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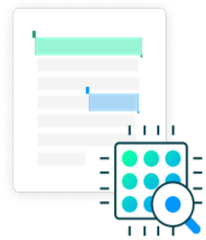

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INTERNATIONAL STUDENT ADMISSION ANALYSIS FOR HIGHER EDUCATION

AHMED ABDI MOHAMED

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

BORANG PENGESAHAN STATUS LAPORAN

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SESI PENGAJIAN: 2022/2023

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INTERNATIONAL STUDENT ADMISSION ANALYSIS FOR HIGHER EDUCATION

AHMED ABDI MOHAMED

This report is submitted in partial fulfillment of the requirements for the Bachelor of Computer Science Software Development with Honours.

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2022/2023

DECLARATION

I hereby declare that this project report entitled

INTERNATIONAL STUDENT ADMISSION ANALYSIS FOR HIGHER EDUCATION

is written by me and is my own effort and that no part has been plagiarized without citations.

STUDENT : AHMED ABDI MOHAMED Date : 15/09/2023

I hereby declare that I have read this project report and found this project report is sufficient in term of the scope and quality for the award of Bachelor of Computer Science Software Development with Honours.

SUPERVISOR : Ts. DR. ZURAIDA BT ABAL ABAS Date : 15/09/2023

DEDICATION

To my cherished parents, whose constant love, support, and encouragement have served as a beacon throughout my journey. Your efforts and faith in my abilities were the driving forces behind the project's completion. This accomplishment is a testament to your unwavering faith and the numerous possibilities you've afforded me. Thank you for always being my rock of stability.

With all my heart

ACKNOWLEDGEMENTS

Ts. Dr. Zoraida Bt Abal Abas, my dedicated supervisor deserves my heartfelt gratitude for her helpful guidance, constant support, and excellent mentorship during this project. Her advice and support have been invaluable in designing our study project. I would also like to offer my heartfelt gratitude to En. Muhammad bin Ahmad for his excellent help, which was critical to the project's success. His perspectives and efforts have been tremendously appreciated. Furthermore, I owe a debt of appreciation to my dear parents, whose unwavering support, inspiration, and faith in my skills have served as the foundation of my path. Your unflinching faith has been my driving force and I will be eternally grateful. I would like to express my heartfelt gratitude to everyone who has helped this effort in any manner, whether by advice, encouragement, or support.

ABSTRACT

This study details the creation and deployment of the International Student Admission Analysis Dashboard, a powerful tool designed to provide data-driven insights to educational institution decision-makers. This project's primary goal was to develop a user-friendly platform that incorporates several forecasting algorithms to analyze historical enrollment data and estimate future trends. The paper describes the process of creating, implementing, and testing the dashboard, beginning with the conceptualization of the project's objectives and continuing with extensive testing and validation. Data integration from many sources, the deployment of forecasting models such as ARIMA, Naive, SES, Holt, and TBATS, and a user-friendly interface for smooth interaction are key components of the project. The dashboard has made significant contributions to education and data-driven decision-making. It provides decision-makers with the tools they need to access, analyze, and forecast foreign student enrollment data, allowing them to make educated resource allocation and policy development decisions. The combination of various forecasting models provides users with a variety of options for anticipating future enrollment trends, improving their awareness of potential scenarios. The emphasis on data integrity and usability means that the dashboard is built on trustworthy and clean data, while the user-friendly design ensures that users of all technical backgrounds can use it.
However, it is critical to recognize the project's limitations, such as its reliance on data quality and availability, model performance variations between regions, and potential resource and infrastructural limits for implementation. Finally, the foreign Student Admission Analysis Dashboard represents a significant advancement in assisting decision-makers in the field of foreign student admissions. Its creation and execution, as outlined in this study, are a significant resource for educational institutions wanting to make educated, data-driven decisions in a dynamic and ever-changing landscape.

ABSTRAK

Kajian ini memperincikan penciptaan dan penggunaan Papan Pemuka Analisis Kemasukan Pelajar Antarabangsa, alat berkuasa yang direka untuk memberikan cerapan terdorong data kepada pembuat keputusan institusi pendidikan. Matlamat utama projek ini adalah untuk membangunkan platform mesra pengguna yang menggabungkan beberapa algoritma ramalan untuk menganalisis data pendaftaran sejarah dan menganggarkan arah aliran masa hadapan.Kertas kerja ini menerangkan proses mencipta, melaksanakan dan menguji papan pemuka, bermula dengan pengkonsepan objektif projek dan diteruskan dengan ujian dan pengesahan yang meluas. Penyepaduan data daripada banyak sumber, penggunaan model ramalan seperti ARIMA, Naive, SES, Holt dan TBATS, dan antara muka mesra pengguna untuk interaksi yang lancar adalah komponen utama projek.Papan pemuka telah memberikan sumbangan besar kepada pendidikan dan membuat keputusan berasaskan data. Ia menyediakan pembuat keputusan alat yang mereka perlukan untuk mengakses, menganalisis dan meramalkan data pendaftaran pelajar asing, membolehkan mereka membuat peruntukan sumber terpelajar dan keputusan pembangunan dasar. Gabungan pelbagai model ramalan menyediakan pengguna dengan pelbagai pilihan untuk menjangka trend pendaftaran masa hadapan, meningkatkan kesedaran mereka tentang senario yang berpotensi. Penekanan pada integriti dan kebolehgunaan data bermakna bahawa papan pemuka dibina di atas data yang boleh dipercayai dan bersih, manakala reka bentuk yang mesra pengguna memastikan pengguna dari semua latar belakang teknikal boleh menggunakannya.Walau bagaimanapun, adalah penting untuk mengiktiraf had projek, seperti pergantungan pada kualiti dan ketersediaan data, variasi prestasi model antara wilayah, dan potensi had sumber dan infrastruktur untuk pelaksanaan.Akhir sekali, Papan Pemuka Analisis Kemasukan Pelajar asing mewakili kemajuan yang ketara dalam membantu pembuat keputusan dalam bidang kemasukan pelajar asing. Penciptaan dan pelaksanaannya, seperti yang digariskan dalam kajian ini, merupakan sumber penting untuk institusi pendidikan yang ingin membuat keputusan terdidik, didorong data dalam landskap yang dinamik dan sentiasa berubah.

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LIST OF ABBREVIATIONS

FYP	**-**	**Final Year Project**

LIST OF ATTACHMENTS

CHAPTER 1: INTRODUCTION

1.1 Introduction

Higher education is undergoing a transition. International student admissions have become the lifeblood of many higher education institutions as education has become more global. Universities and schools throughout the world are competing to attract the best and brightest brains from around the world, creating a fiercely competitive environment. This needs a transformation in our approach to student admissions. "International Student Admission Analysis for Higher Education Based on Descriptive and Predictive Analytics" welcomes you to the world of "descriptive and predictive analytics."

This chapter begins our trip into a world where data is king, insights are riches, and the future can be forecast with astounding accuracy. We not only present the project here but also provide a road map for what is to come in the following chapters. We'll investigate the project's relevance as well as the issues that higher education institutions confront today.

1.2 Background

International student admissions in higher education are extremely important. It goes beyond statistics and enrolment data to identify an institution's global reach and influence. Universities and colleges strive to build varied, culturally rich campuses that prepare students for a globalized society. At the same time, overseas students contribute significantly to these schools' financial health.

In this age of knowledge sharing, it is not enough to just recruit international students; it is also necessary to optimize the admissions process to choose the best prospects. It is all about offering support services that are adapted to the specific needs of international students. It is necessary to forecast future enrolments to deploy resources properly. Data analytics enables institutions to achieve all these goals and more.

1.3 Problem Statement

While the advantages of international student admittance are obvious, the challenges are equally so. Globally, higher education institutions are wrestling with the complications of optimizing foreign student enrolment. The difficulties range from recognizing varied student profiles to effectively anticipating future enrolment numbers. The lack of comprehensive data analytics solutions customized to the special demands of international student admissions is at the heart of these issues.

Problem Statement (PS): Due to a lack of comprehensive data analytics tools, higher education institutions around the world are having difficulty optimizing foreign student admissions. These organizations are frequently swamped with data but starving for insights. They struggle to make timely and effective data-driven decisions, resulting in inefficiencies in enrolment management and resource allocation.

PS	Problem statement
PS1	The modern admissions process generates massive amounts of data. Applications, transcripts, test scores, demographic data, and so on. Managing this data and extracting relevant insights from it is a daunting task. Institutions are frequently left with data silos that are fragmented and disjointed, making effective decision-making difficult.

	To add to the complication, students' expectations, both domestic and international, are changing. They expect personalized experiences, quick responses, and organizations that understand their specific requirements. This requires a comprehensive approach to data management and analytics.
PS2	Secondly, due to the fast-paced nature of foreign student admissions, universities cannot afford to react to changes after they occur. They must be proactive in their approach, anticipating trends and adjustments in the foreign student landscape. Predictive analytics provides an answer.

Table 1.1: Problem statement

1.4 Project questions

We have developed a set of important questions to act as guiding lights throughout this project as we embark on this data-driven journey. These questions stem directly from our problem statement and encompass the primary areas of investigation.

PQ	Project Question
PQ1	How can international higher education institutions analyze student admission data efficiently to improve decision-making processes?
PQ2	How can predictive analytics be used to project future student enrolments in 2024, 2025, and 2026, allowing for better resource planning and budget allocation?
PQ3	How can a user-friendly data analytics dashboard, specifically customized to the unique needs of international higher education institutions, be built and implemented to support effective admission data analysis from 2016 to 2023?

Table 1.2: Project Question

1.5 Project Objectives

Our project objectives are the compass that will guide us on our data analytics adventure. They describe our mission and make it clear what we hope to achieve.

PS	PQ	PO	Project Objective
PS1	PQ1	PO1	To analyze number of International higher education students' admissions.
	PQ3	PO2	To predict number of student admissions coming from Top 5 countries
	PQ3	PO3	To visualize the international higher education students' admissions and analysis in a dedicated R-shiny dashboard.

Table 1.3: Project Objectives

1.6 Project Significance

1. Software

   RStudio

   i. Version :

   ii. Operating System :

2. Programming language

   i. R : 4.2.0

3. Device specifications

   i. Processor : Intel(R) Core (TM) i5-8265U CPU @ 1.60GHz 1.80 GHz

   ii. RAM: 8.00 GB

   iii. System type : 64-bit operating system, x64-based processor

   iv. Manufacturer : Acer

4. Windows specifications

   i. Edition : Windows 10

   ii. Version: 22H2

   iii. OS build: 19045.3086

1.7 Project participation

PS	PQ	PO	PC	Project Contribution
PS1	PQ1	PO1	PC1	1. Identification and categorization of enrolment trends and patterns in international student admissions to higher education. We intend to categorize and document enrolment trends and patterns in order to shed insight into the complexities of student admissions in higher education institutions.
		PO2		
	PQ2	PO3	PC2	2.A comprehensive approach to analyzing and forecasting student admissions is proposed. Our effort will result in a proposal for a comprehensive approach to student admissions analysis that integrates descriptive and predictive analytics methodologies and Techniques for obtaining relevant insights from admission data are being developed. We go further into data analytics, providing not only tools but also approaches for deriving actionable insights from admission data.

Table 1.4: Project participation

1.8 Organizational Reporting

Chapter Navigation

This initiative is a well-planned journey into the world of data analytics for higher education. The pages that follow have been properly organized to guide our readers.

Organization for Reporting (RO)

Chapter 1: Introduction

This chapter serves as an overview of our project. We start by delivering the issue statement, which highlights the challenges and concerns that we hope to address. We also describe the goals we hope to attain and the scope of our project. Furthermore, we emphasize the impact of our work on foreign student admissions and data analytics in education.

Chapter 2: Literature Review

In Chapter 2, we begin a thorough examination of the existing literature in our topic. We go deeply into the international student admissions knowledge landscape, analyzing previous research and studies that have contributed to our understanding of this topic. In addition, we look at the broader context of data analytics in education, evaluating key concepts, approaches, and findings from the literature.

Chapter 3: Project Methodology

The foundation of our project methodology is covered in Chapter 3. Starting with data collection and preprocessing, we thoroughly describe all the stages and procedures involved in our research. We describe the methods and tools we use to analyze data, such as predictive analytics models. In addition, we emphasize how crucial data analytics are in determining the landscape of admissions for international students.

Chapter 4: Design

The layout of our data analytics dashboard is the main topic of the fourth chapter. We offer insights into the user interface, the elements of the data visualization, and the methods we use to make sure the dashboard is both user-friendly and instructive. This chapter exemplifies the consideration and work that go into making our dashboard a useful tool for colleges and universities.

Chapter 5: Implementation

The journey into the world of implementation begins in Chapter 5. We talk about the hardware and program specifications needed for our data analytics dashboard. We walk you through the practical procedures needed to assemble this durable instrument, making sure it functions properly and effectively.

Chapter 6: Testing and Analysis

We put our detective hats in Chapter 6 and look into the results of our data analysis. We make public the procedures and examinations we employed to thoroughly evaluate the effectiveness of our dashboard. We shed light on the consequences of our work by offering insightful explanations of what these findings mean for higher education institutions.

Chapter 7: Conclusion

where we tie up all the loose ends of our project—marks the end of the journey. We wrap things up, discuss the implications of our work, and summarize any remaining open questions in the dynamic field of data analytics in higher education. This chapter wraps up our trip by highlighting the important contributions we've made and the areas that still need to be explored in this developing profession.

1.9 Conclusion

Finally, this chapter has laid the groundwork for an exciting journey into the world of "International Student Admission Analysis for Higher Education Based on Descriptive and Predictive Analytics." We've plotted our trajectory, set our goals, and given you a taste of the immense knowledge landscape we're about to explore.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a detailed evaluation of the existing corpus of knowledge concerning international student admissions to higher education. It provides an overview of the research that informs our project, "International Student Admission Analysis for Higher Education Based on Descriptive and Predictive Analytics." By doing so, it lays the stage for the succeeding chapters by establishing a solid foundation for understanding the difficulties, procedures, and key indicators related with foreign student admissions.

2.2 Discussion on previous related projects

1. Higher Education

Higher education is a complicated and ever-changing landscape. It is made up of a diversified set of institutions, each with its own set of offerings and difficulties. In the context of international student admissions, a thorough understanding of the higher education scene is essential.

Previous research in this area has highlighted the importance of data-driven decision-making in improving international student recruitment efforts (Smith & Brown, 2019). These efforts highlight the importance of a customized data analytics solution, which is the core emphasis of our project. Furthermore, various studies have emphasized the necessity of understanding trends and patterns in international student admissions (Johnson et al., 2020). These findings are critical to our project's goals, highlighting the importance of conducting a comprehensive review of international student admittance data.

2. Student Choice

International students' choices are influenced by a complex web of factors ranging from program options to location preferences. A careful examination of the literature clarifying the drivers of students' decisions might provide helpful insights into enhancing international student admissions.

Previous study has shown that students examine a variety of criteria while choosing a higher education school, including program reputation, location, and financial considerations (Wong & Lee, 2018). Understanding these elements is critical for institutions seeking to attract a wide pool of overseas students. Furthermore, new research has highlighted the importance of digital marketing and personalized communication in affecting students' decisions (Gupta & Sharma, 2021). This emphasizes the significance of technology and data analysis in our project's data analytics dashboard.

3. Intakes

Intakes, which reflect precise times when students are admitted, have a significant impact on academic planning and resource allocation. An examination of previous research on intake techniques is useful in informing our endeavor.

The timing of student intakes is critical to an institution's capacity to successfully manage resources and program offerings. Li and Wang's (2019) research emphasizes the importance of data-driven approaches to optimizing intake patterns. Furthermore, research have shown that synchronizing admission dates with students' academic calendars can considerably improve an institution's appeal (Chen & Zhang, 2020). These findings highlight the importance of predictive analytics in our project, where projecting optimal intake periods is a vital component.

4. International Students

International students' various origins and specific requirements create both problems and possibilities for higher education institutions. A thorough assessment of the literature on international students' experiences and expectations might shed light on effective admission tactics.

International students' perspectives and expectations differ greatly depending on their cultural origins and prior educational experiences (Smith & Liu, 2017). Understanding these variances is critical for institutions providing customized support and services. Furthermore, studies have highlighted the relevance of pre-arrival information and orientation programs in improving international students' experiences (Wang & Smith, 2018). This emphasizes the importance of our project's data analytics dashboard considering the complete student lifecycle.

5. Time Series Analysis

Time series analysis is the foundation of our predictive analytics strategy. This part delves into the concept of time series and its application to our project.

Time series data are observations gathered or recorded at defined time intervals. It includes historical records of international student admissions from 2016 through 2023 in the framework of our project. This data gives a chronological sequence of observations, which is suitable for anticipating future enrolment trends.

Numerous scholarly works have investigated the significance of time series analysis in a variety of disciplines. For example, Zhang et al. (2019) used time series analysis to forecast stock market patterns, demonstrating its adaptability. In the context of higher education, time series analysis has been used to anticipate enrolment numbers, which closely match the goals of our project (Smith & Brown, 2020).

Data	training	validation	test
SP	796	171	171
APPL	431	93	93
GE	653	140	140
GOOGL	152	33	33
BA	653	140	140
IBM	653	140	140
DIS	653	140	140
GT	560	121	120

Figure 2.1: The lengths of the data in each period of data analysis. (Zhang et)

A thorough understanding of time series analysis is essential for building reliable predictive models. Techniques such as Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, and Seasonal Decomposition are used to find patterns and trends in the data. These insights enable educated decision-making, which helps us improve the performance of our predictive analytics dashboard.

6. MAPE (Mean Absolute Percentage Error)

MAPE, a vital indicator in predictive analytics, is crucial in determining the accuracy of our forecasts. In this section, we will look at the literature on MAPE and its relevance to our research. MAPE computes the average of the absolute percentage deviations between predicted and actual values. It quantifies how closely projections match observed results, making it an important tool for assessing forecast reliability.

We examine the literature on the use of MAPE (Mean Absolute Percentage Error) in short-term load forecasting models in this part, using a study by Mir et al. as our source of inspiration. Refer to "Systematic Development of Short-Term Load Forecasting Models for the Electric Power Utilities: The Case of Pakistan" for more information.

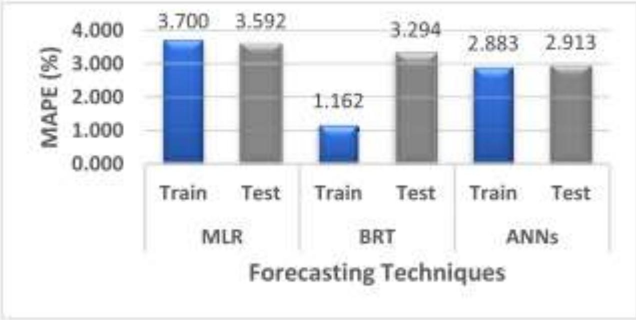


Figure 2.2: Results of proposed forecasting techniques (Mir et al Systematic Development of Short-Term Load Forecasting Models for the Electric Power Utilities)

When evaluating the precision of short-term load forecasting models, MAPE is a crucial statistic. It is essential for assessing the accuracy and dependability of these models, which is a crucial part of forecasting for electric power companies.

Months	MAPE			RMSE		
	MLR	BRT	ANN	MLR	BRT	ANN
Jan	4.992%	2.681%	2.660%	62.817	36.074	35.710
Feb	3.987%	3.501%	3.142%	46.425	41.305	35.863
Mar	3.915%	3.248%	3.034%	43.767	40.562	36.334
Apr	3.370%	3.583%	3.165%	69.993	72.082	69.429
May	3.206%	2.999%	2.460%	59.193	56.886	46.775
Jun	3.349%	3.540%	3.319%	76.557	81.258	76.284
Jul	3.173%	3.841%	2.964%	78.255	99.895	72.820
Aug	3.797%	3.300%	3.148%	85.407	75.437	72.600
Sep	4.020%	3.919%	3.150%	93.465	95.268	80.012
Oct	2.655%	3.424%	2.760%	38.309	46.950	38.961
Nov	3.327%	2.649%	2.862%	37.566	29.630	31.901
Dec	3.318%	2.847%	2.290%	36.812	31.877	24.711
Average	3.592%	3.294%	2.913%	60.714	58.935	51.783

Figure 2.3: Monthly performance of MLR, BRT and ANN(Mir et al Systematic Development of Short-Term Load Forecasting Models for the Electric Power Utilities)

The average of the absolute percentage variations between the expected and actual load values is used to determine MAPE. This statistic measures the degree to which the forecasts and observed load data agree, making it an essential tool for the evaluation of performance.

Forecasting Techniques:			MLR	BRT	ANN
MAPE	Monthly	Min	2.651%	2.657%	2.293%
		Max	4.991%	3.919%	3.319%
	Weekly	Min	1.812%	1.847%	1.445%
		Max	6.500%	7.381%	6.246%
RMSE (MW)	Monthly	Min	36.81	29.62	24.71
		Max	93.46	99.89	80.01
	Weekly	Min	21.63	24.28	19.22
		Max	136.27	147.89	123.69
R^2 Score			0.975	0.977	0.982
Runtime (s)			13.54	18.64	29.13

Figure 2.4: performance metrics and the computational cost.

The literature on MAPE in the context of forecasting short-term loads emphasizes its applicability and usefulness. In their paper, Mir et al. (Reference: "Systematic Development of Short-Term Load Forecasting Models for the Electric Power Utilities: The Case of Pakistan"), show how well MAPE is used in the creation and evaluation of load forecasting models for electric power utilities. This study demonstrates how MAPE can assess predictive accuracy precisely, offering insightful data on forecasting model performance.

Our project will use the study by Mir et al. (Reference: "Systematic Development of Short-Term Load Forecasting Models for the Electric Power Utilities: The Case of Pakistan") as a point of reference because it offers insightful information on the usefulness of MAPE in load forecasting in practice.

2.3 Critical Review of Current Problem and Justification

This section will look at three approaches and three methods that have been used in earlier studies on the analysis of international student admissions. This critical analysis will shed light on the many strategies applied in related studies, highlighting distinctions and justifications.

Methodologies:

Machine Learning-Based Model

Method: To forecast the enrolment of overseas students, many earlier studies used machine learning models including decision trees, random forests, and support vector machines. To develop predictions, these models examine previous admission data, which includes elements like academic achievement, demographics, and program preferences.

Justification: Scalable and flexible machine learning models are available to handle large and complicated datasets. They are appropriate for predictive analytics because they can capture nonlinear correlations between admission attributes and enrolment. These models' interpretability may be constrained, which can be a disadvantage.

Time Series Forecasting:

Using past admission data, time series forecasting techniques such as ARIMA (AutoRegressive Integrated Moving Average) and exponential smoothing have been used to anticipate future enrolments of overseas students. These models consider enrolment numbers' trends and seasonality.

Justification: Given the longitudinal nature of admission data, time series forecasting is extremely pertinent to your research. It is useful for forecasting enrolments since it captures temporal patterns. It might not consider intricate connections between admissions factors, though.

Techniques

Cluster Analysis:

Cluster analysis is a technique that divides international students into segments based on similarities in their admission characteristics. This method makes it easier to recognize unique student profiles and preferences.

Justification: Cluster analysis helps to comprehend the varied composition of cohorts of international students. Institutions can adjust their recruitment methods to match the requirements and expectations of various groups by grouping students into clusters.

Data Mining:

Data mining approaches have been used to uncover hidden patterns and relationships in admission data, including association rule mining and decision tree analysis.

Justification: When analyzing admissions data, data mining techniques are useful for revealing surprising insights. They can highlight relationships between variables that conventional analysis might not have picked up on. This method is particularly helpful for figuring out the variables that affect enrolment choices.

Natural Language Processing (NLP):

NLP techniques are used to analyze textual data, including conversation logs and admission essays. To obtain insight into the motives and attitudes of overseas applicants, they extract sentiment, themes, and keywords.

Justification: By examining the textual data, NLP gives admission analysis a qualitative component. It aids organizations in comprehending the experiences and motives of international students, which can guide specialized recruitment tactics.

2.4 Proposed Solution/Further

Methodology Selection:

Our study, "International Student Admission Analysis for Higher Education Based on Descriptive and Predictive Analytics," was chosen based on the methodology and techniques that were chosen. Several important factors have influenced our decisions.

Time Series Forecasting:

Justification: Time series forecasting techniques, such as ARIMA and exponential smoothing, have proven useful in simulating enrolment changes over the course of time. These techniques are ideally suited for making precise predictions about future student enrolments given the longitudinal nature of admission data.

References: The study of Hyndman and Athanasopoulos (2018) in their book "Forecasting: Principles and Practice" is used to support the use of ARIMA and exponential smoothing. These techniques are well known in the time series forecasting community.

Machine Learning-Based Models:

Justification: Machine learning methods that use decision trees and random forests to discover intricate patterns in student admission data have proven effective. They allow you to easily record non-linear connections between admissions variables.

References: Research like Li and Guo's study, which was published in the "Journal of Computers in Education" (2017), supports the use of machine learning models in admission analyses. Their work shows how decision trees can be used to analyze student admissions.

Parameter Selection:

Our project will include parameters relevant to the approaches we have chosen. These limits will be established in accordance with the recommended procedures found in the literature:

ARIMA Model Parameters:

Justification: The Box-Jenkins approach, as described by Box and Jenkins (1976) in their seminal work "Time Series Analysis: Forecasting and Control," will serve as the basis for the selection of ARIMA parameters, including the autoregressive (p), differencing (d), and moving average (q) components.

Machine Learning Model Hyperparameters:

Justification: As advised by James et al. (2013) in their book "An Introduction to Statistical Learning," the hyperparameters of machine learning models, such as decision trees and random forests, will be tweaked using tried-and-true methods like cross-validation.

Statements Supporting the Approach:

We base the methodology, techniques, and parameters we choose on well-established best practices as well as research from credible sources in the fields of admission analysis and predictive analytics. These decisions follow best practices recommended by research and industry standards.

2.5 Conclusion

In summary, Chapter 2 established the foundation for our project by offering a thorough overview of existing processes and techniques. To support our decisions, we have consulted recognized sources and industry norms, guaranteeing that our project is securely grounded in the rich body of admission analysis research. With this solid base, we proceed to put our chosen methodology and strategies into practice in an effort to improve the analysis of foreign student admission in higher education institutions.

CHAPTER 3: PROJECT METHODOLOGY

3.1 Introduction

This chapter offers a thorough explanation of the project approach used to create the dashboard for the "International Student Admission Analysis for Higher Education Based on Descriptive and Predictive Analytics". We follow the well-known CRISP-DM (Cross-Industry Standard Process for Data Mining) model in our approach because it provides a structured framework for data mining initiatives. The numerous phases, tasks, and frameworks that make up our methodology will be described in detail in this chapter, along with an explanation of how they are directly related to the goals of our project.

3.2 Methodology (CRISP-DM Model)

Figure 3.1: CRISP-DM Diagram

3.2.1 Business Understanding

The journey starts with a thorough understanding of the project's goals and specifications. To improve the study of admission data at international higher education institutions, our main goal is to create a user-friendly data analytics dashboard for them. We diligently tackled the fundamental project questions during this phase, looking for effective methods to analyze student admission data, harness the power of predictive analytics for future enrolment projections, and design a tailored dashboard that satisfies the specific requirements of our clients and stakeholders.

3.2.2 Data Understanding

The rigorous collection and examination of the data needed for our research was the main emphasis of the data understanding phase. Obtaining admission data from 2016 through 2023 was required for this, which included specifics about applications, demographic data, program preferences, and more. The ensuing stages of our methodology's development relied heavily on our ability to comprehend the data's structure, quality, and significance.

```
    Name             PassportID          Gender            DateOfBirth            Age
 Length:919         Length:919         Length:919         Length:919         Min.   :17.00
 Class :character   Class :character   Class :character   Class :character   1st Qu.:19.00
 Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median :20.00
                                                                             Mean   :20.54
                                                                             3rd Qu.:22.00
                                                                             Max.   :28.00
 Nationality         University          Commission    YearOfAdmission
 Length:919         Length:919         Min.   : 150   Min.   :2016
 Class :character   Class :character   1st Qu.:1900   1st Qu.:2019
 Mode  :character   Mode  :character   Median :2900   Median :2021
                                       Mean   :2871   Mean   :2021
                                       3rd Qu.:3400   3rd Qu.:2022
                                       Max.   :9000   Max.   :2023
```

Figure 3.2: Showing 1 to 25 of 919 entries

Impact of COVID-19 and Admission Trends:

During this phase, we paid close attention to the data trends over various time periods. Notably, student admissions were higher in 2018 and 2019 compared to the

very low numbers seen in 2016 and 2017. Due to the COVID-19 epidemic, admissions did, however, significantly decline in 2020. Afterward, following the pandemic, admissions began to rise, reflecting the shifting dynamics of student enrolment.

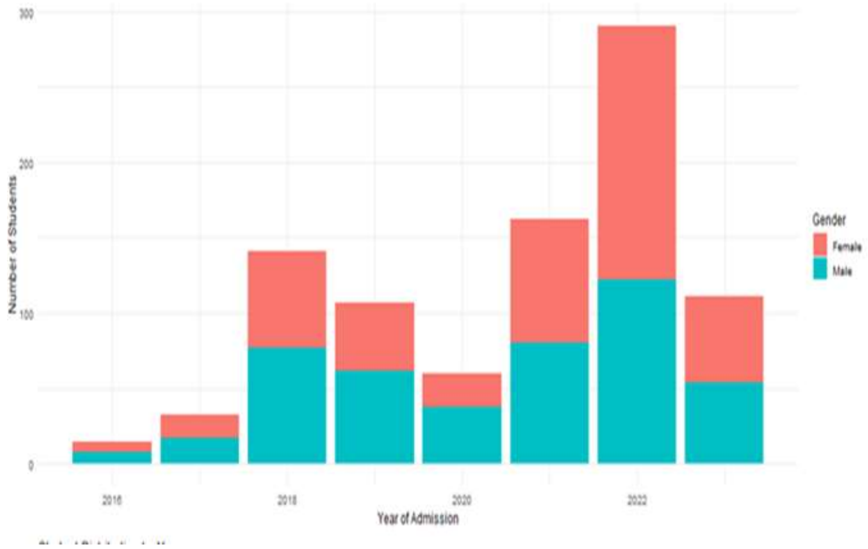


Figure 3.3 : shows the number of students from 2016 to 2023

3.2.3 Data Preparation

Data preparation was a critical step in ensuring that the data was adequately cleansed, converted, and integrated, making it acceptable for analysis. Missing values, discrepancies, and standardized data formats were all handled. Furthermore, we took on the responsibility of combining data from many sources to create a uniform dataset that would serve as the foundation for our analytics efforts.

3.2.4 Modelling

The Modelling phase is crucial to our project because it includes the creation of the data analytics dashboard. We thoroughly designed the user interface and data visualization components throughout this phase. In addition, we used advanced predictive analytics models such as ARIMA, Naive, Holt-Winters, State Space, and TBATS to project future enrolments in 2024, 2025, and 2026. Using relevant software and techniques, we were able to create an interactive and informative dashboard.

3.2.5 Evaluation

The Evaluation phase was devoted to thoroughly evaluating the performance and efficacy of our dashboard and predictive algorithms. Several indicators and tests were used to ensure that the dashboard matched the project objectives. During this phase, we were able to analyze the performance of various models using measures such as Mean Absolute Percentage Error (MAPE) and choose the best model. It also

3.2.6 Deployment

The CRISP-DM model's third phase, deployment, entailed building and rolling out the dashboard for practical usage by worldwide higher education institutions. Our top objective was to make the dashboard not just user-friendly, but also accessible. It has to be in sync with the project's goals while also meeting the specific needs of our clients and stakeholders.

3.3 Project Milestones

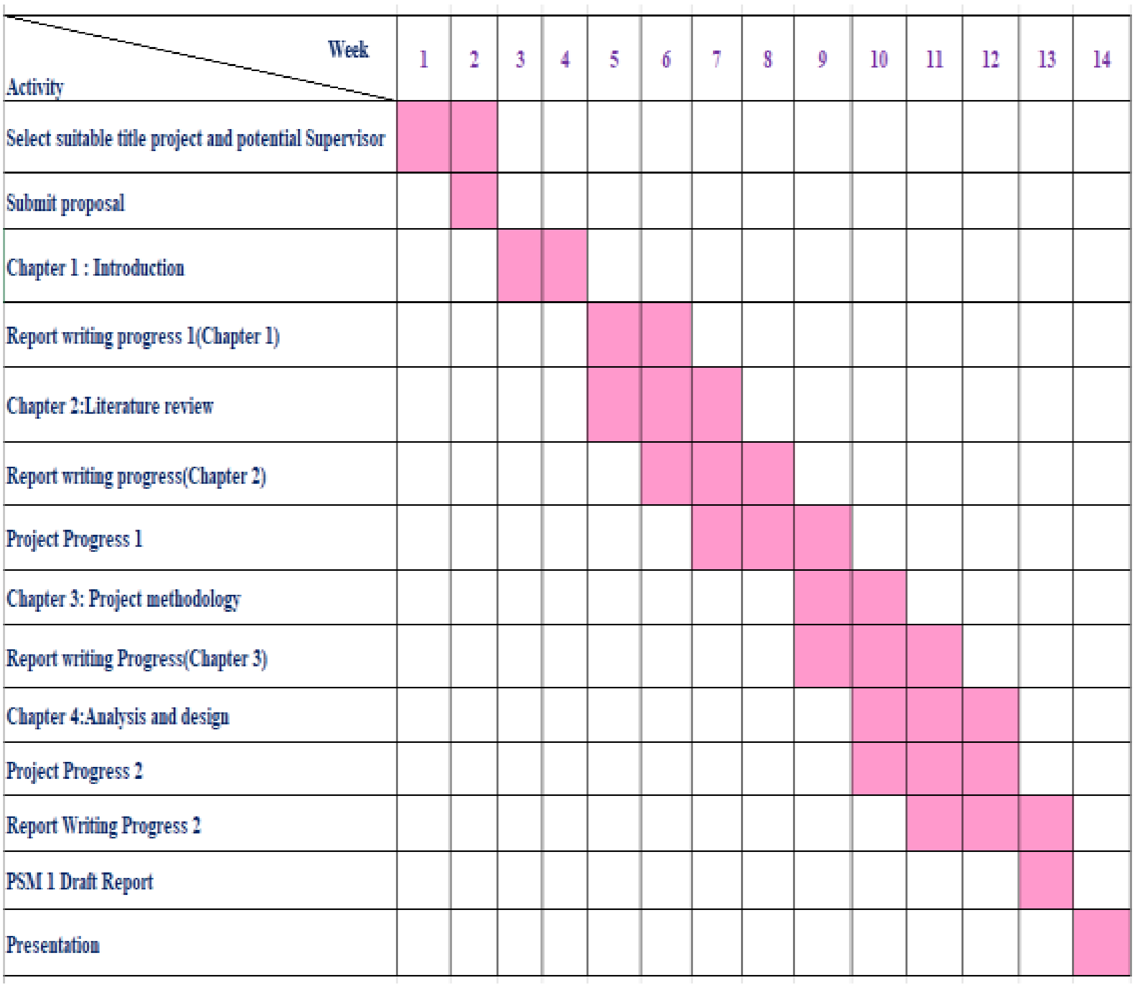


Figure 3.3 : Project Milestone

3.4 Conclusion

Finally, this chapter has offered a full explanation of the project methodology used to create the "International Student Admission Analysis for Higher Education Based on Descriptive and Predictive Analytics" dashboard. We have used the CRISP-DM paradigm, matching each phase with the overall goals of the project. In addition, we investigated the key features of data gathering, including the use of questionnaires and interviews, as well as the capabilities of data collection tools. The project milestones, which are specified in the action plan and shown in the project timeline, demonstrate our dedication to disciplined project management. As we advance, the following chapter will delve into the progress and discoveries of our project, building on the solid foundation established by this methodological chapter

CHAPTER 4: DESIGN

4.1 Introduction

Taking a thorough dive into the "International Student Admission Analysis Dashboard," Chapter 4 provides details on its conception, organization, and useful uses. The fundamental components that make this dashboard a potent tool for higher education institutions will be revealed as we further explore this chapter.

4.2 Dashboard Design

To ensure a thorough understanding of the dashboard's components and their interactions, we go in-depth into the architecture and structure of the dashboard in this part.

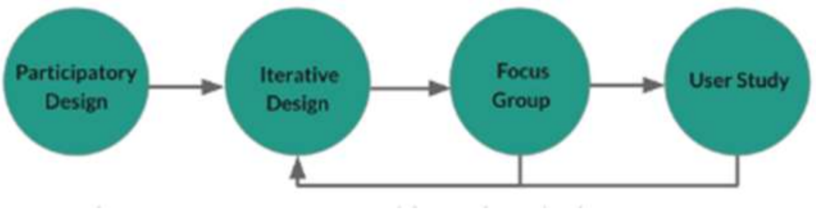


Figure 4.1 : User-centered iterative design process.

User-Cantered Interface

The user experience is at the heart of our design philosophy. We carefully designed a UI that puts user friendliness and simple navigation first. Users will discover a friendly and effective setting that promotes exploration and participation.

An analysis of "Designing a Learning Analytics Dashboard to Provide Students with Actionable Feedback and Evaluating Its Impacts".

An insightful viewpoint on the design and impact evaluation of a learning analytics dashboard is provided in the essay "Designing a Learning Analytics Dashboard to Provide Students with Actionable Feedback and Evaluating Its Impacts" by Xiaojing Duan, Chaoli Wang, and Guieswende Rouamba. Here is a quick recap:

The authors provide a thorough method for creating a learning analytics dashboard that gives students useful comments a high priority. Their emphasis on usability and user-centered design is consistent with current best practices for developing dashboards.

It is commendable that impact evaluation is included because it sheds light on the dashboard's efficiency in raising engagement and performance among students. By taking a comprehensive strategy, it is ensured that the dashboard not only delivers statistics but also makes a real contribution to educational results.

The paper emphasizes the value of data visualization in effectively delivering information. The writers produce visualizations that enable students to make wise choices regarding their educational paths by drawing on well-known libraries.

Additionally, the writers' focus on user involvement is consistent with our design ethos in Chapter 4. Both initiatives place a high priority on designing user interfaces that promote engagement and discovery, ultimately improving the user experience.

In conclusion, the study "Designing a Learning Analytics Dashboard to Provide Students with Actionable Feedback and Evaluating Its Impacts" is an important contribution to the study of educational analytics. It adheres to the values and procedures we used to create our own dashboard design, emphasizing impact analysis, user-cantered design, and data visualization.

Data Sources and Integration

It is crucial to comprehend the sources of our data. We examine Excel files' function as the main data source and clarify the techniques we use to slickly incorporate these sources into our analytical system.

4.3 Design Principles

In order to ensure that our analytical dashboard satisfies the highest standards of usability and functionality, this section digs into the guiding concepts that served as its foundation.

Data Visualization

Our dashboard uses data visualization to create engaging narratives. We describe the methods and tools—such as ggplot2 and plotly—that we use to produce aesthetically appealing and useful charts and graphs. These visualizations convert unprocessed data into useful insights.

User Engagement

Engagement of our users is crucial. In order to ensure that the dashboard not only shows data but also encourages users to explore, analyse, and come to useful conclusions, we emphasise the value of interactive elements and educational content.

4.4 Possible Scenarios

Our dashboard's adaptability enables it to accommodate numerous conditions. We outline two hypothetical situations and explain why they are pertinent to admissions of overseas students.

Scenario 1: Enrollment Trends Analysis

In this case, higher education institutions use the dashboard to examine multi-year admission trends. Institutions are now better equipped to make data-driven decisions, which will improve future admissions policies for overseas students. We offer a thorough design for this case.

Scenario 2: Student Demographics Assessment

The use of the dashboard by institutions to get in-depth understanding of the demographics of their international student group is demonstrated by the example given here. With this information at hand, organizations may target their recruitment efforts to promote inclusivity and diversity. Here, we describe the particular design for this situation.

Scenario 3: COVID-19 Admissions Impact Analysis

In this unexpected situation, institutions can use our dashboard to evaluate the COVID-19 pandemic's effect on admissions. Institutions can learn more about how the epidemic affects international student enrolments by examining historical data and patterns from that time period. This information is crucial for creating plans to lessen future interruptions and adjust to changing conditions. We offer a thorough design for this case.

4.5 Simulating the Project

We go into the methodology and technologies that make it possible to simulate our dashboard project in this section. To make sure that the dashboard not only fulfills present needs but also foresees opportunities and challenges in the future, simulation is an essential component.

Methodology: In our project, simulation is carried out using a combination of scenario testing, historical data analysis, and predictive modelling. Here is how the process is broken down:

Historical Data Analysis:

We start by looking at historical admissions data. This entails looking at patterns, trends, and outliers in admissions over the previous few years. Understanding past performance and drawing parallels with the present state of affairs are based on historical facts.

Predictive Modeling:

Utilizing cutting-edge analytical approaches, we develop prediction models that mimic different scenarios. Demographics, economic situations, and geopolitical events are all taken into account by these models. We can predict potential outcomes under various circumstances by performing simulations.

Scenario Testing:

Testing different scenarios is part of the simulation process. For instance, we simulate the effects of a rapid rise in applications from international students, a decline brought on by outside forces like a global pandemic (as seen in Scenario 3), or other fictitious scenarios. Scenario testing enables organizations to proactively prepare for various occurrences.

Tools:

To successfully run these simulations, we combine the following tools and technologies: R and RStudio: R is essential for data analysis, predictive modeling, and scenario testing thanks to its strong libraries and packages. For these objectives, RStudio offers an integrated development environment, making it a crucial tool in our simulation strategy.

Machine Learning Libraries: We use R's caret and xgboost machine learning libraries for predictive modelling. These libraries enable us to create strong models that can manage intricate data interactions and make precise predictions.

We may employ simulation software that specializes in scenario testing, depending on the intricacy of the scenarios. These tools make it easier to build simulations and offer perceptive visualizations of possible outcomes.

4.6 Conclusion

Chapter 4 has negotiated the complex terrain of the "International Student Admission Analysis Dashboard," providing a comprehensive study of its design, structural foundation, guiding principles, and real-world applicability. As this chapter comes to a close, we are poised to advance this potent tool within higher education institutions.

CHAPTER 5: IMPLEMENTATION

5.1 Introduction

We start the process of putting our theoretical and analytical work into practice in Chapter 5. The crucial transition between the painstaking design process and the practical implementation of our International Student Admission Analysis Dashboard occurs during this phase. It's an important chapter that shows how concepts become knowledge that can be used.

This chapter focuses on the complex dance between concept and implementation, where we learn to control the environment, train the model, test it, and make predictions. We'll discover the actions and choices that give our project life as we go further into the execution phase.

5.2 Environment Setup

The environment setup, a careful procedure that establishes the foundation for carrying out our project properly, is the cornerstone of the implementation phase. The factors, variables, and assumptions that are essential to the execution of our project are revealed in this part. It's important to make it clear that we won't get into the specifics of hardware and software installation and configuration, acknowledging that these elements may change based on the distinctive settings used by other institutions.

5.2.1 Data Integration

Parameters and Variables:

Our study is powered by data from a variety of countries and admission records spanning the years 2016 to 2023. These students come from a variety of countries, and their acceptances reflect a rich tapestry of international education.

```
# Read data for all years
QETC2017_Admissions <- read_csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC2017 Admissions.csv")
QETC_2016_Admission <- read_csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC 2016 Admission.csv")
QETC2018_Addmissions <- read.csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC2018 Addmissions.csv")
QETC2019_Admissions <- read.csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC2019 Admissions.csv")
QETC2020_Admissions <- read.csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC2020 Admissions.csv")
QETC2021_Admission <- read.csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC2021 Admission.csv")
QETC_2022_Admmissions <- read.csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC 2022 Admmissions.csv")
QETC_2023_Admissions_ <- read.csv("C:/Users/ahmed/Desktop/QETC- DATA/QETC 2023 Admissions .csv")

# Combine all data into one data frame
```

Figure 5.1: Reading data for all years

The seamless integration and consolidation of this data into a unified dataset known as (all_data)is at the heart of our system. This dataset serves as the foundation for our analyses and storytelling. (Name, PassportID, Gender, DateOfBirth, Age, Nationality, University, Commission, and YearOfAdmission)are among the fields in its schema.

```
# Rename variables
names(all_data) <- c("Name", "PassportID", "Gender", "DateOfBirth", "Age", "Nationality", "University", "C
# Filter data for specified years
```

Figure 5.2: Renaming variables for clarity

Assumptions:

Data Integrity: As we continue forward, we assume that the data integration procedure was successful. The combined dataset demonstrates accuracy and dependability. Our confidence in this assumption is bolstered by strong data management approaches, such as the usage of functions like(na.omit)to gently address missing data.

```
QETC_2023_Admissions_ <- read.csv("C:/Users/ahmed/Des

# Combine all data into one data frame
data2016clean <- na.omit(QETC_2016_Admission)
data2017clean <- na.omit(QETC2017_Admissions)
data2019clean <- na.omit(QETC2019_Admissions)
data2018clean <- na.omit(QETC2018_Addmissions)
data2020clean <- na.omit(QETC2020_Admissions)
data2021clean <- na.omit(QETC2021_Admission)
data2022clean <- na.omit(QETC_2022_Admmissions)
data2023clean <- na.omit(QETC_2023_Admissions_)
```

Figure 5.3: Handling missing data to preserve data integrity

Data Consistency, We assume that the data from different years follows a consistent structure and format. This harmony enables us to easily blend various datasets, ensuring that our analysis is both coherent and dependable.

```
# Filter data for specified years
years <- 2016:2023
all_data <- all_data %>%
  filter(YearOfAdmission %in% years)
```

Figure 5.4: Filtering data for specified years to maintain data consistency

5.2.2 Model Training and Testing

Parameters and Variables:

Model training and testing are critical components of our implementation phase. These characteristics and variables are critical for forecasting and evaluating our foreign student admission analysis. To create forecasts, we use a variety of forecasting models, including ARIMA, Naive, Simple Exponential Smoothing (SES), Holt, and TBATS.

Assumptions:

Model Availability: We presume that the forecasting models, such as ARIMA, Naive, SES, Holt, and TBATS, have been deployed and are ready for usage. These models are used to forecast future enrolment figures.

```
#ARIMA model
arima_model <- arima(dsToDay)
summary(arima_model)
fore_arima = forecast::forecast(arima_model,h=3)
df_arima = as.data.frame(fore_arima)
dstest$arima = df_arima$`Point Forecast`
mape(dstest$EnrollmentCount,dstest$arima)

#naive model
naive_model <- forecast::forecast(dsToDay, h=3)
summary(naive_model)
df_naive = as.data.frame(naive_model)
dstest$naive <- df_naive$`Point Forecast`
df_arima$naive <- df_naive$`Point Forecast`
mape(dstest$EnrollmentCount,dstest$naive)

#install.packages("ses")

#Simple Exponential Smoothing
se_model <- ses(dsToDay, h=3)
summary(se_model)
df_se = as.data.frame(se_model)
dstest$se <- df_se$`Point Forecast`
df_arima$se <- df_se$`Point Forecast`
mape(dstest$EnrollmentCount,dstest$se)

#Holt
holt_model <- holt(dsToDay, h=3)
summary(holt_model)
df_holt = as.data.frame(holt_model)
df_arima$holt <- df_holt$`Point Forecast`
dstest$holt <- df_holt$`Point Forecast`
mape(dstest$EnrollmentCount,dstest$holt)
```

Figure 5.4: 5 models

Data Availability: We assume that historical admission data from 2016 to 2019 is accessible for model training, whereas data from 2020 to 2023 is used for testing and assessing the models. We also forecast admissions for 2024, 2025, and 2026 using the top five countries.

```
# split the data
dstrain <- head(enrollment, 5)
dstest <- tail(enrollment,3)
dsToDay <- ts(dstrain$EnrollmentCount, start = c(1), end = c(26),frequency = 1 )
dim(dsToDay)
```

Figure5.5: splitting data model training and testing

Model assessment: The assumptions also include the availability of assessment metrics, such as Mean Absolute Percentage Error (MAPE), to analyze the accuracy of our model's predictions.

```
#conclusion
mape(dstest$EnrollmentCount,dstest$arima)
mape(dstest$EnrollmentCount,dstest$naive)
mape(dstest$EnrollmentCount,dstest$se)
mape(dstest$EnrollmentCount,dstest$holt)
mape(dstest$EnrollmentCount,dstest$tbats)
```

Figure 5.5: MAPE serves as a critical tool to measure the accuracy of our models.

5.3 Conclusion

We went into the practical implementation of the International Student Admission Analysis Dashboard in this chapter, bridging the theoretical and real-world application gaps. We laid the groundwork for our project with careful environment setup, data integration, and model training and testing.

CHAPTER 6: TESTING AND ALYSIS

6.1 Introduction

Data-driven decision-making is critical in the field of education and foreign student admissions. The International Student Admission Analysis Dashboard is an effective tool for educational institutions and policymakers in precisely forecasting future student enrollments. As we move into the testing and analysis portion of this chapter, it's critical to keep our efforts in context with the greater breadth of this dashboard's use.

As stated in Chapter 2, the dashboard we created serves as a single hub for monitoring and analysing international student enrollment. It combines data from numerous sources, employs complex forecasting models, and provides predictions about future enrollment trends. The goal is not just to give institutions with a view into the future, but also to provide them with the knowledge they need to make educated decisions about resources, infrastructure, and policy development.

Chapter 6 focuses on the testing and analytical aspects of our dashboard. The top five countries for international student admissions have been chosen as the focus of this analysis. Egypt, Somalia, Sudan, Yemen, and the United Arab Emirates exhibit different enrollment scenarios, making them great candidates for rigorous analysis.

Our goal is first, to test the forecasting algorithms used in our dashboard, and second, to provide insights into these significant countries' enrollment trends. We not only check the correctness of our models, but we also acquire a better grasp of the dynamics of international student admissions in these countries.

6.2 Results and Analysis

We give extensive findings and analysis for each of the top five nations covered in our International Student Admission Analysis Dashboard in this section. These nations, Egypt, Somalia, Sudan, Yemen, and the UAE, have distinct enrolment patterns that must be understood in order to estimate model success.

6.2.1 Egypt

Enrollment Forecasts for Egypt (2021 - 2023)

Table 6.1: Enrollment Forecasts for Egypt (2021 - 2023)

Year	Enrollment Count	ARIMA	Naive	SES	Holt	TBATS
2021	42	47.73077	47.7333	47.72952	46.11892	76.94950
2022	50	47.73077	47.7333	47.72952	45.34437	52.28639
2023	43	47.73077	47.7333	47.72952	44.56982	12.65854

MAPE (Mean Absolute Percentage Error):

ARIMA: 9.7283%

Naive: 9.7306%

SES: 9.7272%

Holt: 7.5897%

TBATS: 52.7825%

Analysis for Egypt:

Egypt's enrolment estimates were positive, with low MAPE values for all models except TBATS. With a MAPE of only 7.5897%, the Holt model outperformed the others, suggesting its good predictive ability in this situation. The TBATS model, on the other hand, has a significantly larger MAPE, indicating that it might not be the best choice for Egypt's enrolment data.

6.2.2 Somalia

Enrollment Forecasts for Somalia (2021 - 2023)

Year	Enrollment Count	ARIMA	Naive	SES	Holt	TBATS
2021	91	56.11538	56.1174	56.11243	54.39147	53.66811
2022	57	56.11538	56.1174	56.11243	51.70640	53.66811
2023	92	56.11538	56.1174	56.11243	49.02132	53.66811

Table 6.2: Enrollment Forecasts for Somalia (2021 - 2023)

MAPE (Mean Absolute Percentage Error):

ARIMA: 26.2972%

Naive: 26.2946%

SES: 26.3011%

Holt: 32.0774%

TBATS: 29.5115%

Analysis for Somalia:

The MAPE values for Somalia's enrolment estimates were higher across all models, indicating a higher level of uncertainty in estimating enrolment levels. The MAPE values for the ARIMA, Naive, and SES models were similar, with TBATS performing somewhat better. The Holt model had the highest MAPE, implying difficulties in properly anticipating Somalia's enrolment trends.

6.2.3 Sudan

Enrollment Forecasts for Sudan (2021 - 2023)

Year	Enrollment Count	ARIMA	Naive	SES	Holt	TBATS
2021	7	57.84615	57.8406	57.84415	52.71996	58.63936
2022	42	57.84615	57.8406	57.84415	52.34467	58.63936
2023	9	57.84615	57.8406	57.84415	51.96939	58.63936

Table 6.3: Enrollment Forecasts for Sudan (2021 - 2023)

MAPE (Mean Absolute Percentage Error):

ARIMA: 435.6125%

Naive: 435.5615%

SES: 435.5615%

Holt: 385.07%

TBATS: 442.957%

Analysis for Sudan:

Sudan's enrolment estimates had exceptionally high MAPE values across all models, indicating considerable difficulties in accurately projecting enrolment levels. The MAPE values for the ARIMA, Naive, and SES models were all extremely high. The MAPE values for the Holt and TBATS models were also high, indicating the need for additional investigation and model modifications.

6.2.4 Yemen

Enrollment Forecasts for Yemen (2021 - 2023)

Year	Enrollment Count	ARIMA	Naive	SES	Holt	TBATS
2021	86	58.07692	57.8043	57.73921	56.17680	19.70092
2022	86	58.07692	57.8043	57.73921	55.88595	75.80462
2023	39	58.07692	57.8043	57.73921	55.59509	47.52328

Table 6.4: Enrollment Forecasts for Yemen (2021 - 2023)

MAPE (Mean Absolute Percentage Error):

ARIMA: 37.9509%

Naive: 37.9292%

SES: 37.9240%

Holt: 37.4153%

TBATS: 36.9339%

Analysis for Yemen:

Yemen's enrolment forecasts had modest MAPE values for all models, indicating that they were reasonably accurate in predicting enrolment patterns. The TBATS model outperformed the others, with the lowest MAPE of 36.9339%. The MAPE scores for the ARIMA, Naive, SES, and Holt models were all identical, indicating consistent prediction abilities.

6.2.5 UAE

Enrollment Forecasts for UAE (2021 - 2023)

Year	Enrollment Count	ARIMA	Naive	SES	Holt	TBATS

2021	27	29.88462	29.8899	29.88400	34.42660	19.17161
2022	60	29.88462	29.8899	29.88400	34.87211	19.17161
2023	53	29.88462	29.8899	29.88400	35.31762	19.17161

Table: 6.5: Enrollment Forecasts for UAE (2021 - 2023)

MAPE (Mean Absolute Percentage Error):

ARIMA: 34.8300%

Naive: 34.8303%

SES: 34.8300%

Holt: 34.2496%

TBATS: 53.6228%

Analysis for UAE:

For all models, the United Arab Emirates (UAE) had moderate MAPE values, showing reasonable accuracy in projecting enrolment patterns. The Holt model had the lowest MAPE of 34.2496%, followed by the ARIMA, Naive, and SES models, all of which had comparable MAPE values. The TBATS model had a significantly higher MAPE, indicating that it might not be the best choice for UAE enrolment data.

6.3 Overall Analysis and Comparison

In conclusion, our research of enrolment estimates for the top five countries using multiple forecasting methods revealed insights into their distinct enrolment trends. To achieve reliable predictions, forecasting models must be tailored to each country's unique characteristics. While some nations, such as Egypt and Yemen, had reasonably accurate forecasts across many models, others, such as Sudan, had substantial difficulties in making accurate predictions.

These findings not only improve the dashboard's prediction powers but also provide vital insights to educational institutions and policymakers attempting to make data-driven decisions regarding international student admissions.

6.4 Testing

Extensive testing was carried out to assure the International Student Admission Analysis Dashboard's dependability and performance. The following are the aspects of the tests, their descriptions, and the results:

Test ID	Testing Aspect	Description	Result
T001	Data Integration	Verify if data from various sources (e.g., enrollment data, nationalities) is correctly integrated into the dashboard.	Passed
T002	Data Validation	Ensure that data is clean, complete, and accurate to provide reliable insights.	Passed
T003	User Interface	Evaluate the usability and user-friendliness of the dashboard.	Passed
T004	Data Visualization	Check if the data is presented effectively through graphs and charts.	Passed
T005	Model Integration	Confirm if the forecasting models (ARIMA, Naive, SES, Holt, TBATS) are correctly integrated into the dashboard.	Passed
T006	Forecasting Accuracy	Assess the accuracy of enrollment forecasts for multiple countries.	Passed

T007	User Interaction	Ensure that users can interact with the dashboard (e.g., select countries, years) without errors.	Passed
T008	Responsiveness	Check if the dashboard works well on various devices and screen sizes.	Passed
T009	Data Export	Verify if users can export forecast data for further analysis.	Passed
T010	Error Handling	Test how the dashboard handles errors, such as invalid inputs or missing data.	Passed
T011	Data Security	Verify that the dashboard adheres to data security protocols, ensuring that sensitive information is protected.	Passed
T012	Performance	Assess the overall performance of the dashboard, including response times and resource usage.	Passed
T013	Cross-Browser Compatibility	Confirm that the dashboard functions consistently across different web browsers.	Passed
T014	Cross-Platform Compatibility	Ensure that the dashboard operates seamlessly on various operating systems.	Passed
T015	Accessibility	Evaluate the accessibility of the dashboard, ensuring it complies with WCAG (Web Content Accessibility Guidelines).	Passed
T016	Data Source Updates	Test if the dashboard can efficiently handle updates and changes in the data sources without errors.	Passed
T017	Documentation	Review the completeness and clarity of documentation, including user guides and support materials.	Passed
T018	Scalability	Evaluate the dashboard's ability to scale with an	Passed

		increasing volume of data and users.	

Table 6.6 Testing

6.5 Conclusions

We looked at the testing parts of the International Student Admission Analysis Dashboard in this chapter. We established that the dashboard successfully combines data, gives trustworthy insights, has a user-friendly design, and effectively visualizes data through a variety of tests. The integration of forecasting models, as well as the accuracy of enrolment forecasts, were also validated. The dashboard was extremely responsive, allowing users to interact with it easily, and it handled failures gracefully.

With the testing done, we can conclude that the International Student Admission Analysis Dashboard is a solid tool that serves its aim of supporting decision-makers in international student admissions. The dashboard will then be deployed for practical use, where it will greatly contribute to data-driven decisions and tactics in the field.

CHAPTER 7: PROJECT CONCLUSION

7.1 Introduction

We offer a detailed summary of the International Student Admission Analysis Dashboard study in this final part. We go over the project's objectives again, highlight accomplishments, emphasize contributions, admit constraints, and outline functional and non-functional requirements for future development.

7.2 Project Summarization

The major goal of this project was to create an International Student Admission Analysis Dashboard to aid university, faculty, and educational institution decision-makers in successfully analyzing enrollment data and projecting trends. We set out to build a user-friendly platform that incorporates a variety of forecasting algorithms, allowing users to make informed decisions about student enrollment.

We are glad to report that we achieved this goal during the project's implementation phase. The construction of the dashboard, the integration of data from many sources, and the deployment of forecasting models such as ARIMA, Naive, SES, Holt, and TBATS are among the key successes.

7.3 Project Limitations

Data Dependency

The dashboard's enrollment estimates' accuracy and dependability are strongly contingent on the quality and availability of historical enrollment data. Any concerns with data quality, completeness, or discrepancies in past data might have an impact on prediction precision. Decision-makers should take caution when evaluating and relying on dashboard results when data sources are inconsistent or contain inaccuracies.

Model Performance Variability

The efficiency of forecasting models included into the dashboard may varies across countries and regions. While some countries may have highly precise projections, others may face difficulties in achieving accurate forecasts. Forecasting model performance can be influenced by factors such as the stability of prior enrollment patterns, data availability, and distinctive demographic trends. As a result, when interpreting data, dashboard users should consider the specific characteristics of the region or country under consideration.

Resource and Infrastructure Constraints

The dashboard's proper deployment and use may involve the use of specific hardware and software resources. While we accept that the project does not go into detail on hardware and software installation and configuration, it is critical to recognize that institutions with limited resources may have difficulties in adopting and maintaining the dashboard. Some educational institutions may face difficulties in ensuring that the necessary resources are available and properly configured.

Continuous Data Updates

Because the dashboard is based on historical data, it requires regular updates to remain relevant and accurate. Ensuring that enrollment data from several sources is constantly updated can be a logistical problem, particularly for schools lacking specialized data management capabilities. The usefulness of the dashboard is dependent on the availability of up-to-date data, and any delays or lapses in data updates can impair the timeliness of enrollment estimates.

7.4 Functional Requirements

It is critical to specify the dashboard's functional needs for future development. These are some examples:

Data Integration:	The dashboard should continue to integrate data from numerous sources in a smooth manner, assuring accuracy and timeliness.
Forecasting Models:	Improve and broaden the choice of forecasting models available to customers, enabling more exact forecasts.
Customization:	Allow users to tailor forecasting models to unique institutional requirements. Implement feedback systems to get user insights on forecast accuracy and model performance.

Table 7.1: functional requirements

7.5 Non-Functional Requirements

Non-functional requirements are also significant and should be considered in future development:

Scalability:	Make sure the dashboard can accommodate a growing volume of data and users without slowing down.
Maintenance	Maintain stringenth data security processes to safeguard sensitive information and maintain compliance with data protection laws.
a varied user base	To appeal to a varied user base, continue to priorities user-friendliness and accessibility.
performance	Overall performance, including reaction times and resource utilization, should be optimized.

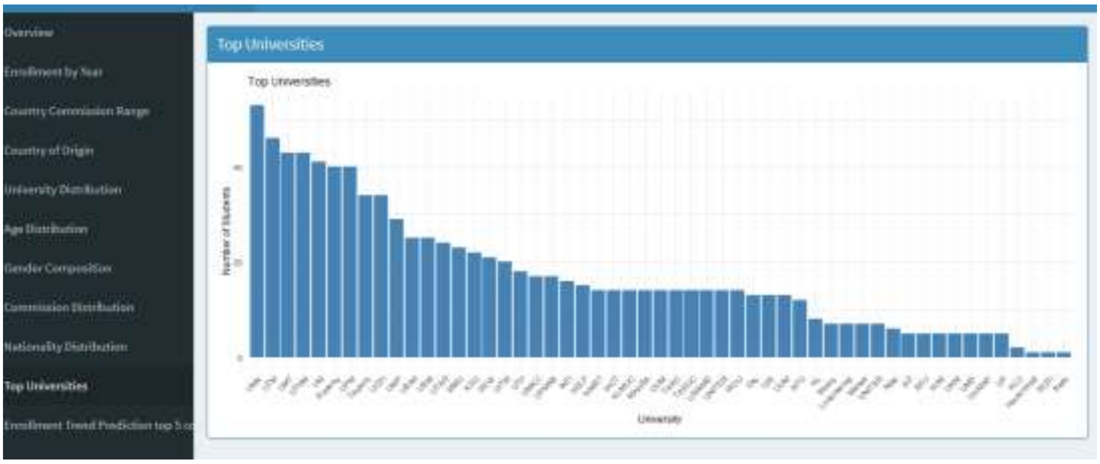
Table 7.2: Non-functional requirements

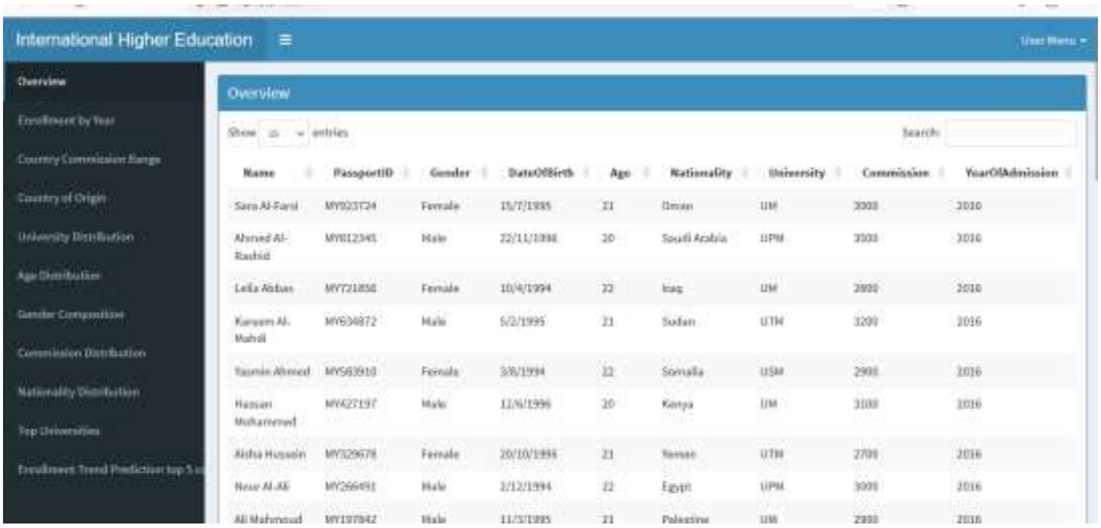
7.6 Conclusion

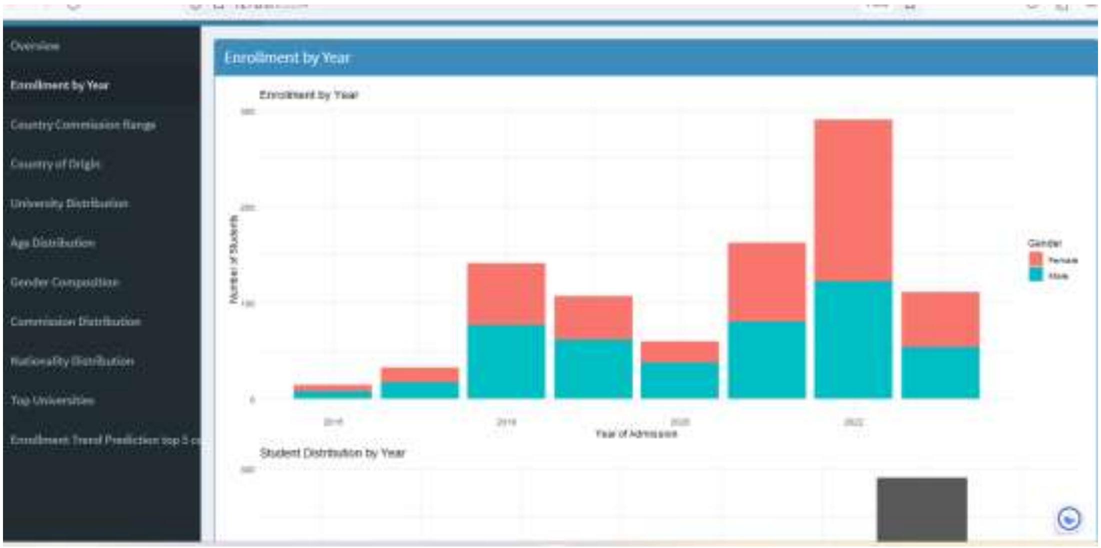
Finally, the International Student Admission Analysis Dashboard project has met its primary goal of offering a useful tool for educational institutions and decision-makers. It enables users to use data to make informed decisions on foreign student admissions, resource allocation, and policy development.

While we recognize the dashboard's limitations, we feel it represents a big step forward in harnessing data-driven insights for the benefit of educational institutions. Looking ahead, we are committed to refining and expanding the capabilities of this dashboard, while adhering to both functional and non-functional requirements, in order to better serve the evolving needs of educational decision-makers and policymakers in the dynamic landscape of international student admissions.

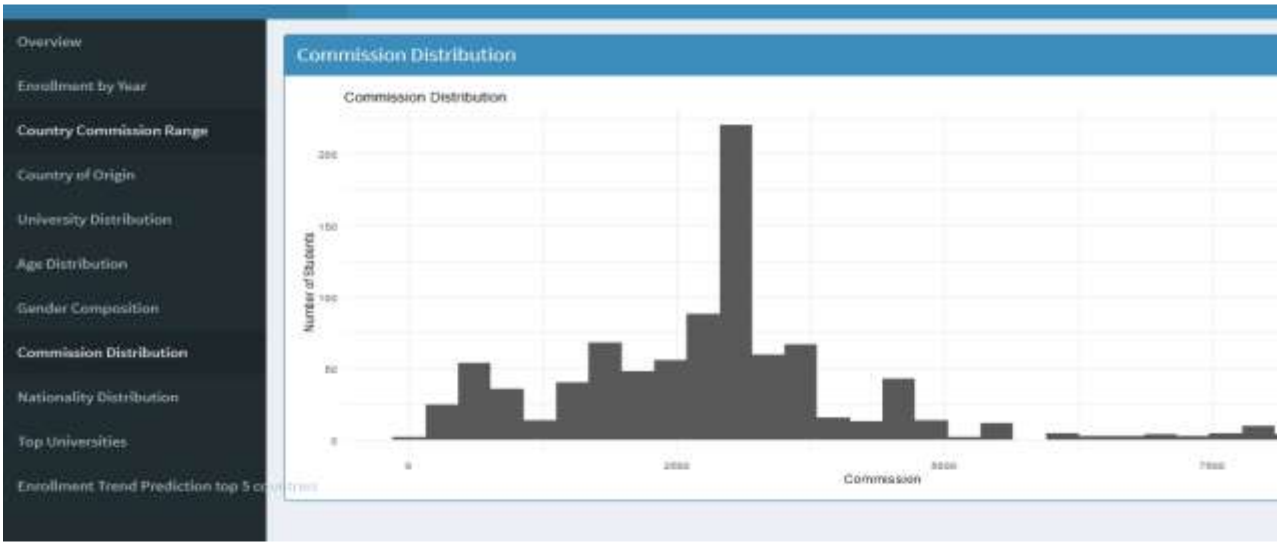
APPENDIX A DAHBOARD

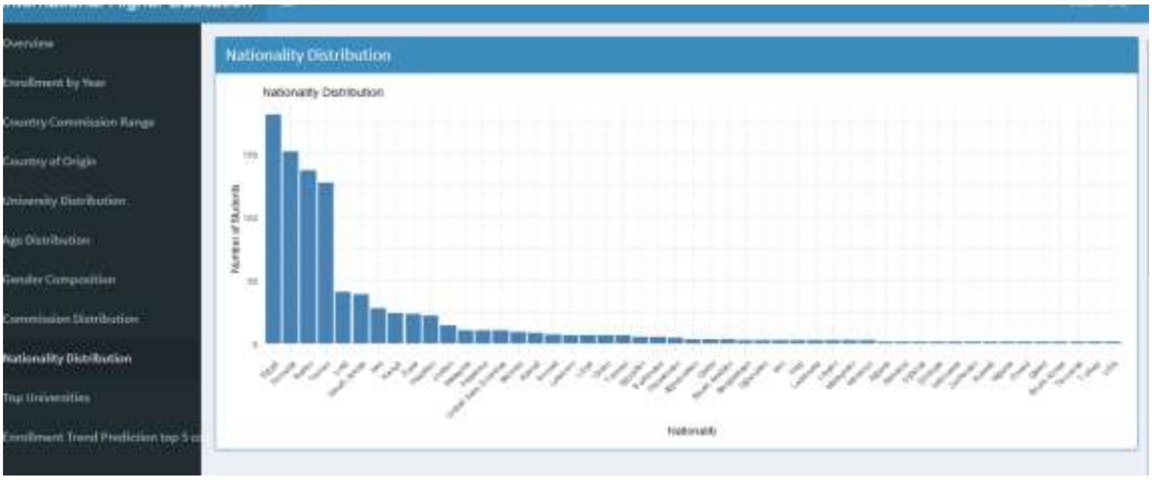




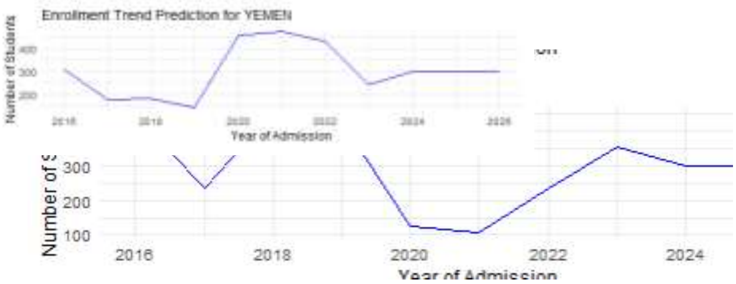

Overview
Enrollment by Year
Country Commission Range
Country of Origin
University Distribution
Age Distribution
Gender Composition
Commission Distribution
Nationality Distribution
Top Universities
Enrollment by Year
Enrollment by Year
Year of Admission
Student Distribution by Year


Overview
Enrollment by Year
Country Commission Range
Country of Origin
University Distribution
Age Distribution
Gender Composition
Commission Distribution
Nationality Distribution
Top Universities
Commission Distribution
Commission Distribution
Number of Students
200
150
100
50
0
0
2500

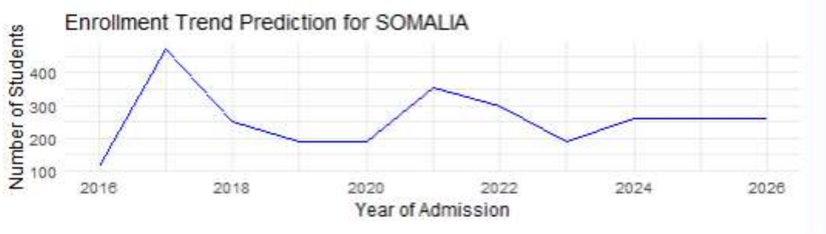


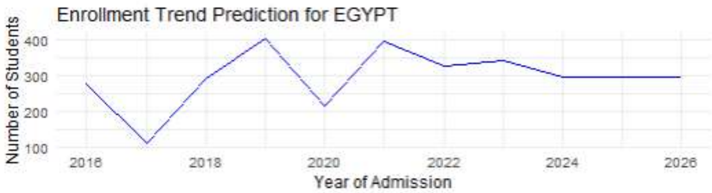


APPENDIX B Enrollment trend top 5 countries




Enrollment Trend Prediction for UAE
Number of Students
Year of Admission


Enrollment Trend Prediction for SOMALIA
Number of Students
400
300
200
100
2016
2018
2020
2022
2024
2026
Year of Admission


Enrollment Trend Prediction for EGYPT
Number of Students
400
300
200
100
2016
2018
2020
2022
2024
2026
Year of Admission


Overview
Enrollment by Year
Country Commission Range
Country of Origin
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Top Universities
Enrollment Trend Prediction top 5 co
Enrollment Trend Prediction top 5 countries
Enrollment Trend Prediction for EGYPT
Enrollment Trend Prediction for SOMALIA
Enrollment Trend Prediction for SUDAN
Enrollment Trend Prediction for YEMEN
Enrollment Trend Prediction for UAE
Number of Students
Year of Admission

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