in-person career counseling services are unavailable in schools, CACGS "evolved as a viable alternative to in-person career counseling." Nevertheless, there is still little data on results: Few studies have compared digital guidance to traditional counseling, according to the OECD. Many tools (like CareerFuture and MyBlueprint) are still in the pilot stage or are private endeavors, and students frequently prefer face-to-face interaction. Crucially, the OECD emphasizes that the availability of guidance is frequently uneven and fragmented; market-driven resources are abundant, but users, particularly students from underprivileged backgrounds, struggle to navigate them.

2.5 Career Guidance Information Systems (CGIS)

With the goal to help people reach their full potential, promote increased productivity in national economies, and guarantee effective human resource management, effective career guidance is essential (CEDEFOP et al., 2019). The key players in charge of academic and career counseling, including career counselors, guidance specialists, and psychologists, are essential to this process (Zhang et al., 2018). One of the most economical ways to support career exploration and planning and offer up-to-date career information is through career information systems (Garcia et al., 2021). When a career counselor needs to help a large number of students, these systems may be able to reach a large number of participants (Garcia et al., 2021). Consequently, people can receive more thorough career guidance from digital career counseling tools (Atay et al, 2024).

Effective career guidance is crucial in order to ensure efficient human resource management, encourage greater productivity in national economies, and assist individuals in realizing their full potential (CEDEFOP et al., 2019). This process depends on the important individuals in charge of academic and career counseling, such as career counselors, guidance specialists, and psychologists (Zhang et al., 2018). Career information systems are among the most cost-effective means of providing current career information and assisting with career planning and exploration (Garcia et al., 2021). These systems might be able to reach a lot of participants when a career counselor needs to assist a lot of students (Garcia et al., 2021). Thus, digital career counseling tools can provide more comprehensive career guidance (Atay el, 2024).

2.6 Machine Learning Models in Career Guidance

Many different ML algorithms are used in modern systems. Decision trees and their ensembles, like Random Forest, are widely used. For example, Bertrand et al. (2025) used Naïve Bayes, Random Forest, and Decision Trees to create a career guidance system. Random Forest provided the best accuracy on student data in that study. Similarly, in their guidance portal, Gokarn et al. (2024) contrasted Random Forest, Decision Trees, Support Vector Machines, and K-Nearest Neighbors. In their dataset, they found that KNN outperformed SVM, RF, and DT, achieving an accuracy of over 94%. To capture intricate patterns, other studies employ hybrid ensembles and gradient-boosting techniques like XGBoost. The use of neural networks is growing; for example, Bahalkar et al. (2024) used an encoder–decoder LSTM model to examine student performance sequences and forecast the best subject or career choices.

In order to incorporate a variety of inputs, such as interests, personality, and academic performance, hybrid approaches are also documented. For example, combining fuzzy logic with machine learning or combining content- and collaborative-filtering techniques. A one-on-one consultation with an experienced career counselor was replicated by the different machine learning techniques used (Betrand, 2025). In their study, Repaso & Caparino (2020) investigated classification methods to forecast graduates' information technology career specialization. Machine learning algorithms with 18 attributes were used to analyze the data. Higher accuracy was shown by the Random Forest and Naïve Bayes models, which had acceptable ROC and RMSE values (Betrand, 2025). As data mining techniques were used to analyze factors and predict career paths using multiple performance evaluation metrics, a variety of academic and personal factors influencing career selection were examined.

As a case study, the research clarifies the intricate dynamics affecting career choices in Zimbabwe's changing labor market. Panthee et al. (2023) proposed a machine learning-based career guidance system that aims to help students choose their job roles by predicting their learning preferences and personality traits. However, the goal of this study is to use a random forest machine learning algorithm to predict students' career paths based on their interests, passions, and subject strengths.

2.7 System Architecture and Development Approaches

A pipeline comprises user profiling, data preprocessing, model training, and recommendation delivery in typical architectures. Academic records, test scores, skills, interests, and even psychometric data are all collected by systems, which then preprocess them using techniques like feature engineering, encoding, and normalization. This data is then used to train machine learning models; Bertrand et al. evaluated DT, RF, and NB models using accuracy, precision, and F1. After that, the system creates subject pathways or ranked career recommendations based on the profile.

An agile or iterative development process is used in many projects. Bertrand et al. (2025) specifically mention an iterative process that incorporates user feedback loops. In a similar vein, student projects that describe agile sprints and rapid prototyping to refine features include the Vikalp mobile app. A user interface (web page or app), a recommendation engine (ML models and logic), and a content database are frequently considered essential components. Naresh Kumar et al. (2024), for instance, describe a Django-based server that is connected to databases of educational programs, skills, and careers. They outline a modular architecture that includes components for data analytics, ML models, and user profiling.

Systems can use collaborative/hybrid or content-based recommendation logic, which matches profile attributes to job or course features. While some designs explicitly encode expert rules (e.g., decision rules from psychometric theory), others use similarity measures (e.g., KNN on skill vectors) to suggest careers similar to others with similar profiles. Hybrid systems combine different methods. For example, some authors mapped grades and personality onto career paths using a "fuzzy N-layered architecture" (PCRS system). There is also discussion of adaptive learning components, which allow systems to modify suggestions in response to user feedback or changes in user profiles. For instance, a student's profile can be updated in real time by chatbots or adaptive tests.

A growing interest in using digital and machine learning (ML) technologies to improve career guidance systems is evident from the review of Zimbabwean and international literature. With interactive, data-driven tools, computer-assisted career guidance systems (CACGS) can greatly assist students in exploring career options, as shown by platforms like CareersPortal.ie, CiCi, MyBlueprint, and C-Game on a global scale. Advanced technologies like AI chatbots, recommendation algorithms, and user profiling dashboards are being progressively integrated into these systems. But as Leung (2022) and the OECD (2024) note, there are still disparities in these systems' contextual relevance, personalization, and efficacy, especially in settings with limited resources.

The landscape in Zimbabwe is still severely limited. Even with the existence of regional edtech platforms like Craydel and isolated innovations like FundoLinker, students in rural and under-resourced areas still have limited access to structured, scalable, and data-informed guidance. According to earlier research (Mutungwe et al., 2010; Farao & Du Plessis, 2024), career counseling in Zimbabwe is primarily unstructured, dispersed, and underfunded. The majority of current systems also lack local labor market data, are not integrated into the national education system, and do not consider infrastructure constraints like device access and poor connectivity.
In the context of career counseling, there is a significant research and application gap at the nexus of machine learning, localized content, and equitable access. Although ML-based systems have shown promise on a global scale, no known implementations have used local data to customize such models to the Zimbabwean labor context and educational system. Many students are thus left without helpful advice on how to match their interests and strengths with feasible career paths.

2.8 Challenges and Best Practices

Data coverage and quality: Comprehensive, current data on users and careers is necessary for career counseling systems. Finding trustworthy training data can be challenging in many situations. For instance, psychometric scores and digital student records might not be available in high schools (Farao and Duplesis, 2024). In order to handle missing or noisy inputs, systems must be built with robust algorithms or encourage users to manually fill in the blanks. To avoid out-of-date advice, the occupational database must be updated on a regular basis.

Fairness and bias: ML models may unintentionally encode biases (regional, gender, and socioeconomic). Bahalkar et al. (2024) specifically address ethical AI: they audited their LSTM model for gender or SES bias and anonymized data. Similarly, OECD guidance emphasizes privacy and transparency, and developers should make sure that data handling is secure (student profile encryption) and prevent bias (e.g., equalizing recommendations across groups).

Digital literacy and user engagement: Students must genuinely use a system for it to be effective. Engagement is aided by features like chatbots, interactive tests, and saved profiles (found in BEYOND). But there are obstacles: according to the OECD, some users might have trouble using online platforms, have outdated technology, or have language problems (OECD, 2024). Designing for low-bandwidth and multilingual use is essential in Zimbabwe and similar situations.

Technical scalability and maintainability: To enable ML models to be retrained as new data becomes available, systems should be constructed modularly. It is necessary to document pipelines (such as those that use ML services or Python notebooks). It is advised to conduct ongoing evaluation; teams frequently choose algorithms by tracking metrics and using cross-validation (Gorkan et al, 2024). Iterative user testing, which gathers input from students and counselors to improve the user interface and logic, is another best practice.

Contextual adaptation: Lastly, local context is important. The curriculum, the languages (English, Ndebele, and Shona), and the economic realities of Zimbabwe must all be reflected in Zimbabwean systems. Advice would be more pertinent, for instance, if it were connected to Zimbabwe's own employment market data (possibly from labor surveys or the Zimbabwe National Statistics Agency). Cultural sensitivity can be guaranteed by working with regional career counselors (such as the Career Advisors Association of Zimbabwe).

Conclusion

As a result, this research is both timely and essential. By investigating how machine learning can be successfully modified for low-resource contexts, it fills important gaps in Zimbabwe's current educational support infrastructure and advances the field as a whole. In line with national objectives of digital transformation and youth empowerment, the creation of a locally relevant, machine learning (ML)-driven career guidance system has the potential to revolutionize the way Zimbabwean students receive career advice, enhance decision-making, and lessen information inequality.

Chapter 3: Research Methodologies

3.0 Introduction

According to Song (2021), research is an organized method of investigation that uses critical evaluation and scientific analysis to methodically look into a particular topic of interest. Methodologies can include exploratory, descriptive, or diagnostic approaches and use either quantitative or qualitative techniques, depending on the goals of the study. The chapter's objective is to provide an explanation of the researcher's methodology. The researcher had to use a mixed-methods approach, combining both qualitative and quantitative research methods, to determine the best ways to accomplish the goals while keeping the topic and objectives in mind. The tools chosen were primarily focused on gathering data that would be relevant to the field of study and aid in the creation of a mobile application for career guidance based on machine learning.

3.1 Research Design and Data Collection Approaches

Students and career guidance teachers were given a pre-system baseline survey. To learn more about the current methods used in Zimbabwean secondary schools to provide career guidance, a descriptive survey research design was used. To guarantee a comprehensive grasp of the research problem, the design integrated both quantitative and qualitative methodologies.

3.1.1 Mixed Method Approach

Structured questionnaires were used to gather quantitative data from teachers and students. These tools recorded quantitative information about ICT infrastructure, digital literacy levels, attitudes toward digital tools, and access to career counseling services. This made it possible to use statistical analysis to pinpoint priorities, gaps, and trends within the ecosystem of career counseling.

Simultaneously, open-ended questionnaire responses and teacher feedback sessions were used to gather qualitative data. Richer, contextual insights into the real-life experiences of educators and students, difficulties with conventional guidance, and comments on the usefulness and applicability of the created system were all offered by these responses. This method allowed the study to examine the subtle opportunities and obstacles that affect the effective integration of machine learning into career counseling, moving beyond simple statistics.

3.1.2Design Science Research Methodology

In order to direct the creation, deployment, and assessment of a mobile-based machine learning career guidance information system, the study also embraced a Design Science Research (DSR) methodology.

• Information Gathering: Past Interests, subject strengths, and aspirations were among the datasets used to train the model. The career recommendation system was created using the dataset. Python was used for this training on Google Collab. The model was put into use for making predictions in real time. The mobile application was powered by the random forest model.

Next, a formative assessment approach that combined quantitative and qualitative techniques was used:

- System usability testing using standardized scales.
- Backend system logs (Supabase) provided usage metrics.
- Post-use surveys and interviews were used to assess impact and satisfaction.

3.2 Population and Sample

Students in Zimbabwe's Bindura district in grades three through six made up the target population, especially those getting ready to apply to universities or choose subjects that would define their careers. The extended population for testing the mentorship and feedback system also included career guidance instructors and mentors.

Using a purposive sampling technique, the following individuals were chosen:

- During a trial period, 30 students from the urban and peri-urban Bindura District who had access to Android devices and actively participated in career decision-making were interviewed and engaged with the system.
- Five career mentors with backgrounds in university program advising and career counseling for students.

  • This sample size was adequate to evaluate the system's functionality, collect a range of input, and assess its initial impact in practical use cases.

However, No direct survey participants were used in training the ML model, but system design was informed by 30 student profiles.

Data for model training was collected from a structured CSV dataset with attributes: interest, subjects, aspirations, and target course labels.

3.3 Research Instruments

Several Instruments were used to gather data for both system evaluation and user feedback.

1. Objective 1

- Student Questionnaire: Focused on existing delivery methods (e.g., teachers, career days), frequency, effectiveness, and satisfaction with guidance.

- Teacher Interviews/Survey: Captured perceptions of preparedness and availability of career guidance services.
- Included Likert-scale items on satisfaction, perceived usefulness and clarity.

2. Objective 2

- Data on students' interests, pastimes, and academic subject strengths were gathered using the Student Profile Questionnaire. multiple-choice questions made to work with machine learning feature extraction. The predictive model that categorizes students into possible career fields was trained using these features.

- Post-use system feedback: To assess the system's accuracy, usability, and user satisfaction following student use. There were both open-ended and Likert-scale questions on the form. This made it possible to refine the front-end interface and the ML model iteratively.

3. Objective 3

- Student feedback survey: This survey was used to find out how users felt about the system's usefulness, usability, and relevance to their choice of career.
- Teacher Evaluation Form: This form was used to determine whether the system can support current career counseling initiatives and is in line with educational goals.
- To gauge feature usage and system engagement, system usage logs were gathered from Supabase, including REST, Auth, Storage, and Realtime request counts.

3.4 Data Analysis Procedure

The collected Data was analyzed using both qualitative and quantitative techniques:

Objective 1

- Quantitative analysis: Frequency tables and percentages were used to analyze responses on guidance delivery methods.
- Qualitative analysis: Thematic analysis was used for open-ended teacher responses.
- Evaluation: The current state was determined by aggregating reported access methods, perceived gaps, and frequency of guidance provision.

Objective 2

To evaluate the machine learning models, the following standard performance metrics were used: Accuracy, Precision and Recall, F1 Score.

Accuracy: The ratio of correctly predicted observations to the total observations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

TP = True Positives (correctly predicted positives)

TN = True Negatives (correctly predicted negatives)

FP = False Positives (incorrectly predicted as positive)

FN = False Negatives (incorrectly predicted as negative)

Precision: The ratio of correctly predicted positive observations to the total predicted positive observations.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- Answers the question: **"**Of all items the model labeled as positive, how many were actually positive?"

F1 Score: The weighted average of Precision and Recall (Recall = TP / (TP + FN)).

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Balances precision and recall, especially when the dataset is imbalanced.

Objective 3

To evaluate the developed system the following metrics were considered.

- Mean Similarity Score (average cosine similarity between student and mentor vectors)

$$\text{Cosine Similarity} = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \times \|\vec{B}\|}$$

$\vec{A}$ and $\vec{B}$ are two vectors (e.g., a **student profile** and a **mentor profile** or **career profile**).

$\vec{A} \cdot \vec{B}$ is the **dot product** of the two vectors.

$\|\vec{A}\|$ and $\|\vec{B}\|$ are the **magnitudes** (lengths) of each vector.

- System logs From Supabase were also collected to validate proper functioning of core features.

3.5 System Development Process

An iterative modular approach combining data engineering, model experimentation, backend services, and frontend development was used to develop the machine learning-based career guidance information system.

3.5.1Data Preprocessing

Data Collection: These models were trained and assessed using the Kaggle dataset for career guidance systems. The module for the career recommendation system was created. Python was used for this training on a Google Collab Notebook. The model was put into use for making predictions in real time. A mobile application developed using the Flutter framework was powered by the model.

3.5.2 Dataset Preparation and Feature Engineering

Prior to training a prediction model, feature selection is an essential step. A dataset's high dimensionality may result in a reduction in performance. Training a model with high complexity takes a long time. To do this, the list of variables must be cleared of any extraneous features. It is essential to select the appropriate algorithm for feature selection. The target variable and the independent variables in the dataset determine which algorithm should be applied. The SelectKBest extraction technique was applied to the career prediction system dataset. With this feature extraction method, the undesirable features in the provided data are eliminated while the pertinent features are kept. From the dataset, pertinent characteristics affecting career decisions were chosen. Google Collab Notebook was used to apply feature engineering techniques.

to derive new features or enhance existing ones. Machine learning algorithms Random Forest was selected in order to map career paths to student attributes. The model was trained and evaluated using Google Collab Notebook. To evaluate model performance, the dataset was divided into training and testing sets, and cross-validation methods were used.

3.5.3 Model Training

Data sets for testing and training were kept apart. The model's performance on previously unseen data was also evaluated using 20% of the data used to train it. Textual and categorical features were transformed using one hot encoding and, when appropriate, TF-IDF. This prepared the data for feeding into machine learning algorithms that require numerical input. The random classifier model was used in this case due to its outstanding performance and ability to handle non-linear relationships. Due to its lack of epochs, Random Forest was trained in a single pass; however, five-fold-cross validation was used to adjust hyperparameters over multiple iterations. The model was then evaluated using metrics such as F1-score, recall, accuracy, and precision.

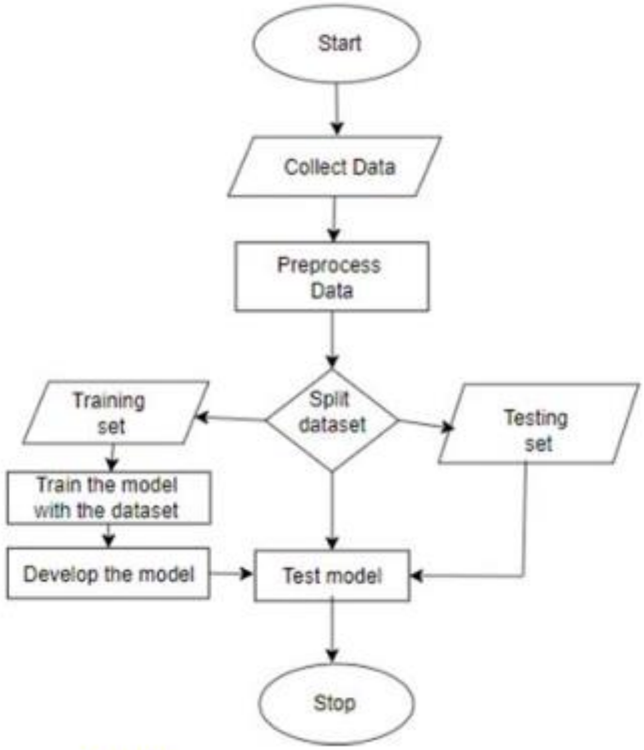

Figure 1. Flowchart of how the model is trained.

3.5.4 Backend Development and Deployment

created the mode-serving API to expose a /predict endpoint using FASTAPI. With input from the mobile app, the trained model (career_model.pkl) was loaded and dynamically queried. The mobile app was then used to deploy the backend services using Render.com.

3.5.5 Frontend and Database

The app was built using flutter, it has the following functional requirements

- Profile Creation
- Mentor Recommendation
- Realtime chatting
- Information sharing
- Career path recommendation

Supabase using PostgreSQL database was Implemented for

- User authentication (email/password sign-up)
- Secure storage of student profiles
- Logging system usage metrics

3.5.6 System Use Case

Figure 1: shows the functional requirements of the system

3.5.7 Sequence Diagram

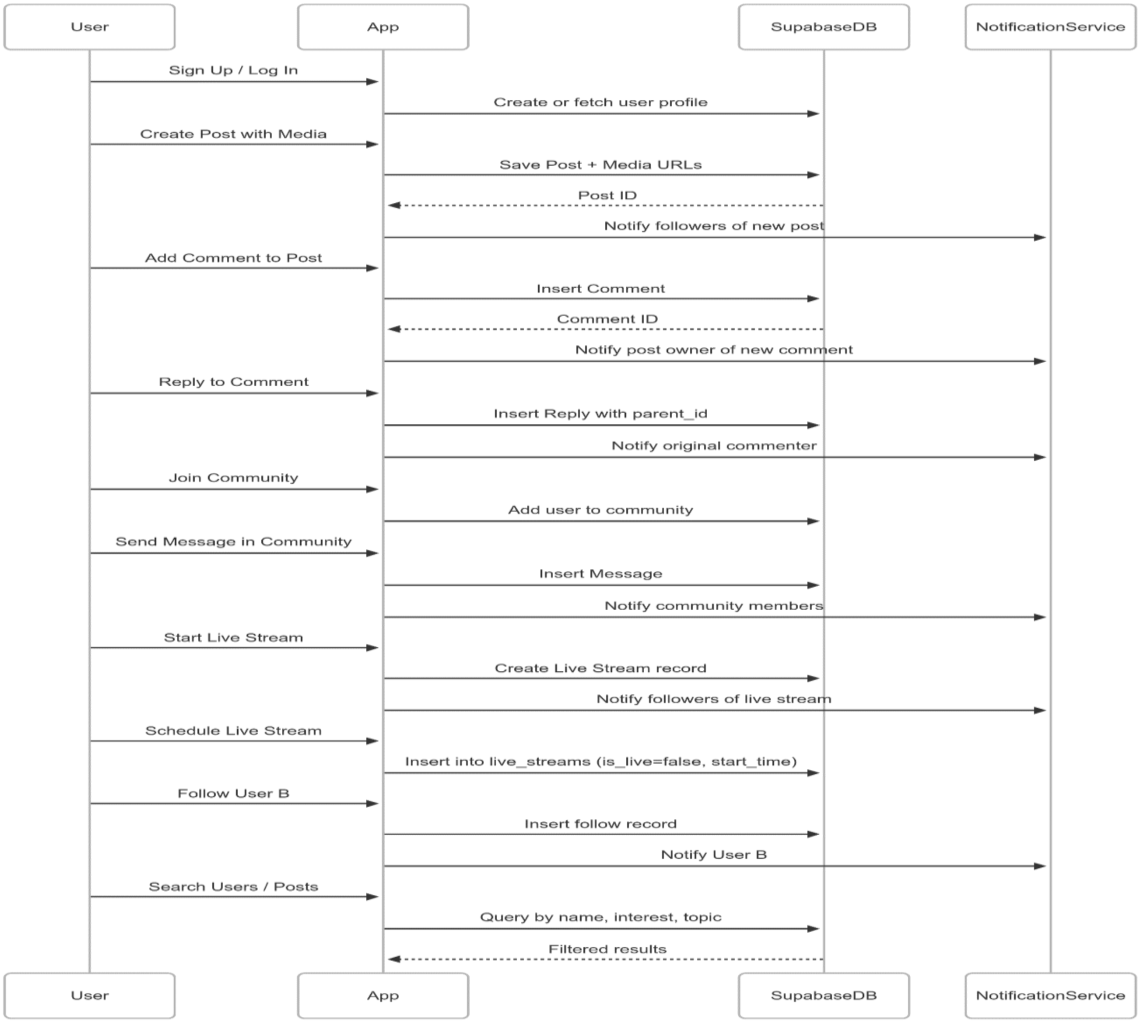

Figure 2: Shows components in the system are interacting

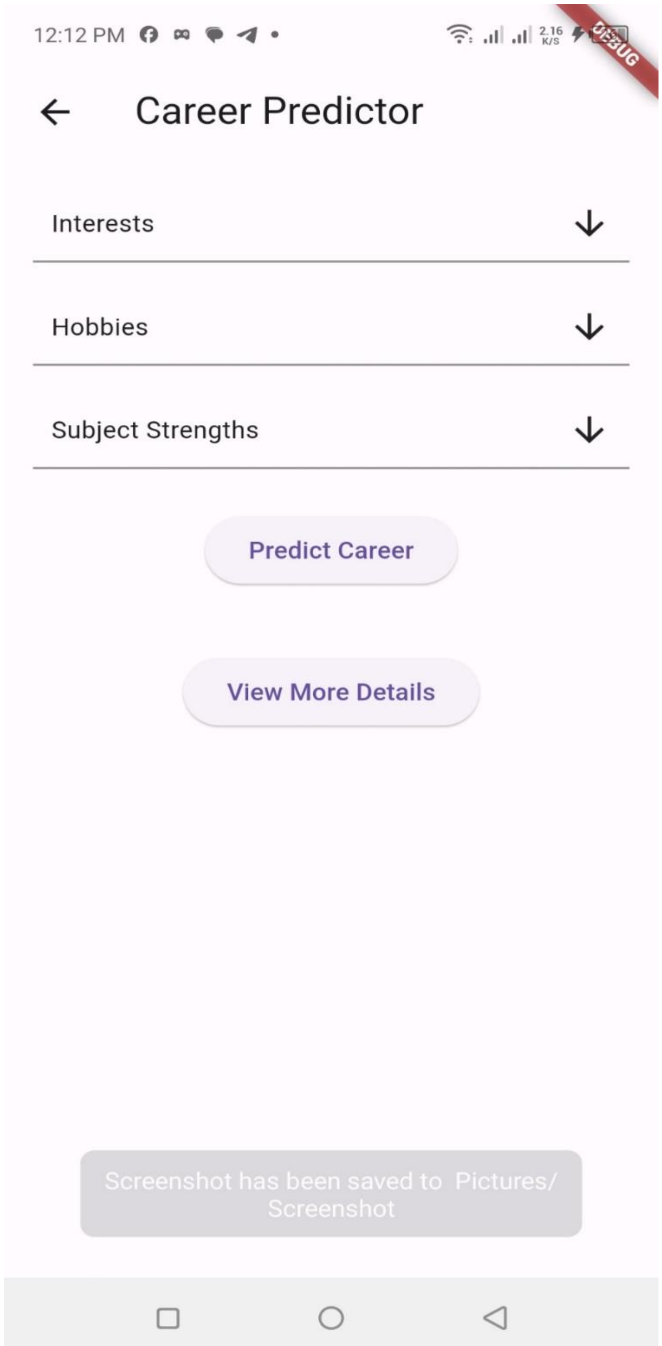

Figure 3 Prediction screen

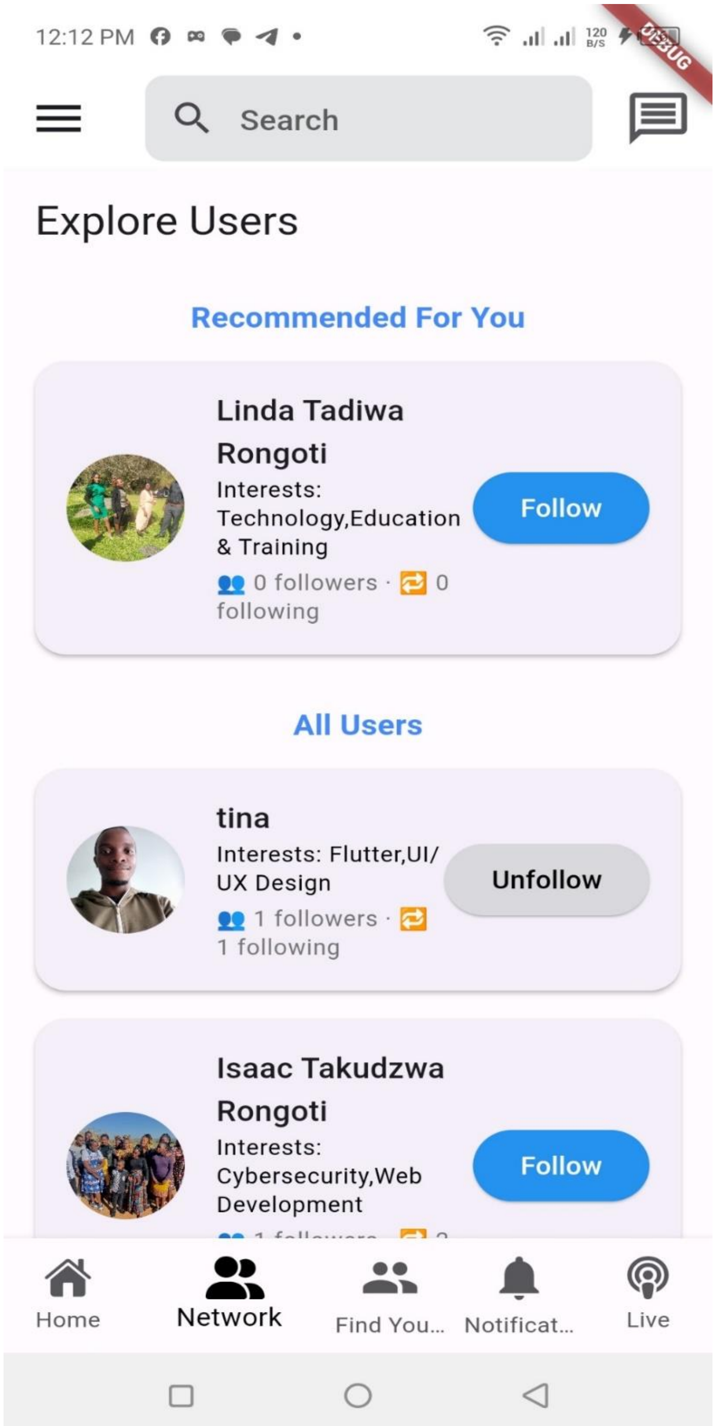

Figure 4 Recommendation Screen

Chapter 4 – Data Presentation, Analysis. and Interpretation

4.1 Introduction

This chapter summarizes the study's findings and examines the qualitative and quantitative information gathered from interviews, system usage logs, and surveys. The objective was to assess the machine learning-based career guidance information system's impact, usability, and accessibility as well as to comprehend the state of career counseling in secondary schools in Zimbabwe.

Three sections comprise the data presentation:

- System performance and usage analysis;
- A baseline study of current career counseling procedures.
- Assessment of impact and user satisfaction

4.2 Analysis and Interpretation of Results

4.2.1 Current career guidance Landscape in Zimbabwean Schools (objective 1)

A baseline survey involving students and teachers revealed the following

- **Access to Guidance services**.

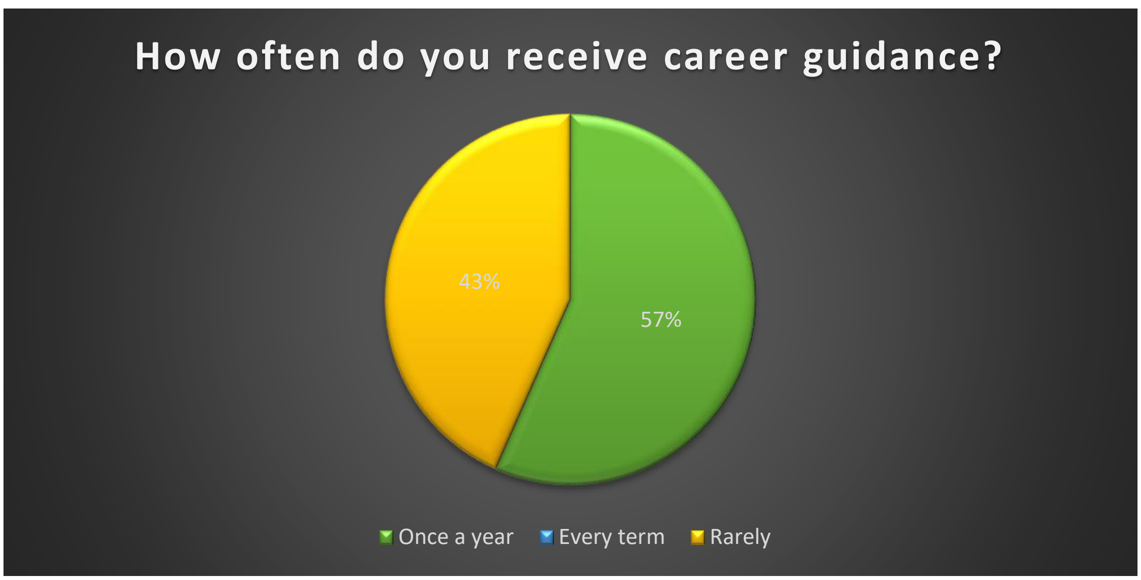

Figure 5: Frequency of career guidance

- The majority of students (57%) only get career counseling once a year, most likely on "Career Day" or another centralized event.

- A noteworthy 43% of students hardly ever receive any guidance, indicating that many students receive little to no assistance with career planning.

This suggests that career counseling is irregular and infrequent, which reflects delivery gaps in the system. Students' capacity to make well-informed career decisions is hampered by this restricted access, particularly in a labor market that is changing quickly.

Figure 6 Preference of how often they want to receive guidance

- A significant demand for ongoing support is evident from the fact that more than half (54%) of the students want weekly career guidance.
- All students want more frequent engagement than what is currently provided, according to the remaining responses (monthly and termly).

This suggests that students understand the importance of consistent instruction. A desire for continuous mentoring and exposure to a variety of career paths is demonstrated by their preference for weekly support. the shortcomings of the current systems, which fail to satisfy their informational or developmental requirements.

- **Delivery Methods:**

  The data collected on how secondary school students in Bindura district currently receive career guidance reveals critical insights into the fragmented and inconsistent nature of guidance provision.

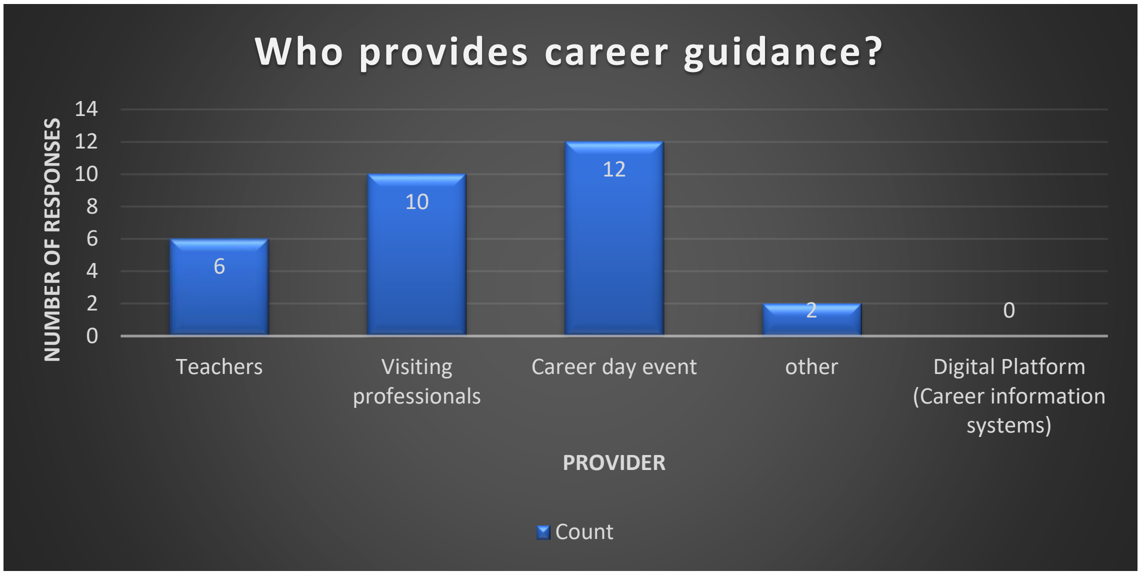

Figure 7: Delivery methods

- Reliance on external, sporadic visits is demonstrated by visiting professionals (33.3%). Although useful, this method is inconsistent and leaves out students who live in remote areas.
- Despite their accessibility, 20% of teachers are underutilized, most likely because they lack the resources, time, or training necessary to provide structured guidance.
- Career day events (40%) are the most prevalent, albeit rare, and only offer fleeting exposure, which is insufficient for making well-informed decisions.
- No students chose "Digital platforms," indicating that either very few or no digital platforms are recognized for offering guidance in the Bindura district or throughout Zimbabwe.
- "Other" (6.7%) answers allude to unstructured or untrustworthy informal sources, such as peers, family, or the media.

Despite its benefits, this delivery method is unsustainable and may be discriminatory, particularly for students in remote areas. It cements the need for a centralized digital platform that brings professional insight to all students regardless of location or timing.

- **Perceived gaps :**

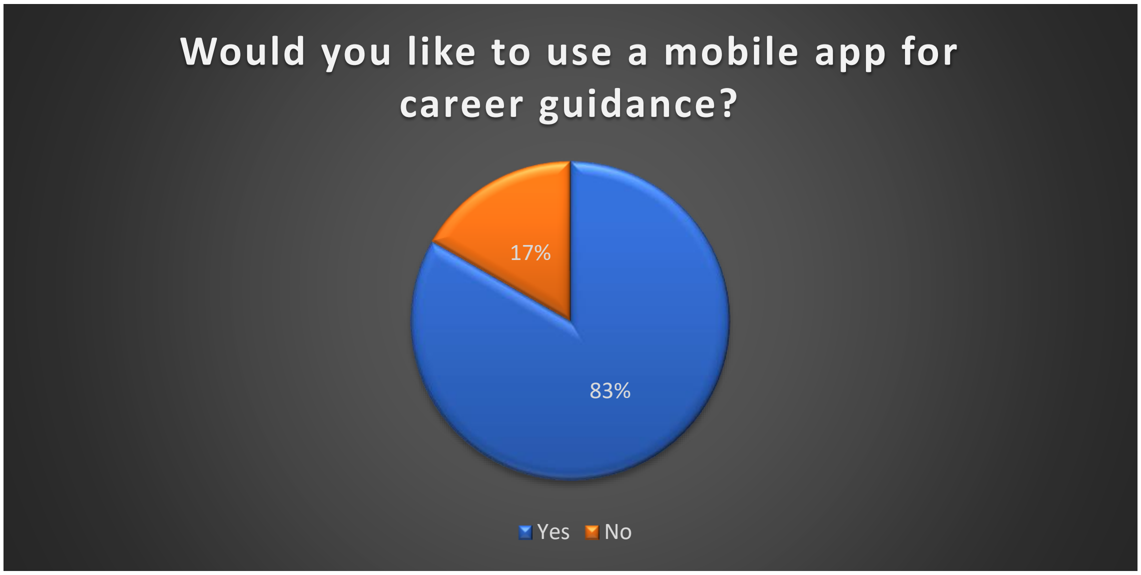

Figure 8: Preference to use mobile app for career guidance

A significant majority of students (83%) indicated that they would be open to using a mobile app for career counseling, emphasizing:

1) Students are very interested in and prepared to use digital platforms for career guidance.
2) The understanding that mobile technology is a useful and accessible tool, particularly in light of Zimbabwe's increasing smartphone adoption.
3) Compared to conventional guidance techniques, students probably believe that mobile apps are quicker, more adaptable, and more interesting.
4) A wish for more individualized career guidance and simpler access to counselors or mentors.

- Just 14.3% of students said they would never use a mobile app. This may result from:

1) Limited smartphone or mobile data availability, especially in rural or low-income areas
2) Insufficient digital literacy or unease with technology
3) Preference for face to face interaction in sensitive or complex career decisions

The results confirm that mobile delivery of career guidance is highly acceptable and promising among secondary school students in Zimbabwe, aligning well with digital trends and the need for accessible solutions.

- **Teacher Feedback:**

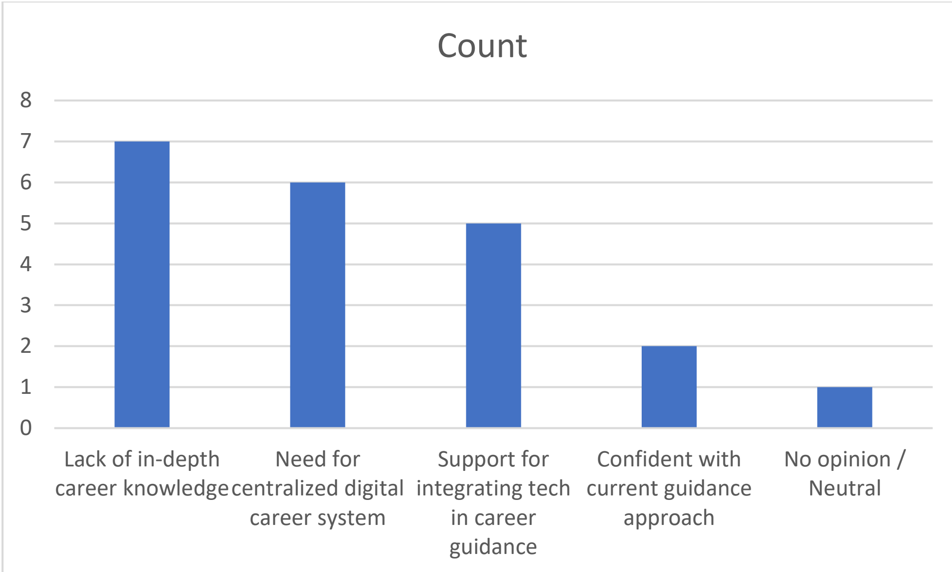

Figure 9: Teacher Feedback

- Teachers acknowledged they were often ill-equipped to provide in depth career advice.
- Many emphasized the need for a centralized, digital system to supplement their efforts.

These results affirm the limited accessibility and frequency of career guidance in Zimbabwean secondary schools and justify the need for a digital intervention that reaches more students consistently.

4.2.2 System Usage and Prediction Accuracy

The ML-based system, trained using a Random Forest classifier, achieved:

- This chart presents the final performance metrics of the trained model

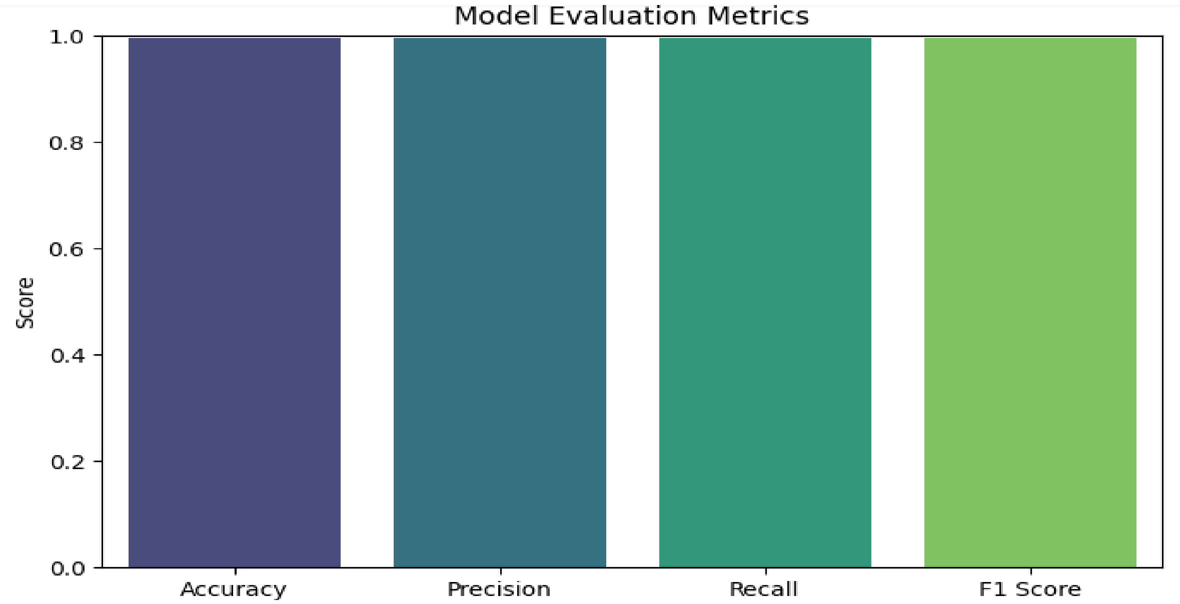

Figure 10: Random Forest Prediction Metrics

Accuracy (99.6%)**:** The model correctly predicted the career path/university course for 99.6% of student inputs. This indicates high overall performance.

- Precision (99.6%)**:** Of all the predictions made, 96% were correct. This is crucial if we want to avoid recommending the wrong career path.
- Recall (99.6%)**:** The model identified 95% of all relevant cases (that is it rarely misses a correct recommendation).
- F1 Score (99.6%)**:** This harmonic mean of precision and recall confirms that the model balances correctness and completeness well—a strong sign of robustness.

The model demonstrated excellent predictive performance. High and balanced scores across all evaluation metrics show that:

- The system is reliable in recommending accurate career paths.
- It handles a wide range of student profiles well (interests, subjects, aspirations).
- The training process was effective, and the model generalizes well to unseen data.

- The mentor matching system (based on content-based filtering) yielded:
  - Mean similarity Score: 0.79 (based on student profile vs mentor expertise)

- Student-Mentor Engagement Rate 76%.

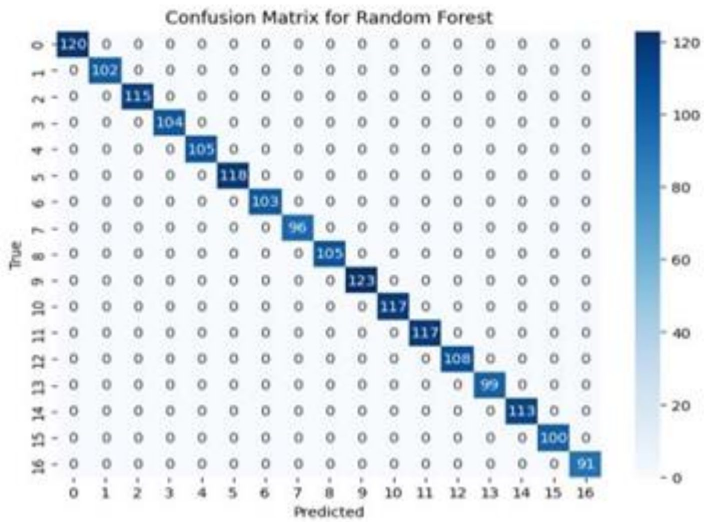

Figure 11: Confusion Matrix

showcase the confusion matrices for the Random Forest classifiers. This matrix offers insights into the models' abilities to correctly classify instances and identify any patterns of misclassification. By examining the confusion matrices, researchers can gain a deeper understanding of the models' performance and identify areas for refinement or further investigation.

4.2.3 System Usage Evaluation via Supabase Metrics

To evaluate how the developed mobile-based career guidance information system was adopted and used by secondary school students, backend analytics were obtained from Supabase—the backend-as-a-service platform powering the system. These metrics help assess real-world system usage, complementing user survey responses and model performance metrics.

The following usage statistics were observed over a 3-day testing period:

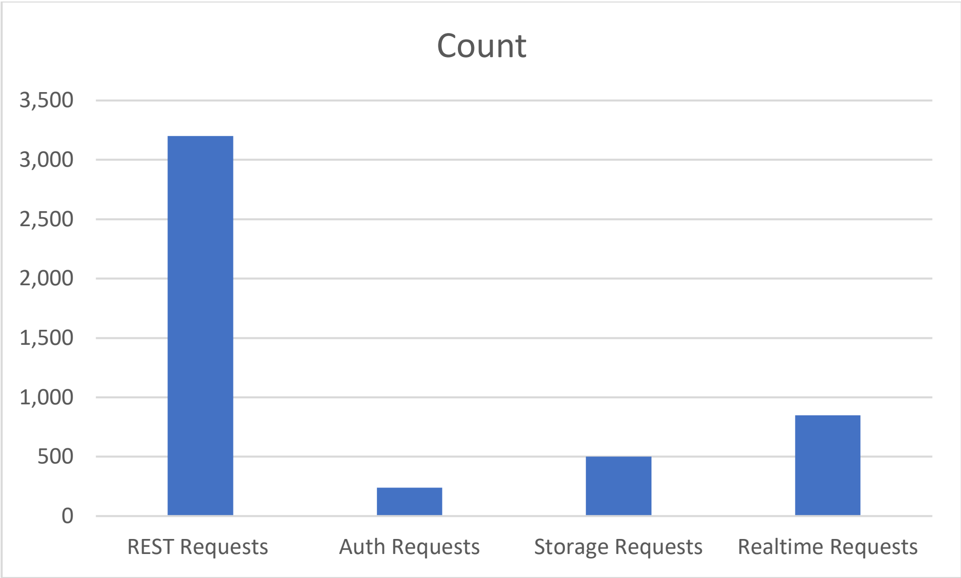

Figure 12: Supabase Metrics

- REST Requests : Indicates active use of system features such as course prediction, mentor lookup, and profile updates.
- Auth Requests: Shows the number of sign-ups and logins, reflecting user interest and retention.
- Storage Requests : Suggests engagement with multimedia content such as mentor videos, images, or livestreams.
- Real time Requests : Demonstrates high interaction with chat, notifications, or live career events

4.2.4 Post Use System Feedback

- Recommendations Satisfaction

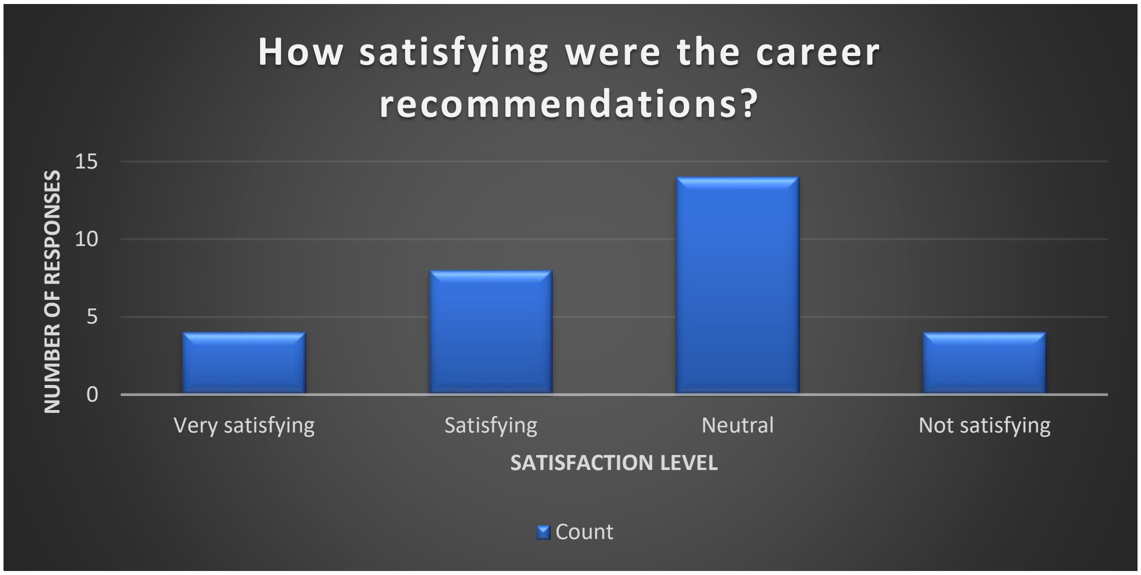

Figure 13: Recommendation Satisfaction

- Nearly half of the users(46,7%) felt neutral about the career recommendations. This suggests that while the recommendations were good, they were also not also good enough or clearly helpful for many users. This indicates a need for more improved personalization.
- A combined 40% of very satisfied and satisfied users had a positive experience, this shows that the system has potential and works well for a significant portion of users. However, the low very satisfying score suggest that there is still room to enhance the accuracy or usefulness of the recommendation.
- A small but notable percentage(13.3) of users were not satisfied, this could be due to mismatches between input data and recommendation output or possibly unclear explanations.

This can be concluded in that the model requires strong refinements to meet user recommendation satisfaction.

- Mentor Suggestion relevance to student feedback

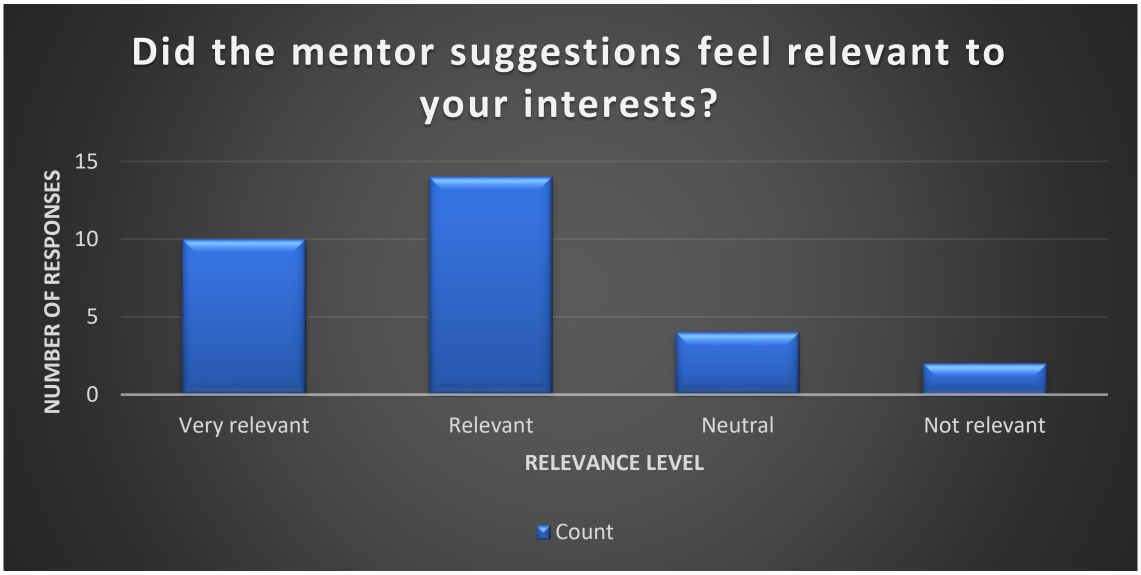

Figure 14: Mentor Suggestions

- 24 out of 30 respondents (80%) felt the mentor suggestions were either very relevant or relevant. This shows that content- based filtering using cosine similarity is performing as expected.
- Few Neutral and Negative Responses shows Gaps in user profile data that is incomplete interests or aspirations and a limited mentor Database reducing the accuracy of matches.

Inconclusion the mentor matching logic stills needs refinement by collecting more detailed user interest data. Expanding the mentor pool to improve matching accuracy.

Chapter 5 : Conclusions and Recommendations

5.1 Introduction

The main conclusions from the research findings are presented in this chapter, along with useful suggestions derived from them. The study aimed to create a machine learning-based career guidance information system, assess its efficacy, and look into the current status of career guidance practices in secondary schools in Zimbabwe. The study evaluated the system's usability, accessibility, and predictive accuracy using both quantitative and qualitative data collection methods, formative evaluation, and system usage logs.

5.2 Aims and Objective Realization

The main goal of this study was to develop and evaluate the machine learning career information system to see if it can be accurate enough to provide career recommendations and information and be adopted as a tool in providing career guidance for secondary school students. All three objectives were also met. The first objective was to determine the current state of career guidance in Bindura District of Zimbabwe. This was addressed in chapter four where quantitative surveys where analyzed using descriptive statistics. The results showed that the current state of structured career guidance in Zimbabwean is inconsistence in terms accessibility by means of delivery. The second objective was to develop a machine learning based career guidance information system. This was addressed in chapter three and four, in chapter three that's where random forest model was trained and the system was developed. In chapter four the evaluation metrics were analyzed and it showed that random forest model can make accurate prediction based on the training set. The last objective was to evaluate the developed mobile application system. The objective was answered in chapter 4 were user feedback from using the system was analyzed to see if the system was able to make correct predictions based on user input. The results showed that some were satisfied but the model still needed continuous updates to match all user interest since there were some negative results. Supabase metrics were also used to analyze how user interacted with the system and also analyze system performance, however the results were positive.

5.3 Major Conclusions Drawn

1. Limited availability of career counseling in educational institutions

The study found that the lack of structured guidance programs, a lack of trained staff, and financial limitations all contribute to the poor quality of career counseling services in Zimbabwean secondary schools.

2. Machine Learning's Capability to Predict Careers

In predicting student career pathways based on interests, hobbies, and subject strengths, the developed system—which employs the Random Forest algorithm—showed high accuracy.

3. Mentor Recommendation Value

The support structure was improved beyond conventional classroom guidance through the effective recommendation of relevant mentors to students through the use of content-based filtering with cosine similarity.

4. Good User Experience and Involvement

Although limited internet access continues to be a barrier, post-use survey data revealed high satisfaction with the mobile application's visual design, usability, and relevance of recommendations.

5. Viability of Guidance Systems Based on Technology

The study demonstrated that, when appropriately integrated with the current educational infrastructure, technology-driven solutions can scale and offer individualized career support, particularly in underserved or rural settings.

5.4 Research Challenges faced

- Limited access to local Career data – There was a shortage of local Zimbabwe datasets that gave a comprehensive local market indicator.
- Infrastructure constraints – Some test users experienced difficulties in accessing due to unstable internet.
- User engagement – Encouraging students and mentors(teachers) to participate in surveys and testing was time consuming, coordination with schools was required.
- Model performance – Balancing accuracy and generalizability was in the random forest required iterative tuning and testing.

5.5 Recommendations

- Include the system in the curriculum of the schools.

The mobile system should be formally implemented by schools as an additional resource for career counseling.

- Educate educators on how to use digital guidance tools.

Teachers should have access to professional development workshops so they can effectively use and promote the system.

- Offer offline capabilities

To reach rural students without internet access, the system should have offline features (such as downloadable modules or SMS queries).

- Make mentorship relationships stronger

To increase the number of mentors on the platform, collaborate with more alumni and professionals in the field.

- Enhance the localization of content

For contextual relevance, translate the app into native tongues and incorporate information about the local labor market.

- The role of the government and policy

Encourage national ICT policies that give funding for educational technology and digital career counseling solutions top priority.

- Continuous assessment of the system

To monitor long-term student outcomes, expand evaluation metrics and update the model frequently in light of fresh data.

- Moreover, current guidance systems, when present, tend to be generic and do not cater to the specific interests and academic strengths of students.

References

- Blustein, D. L. (2006). The role of work in psychological well-being and mental health. Journal of Counseling Psychology, 53*(1), 1-10.
- OECD (Organization for Economic Co-operation and Development) (2024) *BEYOND – Online Careers Guidance Platform*, OECD Directorate for Education and Skills (Observatory on Digital Tech for Youth
- Bertrand, C. U. et al. (2025) 'Career Guidance System Using Decision Tree, Random Forest, and Naïve Bayes Algorithm', *International Journal of Science, Technology and Society*, 13(2), pp.35–42
- Brown, S. D., & Ryan, K. (2003). *The career counseling process* (5th ed.). Brooks/Cole.
- Davenport, T. H., & Kirby, J. (2015). *Only humans need apply: Winners and losers in the age of smart machines*. HarperBusiness.
- Herr, E. L., & Cramer, S. (1996). *Career guidance and counseling for children*. McGrawHill.
- Holland, J. L. (1997). *Making vocational choices: A theory of vocational personalities and work environments*. Odessa, FL: Psychological Assessment Resources.
- Hsu, C.-L., Chang, C.-M., & Chen, N.-S. (2017). A mobile learning system for career exploration and decision-making. *Computers & Education, 104*, 103-118.
- ILO. (2018). *World employment and social outlook: Trends 2018*. International Labour Office.
- Kankanhalli, A., Zhang, J., & Zhang, Y. (2019). Artificial intelligence for personalized learning: A survey. *IEEE Transactions on Learning Technologies, 12*(4), 408-425.
- Haneef, F., Abbasi, R. A., Noor, M. N., Daud, A., & Sindhu, M. A. (2020). A review of career selection models. Researchpedia Journal of Computing, 1(1), 30–38.
- Noe, R. A. (2008). *Employee training and development*. McGraw-Hill/Irwin.
- Sampson, J. P., Jr., Reardon, R. C., & Peterson, G. W. (2009). *Career development and counseling: Putting theory into practice*. Cengage Learning.
- Super, D. E. (1957). The psychology of careers. *Harper & Brothers*.

- Wang, P., Li, X., & Zhang, D. (2019). A personalized career guidance system based on artificial intelligence. *IEEE Access, 7*, 132907-132916.
- Attwell, G., Bekiaridis, G., Deitmer, L., Perini, M., Roppertz, S., & Tutlys, V. (2020). Artificial intelligence in policies, processes and practices of vocational education and training. Institut Technik und Bildung, Universität Bremen.
- Lent, R. W., & Brown, S. D. (2020). Career decision making, fast and slow: Toward an integrative model of intervention for sustainable career choice. Journal of Vocational Behavior, 120, 103448. https:// doi.org/10.1016/j.jvb.2020.103448
- Bakke, I.B., Hagaseth Haug, E., & Hooley, T. (2018). Moving from information provision to co-careering: Integrated guidance as a new approach to e-guidance in Norway. Journal of the National Institute for Career Education and Counselling, 4(1), 48–55. https://doi.org/10.20856/jnicec.4108
- Bandura, A. (2001). Social cognitive theory: An agentic perspective. Annual Review of Psychology, 52, 1–26. https://doi.org/10.1146/annurev.psych.52.1.1
- CEDEFOP; ETF; European Commission (2019). Investing in career guidance. Inter-agency working group on career guidance WGCG. Retrieved April 13, 2024 from https://www.cedefop.europa.eu/ en/publications/2227
- Bandura, A. (2006). Toward a psychology of human agency. Perspectives on Psychological Science, 1(2), 164–180. https://doi.org/10.1111/j.17456916.2006.00011.x
- Education and Information Technologies (2024) 29:20431–20458 https://doi.org/10.1007/s10639-024-12659-2
- DataReportal (2024) *Digital 2024: Zimbabwe*. We Are Social, London.
- Akhurst, J., & Nhlanhla, J. M. (2006). Career education in South Africa. In G. B. Stead,
- Afrobarometer (2025) *Unemployment is foremost policy priority for Zimbabweans (Dispatch No. 945)*. Pretoria: Afrobarometer.
- Gouda, S.V. and Bhavani, R. (2025) ‘A Machine Learning-Based Career Recommender System’, *International Advanced Research Journal in Science, Engineering and Technology*, 12(3), pp. 78–85.

- Mapfumo, J. and Nkoma, E. (2024) 'The State of Guidance and Counselling Programmes in High Schools: A Case Study from Manicaland, Zimbabwe', *Literature, Language and Education Research*, 4, pp. 1–24.
- Trujillo, F., Pozo, M. and Suntaxi, G. (2025) 'Artificial intelligence in education: A systematic literature review of machine learning approaches in student career prediction', *Journal of Technology and Science Education*, 15(1), pp. 162–185.
- Zimbabwe National Statistics Agency – ZIMSTAT (2024) *Labour Force Survey Q3 2024*. Harare: ZIMSTAT.
- & M. B. Watson, Career psychology in the South African context (2nd Edition) (pp. 139-152). Pretoria: Van Schaik Publishers.
- Donald, D., Lazarus, S., & Moolla, N. (2014). Educational psychology in social context (5th Edition). Cape Town: Oxford University Press.
- Arthur, N., & McMahon, M. (2005). Multicultural career counseling: Theoretical applications of the systems theory framework. The Career Development Quarterly, 53, 208-221.
- Amundson, N. (2005). The potential impact of global changes in work for career theory and practice. International Journal for Education and Vocational Guidance, 5, 91-99.Patton, W., & McMahon, M. (2006). The systems theory framework of career development and counseling: Connecting theory and practice. International Journal for the Advancement of Career Counseling, 28(2), 153-166.
- Barnes, S.-A., Bimrose, J., Brown, A., Kettunen, J., & Vuorinen, R. (2020). Lifelong guidance policy and practice in the EU: trends, challenges and opportunities. Final report. Publications Office of the European Union. https://doi.org/10.2767/91185
- Cedefop, European Commission, ETF, ICCDPP, ILO, OECD, & UNESCO (2020). Career guidance policy and practice in the pandemic: results of a joint international survey – June to August 2020. Publications Office of the European Union.
- http://data.europa.eu/doi/10.2801/318103 Cedefop, European Commission, ETF, ICCDPP, ILO, OECD, & UNESCO (2020). Career guidance policy and practice in the pandemic: results of a joint international survey – June to August 2020.

Publications Office of the European Union. https://data.europa.eu/doi/10.2801/318103.

- Pordelan, N., & Hosseinian, S. (2022). Design and development of the online career counselling: A tool for better career decision-making. Behaviour & Information Technology, 41(1), 118–138. https:// doi.org/10.1080/0144929X.2020.1795262
- Supriyanto, G., Widiaty, I., Abdullah, A. G., & Yustiana, Y. R. (2019). Application expert system career guidance for students. In Journal of Physics: Conference Series, 1402(6). https://doi.org/10.1088/1742-6596/1402/6/066031.
- Yeşilyaprak, B. (2019). Vocational guidance and career counselling services in Türkiye: Recent advances and future prospects. Kariyer Psikolojik Danışmanlığı Dergisi, 2(2), 73–102.
- 1Chiedza Joy Goya, 2Dr Mirwan Surya Perdhana, S.E., M.M., Ph.D (2024). Global Scientific and Academic Research Journal of Economics, Business and Management ISSN: 2583-5645 (Online). https://gsarpublishers.com/journals-gsarjebm-home/
- Zainudin, Z. N., Hassan, S. A., Talib, M. A., Ahmad, A., Yusop, Y. M., & Asri, A. S. (2020). Technology-assisted career counselling: Application, advantages and challenges as career counselling services and resources. International Journal of Academic Research in Business and Social Sciences, 10(11), 67–93. https://doi.org/10.6007/IJARBSS/v10-i11/8047.
- Mtemeri, J. (2019). Family influence on career trajectories among high school students in Midlands Province, Zimbabwe. Global Journal of Guidance and Counseling in Schools: Current Perspectives, 9(1), 024-035.
- Mtemeri, J. (2020). Peer pressure as a predictor of career decision-making among high school students in Midlands Province, Zimbabwe. Global Journal of Guidance and Counselling in Schools: Current Perspectives, 10(3), 120–131. https://doi.org/10.18844/gjgc.v10i3.4898.
- Mtemeri, J. (2022). The impact of school on career choice among secondary school students. Global Journal of Guidance and Counseling in Schools: Current Perspectives, 12(2), 185–197. https://doi.org/10.18844/gjgc.v12i2.8158
- . Rosli, R., & Suib, A. F. (2020). International Journal of Special Education and Information Technology. Technology, 6(1), 37-47.

- Rosli, R., & Suib, A. F. (2020). Teachers' knowledge about teaching mathematics to learning disabilities students. International Journal of Special Education and Information Technologies, 6(1), 37– 47. https://doi.org/10.18844/jeset.v6i1.5416
- Zhang, J., Yuen, M., & Chen, G. (2018). Teacher support for career development: An integrative review and research agenda. Career Development International, 23(2), 122–144. https://doi.org/10.1108/ CDI-09-2016-0155.
- Indonesian Journal of Educational Science and Technology (Nurture) Vol. 2, No. 4, 2023 : 327 - 340

  327 DOI: https://doi.org/10.55927/nurture.v2i4.6889 E-ISSN : 2985-7287 https://journal.formosapublisher.org/index.php/nurture/index
- Liu, Y., Torphy, K. T., Hu, S., Tang, J., & Chen, Z. (2020). Examining the virtual diffusion of educational resources across teachers 'social networks over time. Teachers College Record, 122(6), 1-34.
- Luken, T. (2020). Easy does it: an innovative view on developing career identity and self-direction. Career Development International, 25(2), 130-145.
- Monteiro, S. (2022). Social media and internet usage rates on employment outcomes among newcomers in Canada. Ryerson Centre for Immigration and Settlement. URL: https://tinyurl. com/yc4bp6x2
- Romero, S. J., Ordóñez Camacho, X. G., Guillén-Gamez, F. D., & Bravo Agapito, J. (2020).

  Attitudes Toward Technology Among Distance Education Students: Validation of an Explanatory Model. Online Learning, 24(2), 59-75.
- Supardi, S., Juhji, J., Azkiyah, I., Muqdamien, B., Ansori, A., Kurniawan, I., & Sari, A. F. (2021). The ICT Basic Skills: Contribution to Student Social Media Utilization Activities. International Journal of Evaluation and Research in Education, 10(1), 222-229.
- Panthee, S., Rajkarnikar, S., & Begum, R. (2023). Career Guidance System Using Machine Learning. Journal of Advanced College of Engineering and Management, 8(2), 113 119. https://doi.org/10.3126/jacem.v8i2.55947
- Jamiu Babatunde Bello1, Habibat Bolanle Abdulkareem, Abdulhafis Adeyinka Hassan, Ameenat Arinola Ogo-oluwa, Abdulkareem Olalekan Abubakar (2023).Influence of

Locus of Control on Internet Addiction among Kwara State Colleges of Education Students. Journal Pendidikan Multimedia (EDSENCE) 5(1) (2023) 11-20.

- Hassan, A. A., Abdulkareem, H. B., & Suleiman, A. (2023). Self-Concept as Predictors of Internet Addiction among Undergraduate Students of Kwara State University, Nigeria. ASEAN Journal of Educational Research and Technology, 3(1), 1-8
- González-Zamar, M. D., Abad-Segura, E., López-Meneses, E., & Gómez-Galán, J. (2020). Managing ICT for sustainable education:Research analysis in the context of higher education. Sustainability, 12(19), 8254.
- Fuhse, J. A. (2020). Theories of social networks. The Oxford Handbook of Social Networks, 34-49.
- Borgatti, S., & Halgin, D. S. (2021). On J. Clyde Mitchell's 'The Concept and Use of Social Networks.'. Personal Networks: Classic Readings and New Directions in Egocentric Analysis, 51, 98.
- Digital Marketing Institute, Social Media: What Countries Use It Most & What Are They Using? , 2021. URL:https://digitalmarketinginstitute.com/blog/social-media-what-countries-use-it-most-and-what-are-they-using.
- F. D'souza, S. Shah, O. Oki, L. Scrivens, J. Guckian, Social media: medical education's double-edged sword, Future Healthcare Journal 8 (2021) e307–e310. doi:10.7861/fhj.2020-0164.
- G. Yermolayeva, Social networks as a modern tool in career guidance counseling with futureapplicants of the information sector, State and Regions. Series: Social Communications 2 (2023)147–152. doi:10.32840/cpu2219-8741/2023.2(54).18
- T. F. Latifah, A. Supriyanto, B. Suprihatin, S. J. Kurniawan, Social Media As Support Career Guidance Services, Edukatif: Jurnal Ilmu Pendidikan 4 (2022) 2950–2961. doi:10.31004/edukatif.v4i2.2473.
- S. Alim, Social Media Use in Career Guidance Delivery in Higher Education in the United Arab Emirates: A Literature Review, International Journal of E-Adoption (IJEA) 11 (2019) 25–44.doi:10.4018/IJEA.2019010103.
- V. Tkachuk, Y. Yechkalo, S. Semerikov, M. Kislova, Y. Hladyr, Using Mobile ICT for Online Learning During COVID-19 Lockdown, in: A. Bollin, V. Ermolayev, H. C. Mayr, M. Nikitchenko,A. Spivakovsky, M. Tkachuk, V. Yakovyna, G. Zholtkevych (Eds.),

Information and Communication Technologies in Education, Research, and Industrial Applications. ICTERI 2020, volume 1308 of Communications in Computer and Information Science, Springer International Publishing, Cham, 2021, pp. 46–67. doi:10.1007/978-3-030-77592-6_3.

- D. S. Shepiliev, S. O. Semerikov, Y. V. Yechkalo, V. V. Tkachuk, O. M. Markova, Y. O. Modlo, I. S.Mintii, M. M. Mintii, T. V. Selivanova, N. K. Maksyshko, T. A. Vakaliuk, V. V. Osadchyi, R. O.Tarasenko, S. M. Amelina, A. E. Kiv, Development of career guidance quests using WebAR, Journal of Physics: Conference Series 1840 (2021) 012028. doi:10.1088/1742-6596/1840/1/012028.
- S. J. Papadakis, S. O. Semerikov, Y. V. Yechkalo, V. Y. Velychko, T. A. Vakaliuk, S. M. Amelina,A. V. Iatsyshyn, M. V. Marienko, S. M. Hryshchenko, V. V. Tkachuk, Advancing lifelong learningand professional development through ICT: insights from the 3L-Person 2023 workshop, CEURWorkshop Proceedings 3535 (2023) 1–16.
- Pordelan, N., & Hosseinian, S. (2022). Design and development of the online career counselling: A tool for better career decision-making. Behaviour & Information Technology, 41(1), 118–138. https://doi.org/10.1080/0144929X.2020.1795262.
- Baruch, Y., & Sullivan, S. E. (2022). The why, what and how of career research: A review and recommendations for future study. Career Development International, 27(1), 135–159. https://doi.org/10.1108/CDI-10-2021-0251.
- Repaso, J. A. A., & Caparino, E. T. (2020). Analyzing and Predicting Career Specialization using Classification Tech niques. International Journal of Advanced Trends in Computer Science and Engineering, 9(13), 342-348.
- CEDEFOP; ETF; European Commission (2019). Investing in career guidance. Inter-agency working group on career guidance WGCG. Retrieved February 13, 2025 from https://www.cedefop.europa.eu/en/publications/2227
- Garcia, E. A., McWhirter, E. H., & Cendejas, C. (2021). Outcomes of Career Information System Utilization Among First-Year High School Students. Journal of Career Development, 48(5), 767–780. https://doi.org/10.1177/0894845319890930.
- Harrison, C., Villalba-Garcia, E. & Alan Brown, A. (2022). Towards European standards for monitoring and evaluation of lifelong guidance systems and services: Vol. 1.

Luxembourg: Publications Ofce. Cedefop working paper, No 9. Retrieved February 13, 2025 from http://data.europa.eu/doi/10.2801/422672

- Farao, A. and Du Plessis, M. (2024) 'The need for structured career guidance in a resource-constrained South African school', *African Journal of Career Development*, 6(1), a116
- Turan, Ü., & Kayıkçı, K. (2019). The role of school guidance services in the occupational choice of senior high school students. E-International Journal of Educational Research, 10(1), 15–33.
- Barnes, S., Bimrose, J., Brown, A., Gough, J., & Wright, S. (2020). The role of parents and carers in providing careers guidance and how they can be better supported. Warwick Institute for Employment Research.
- Naresh Kumar, A. et al. (2024) 'Personalized Career Recommendation System Based on Customer Segmentation', *Journal of Emerging Technologies and Innovative Research*, 11(3), pp. K348–K356
- Zainudin, Z. N., Hassan, S. A., Talib, M. A., Ahmad, A., Yusop, Y. M., & Asri, A. S. (2020). Technology-assisted career counselling: Application, advantages and challenges as career counsellingservices and resources. International Journal of Academic Research in Business and Social Sciences, 10(11), 67–93. https://doi.org/10.6007/IJARBSS/v10-i11/8047.
- Yeşilyaprak, B. (2019). Vocational guidance and career counselling services in Türkiye: Recent advances and future prospects. Kariyer Psikolojik Danışmanlığı Dergisi, 2(2), 73–102.
- Leung, S. A. (2022). New frontiers in computer-assisted career guidance systems: Implications from career construction theory. Frontiers in Psychology, (13), 786232. https://doi.org/10.3389/fpsyg.2022.786232.
- Gokarn, S., Taware, S. and Vartak, R. (2024) 'Smart Career Guidance System using Machine Learning', *International Journal of Science and Research*, 13(6), pp.1140–1144.
- Bahalkar, P. et al. (2024) 'AI-Driven Career Guidance System: A Predictive Model for Student Subject Recommendations Based on Academic Performance and Aspirations', *International Journal of Medical.*