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Interactive Visual Analytics: A Deep Dive into The Global Cost of Living

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ABSTRACT

Cost of living significantly impacts individuals, businesses, and policymakers by shaping financial stability and economic decisions. Variations in cost of living arise from economic, geographical, and cultural factors, often leading to financial stress, particularly during periods of rising expenses and stagnant wages. The complexity of cost-of-living metrics, such as the Consumer Price Index (CPI), poses challenges for understanding and effective decision-making. This study addresses these issues by developing an interactive data visualization dashboard, designed to transform complex data into clear and actionable insights. By integrating Big Data Architecture, Agile Methodology, and a Random Forest model for predictive analysis, the tool offers accurate visualizations and interactive features that support financial literacy and informed decision-making. Users can compare cost indices across 131 countries and 2,408 cities, predict salaries based on cost-of-living data, and identify budget-friendly travel destinations. The system testing achieved an excellent System Usability Scale (SUS) score of 88.96, validating its usability and effectiveness. By simplifying global cost-of-living data, the dashboard empowers users to plan financial stability and respond proactively to economic challenges, bridging the gap between complex data and practical decision-making.

1. Introduction

1.1 Research Background

In recent decades, there has been growing interest in understanding the variations in the global cost of living. "Living" refers to the state of being alive, while the quality of this experience often referred to as the standard of living varies across different regions and populations. The standard of living measures the quality of life and the level of material prosperity enjoyed by individuals, as highlighted by Latimaha *et al.,* [1]. It is influenced by economic, geographical, and cultural factors. Economically, the standard of living is closely tied to income levels, employment opportunities, and the cost of goods and services. Geographical factors, such as climate, infrastructure, and resource access, as well as cultural aspects like societal norms, values, and traditions, also play a role.

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A key economic factor affecting the standard of living is the cost of living. Defined as the expense required to maintain a basic standard of living, it is shaped by the prices of essential goods and services such as food, housing, healthcare, and transportation, as described by Latimaha *et al.,* [1].

This metric is often used to compare affordability across locations or assess a region's economic health. In recent years, a global cost-of-living crisis has emerged, marked by rapid increases in the prices of essential goods and services, outpacing wage growth. This has led to financial strain for many households. For example, the United Nations Development Programme reports that the current crisis has pushed over 51 million people into extreme poverty, as reported by Webster [2]. Beyond its economic implications, this crisis poses significant public health concerns, contributing to mental health issues and other health challenges, as noted by Broadbent *et al.,* [3].

Factors contributing to the cost-of-living crisis include wage inequality, inflation, and policy decisions. Wage inequality, where significant income disparities exist, can worsen the financial burden on lower-income households, as described by Polacko [4]. Inflation, which erodes purchasing power through rising prices, further exacerbates this issue, with studies, such as that by Ahmet Coibion Bozkurt *et al.,* [5], affirming its direct impact on living costs. Policy decisions, such as changes in taxation or social benefits, can also influence the severity of cost-of-living challenges. Affected stakeholders include individuals, families, businesses, and governments. For individuals and families, the crisis leads to financial stress and a reduced quality of life. Businesses face increased operational costs, while governments must develop policies to mitigate the socio-economic impacts of the crisis. The consequences of ignoring this issue include increased poverty, social unrest, and economic instability, highlighting the need for effective solutions.

Despite the importance of understanding the cost of living, many existing studies rely on static formats, such as traditional reports or isolated indices, which lack interactivity and accessibility. Previous research has focused on specific cost indices, such as the Consumer Price Index (CPI), or regional trends, without integrating diverse datasets into a unified, interactive framework. This research aims to fill this gap by developing an interactive data visualization tool that integrates Big Data Architecture and Agile methodology. This tool enhances user engagement by offering dynamic data exploration, allowing users to personalize their analysis and gain deeper insights into cost-of-living challenges.

The scope of this project addresses several key dimensions. Stakeholders benefiting from this research include individuals, researchers, businesses, and policymakers seeking informed perspectives on the cost of living. The project provides outputs such as comparative insights into cost-of-living indices across cities and countries, as well as predictive analysis supported by machine learning algorithms. These features enable users to compare predicted and actual salaries based on cost-of-living indices, aiding in better financial planning. The project uses two primary datasets: the Cost of Living Index dataset, covering data from 138 countries, and the Global Cost of Living dataset, which includes over 4,500 cities globally. These datasets, sourced from Kaggle, form a solid foundation for analysis. Visualization tools like Power BI and RapidMiner are used to implement the project's interactive and predictive features.

This project’s significance lies in its potential societal and economic impact. The interactive data visualization tool promotes public awareness and financial literacy by offering a deeper understanding of cost-of-living dynamics. By enabling comparisons across cities and countries, it helps individuals make informed decisions about where to live and work. The predictive analysis feature also supports businesses and governments in anticipating future trends, helping them formulate proactive strategies to address economic challenges. Ultimately, this research contributes to mitigating the adverse effects of the cost-of-living crisis, fostering better decision-making at both individual and institutional levels.

To guide readers through the discussion, this paper is organized into several key sections. The introduction outlines the research problem, objectives, and significance, providing a foundation for understanding the study's relevance. A review of existing literature and visualization methods highlights the current gaps in cost-of-living analyses. The methodology section details the integration of Big Data Architecture and Agile practices used in the dashboard's development. The results and discussion present the interactive visualization features and their implications, while the conclusion synthesizes the findings and suggests directions for future work.

1.2 Literature Review
1.2.1 Cost of living

The cost of living refers to the amount of money required to maintain a certain standard of living, accounting for necessary expenses such as housing, food, taxes, and healthcare. It extends beyond mere price increases and differs from inflation, though they are related, according to Bank Negara Malaysia [6]. The cost of living can vary significantly based on factors like income level, geographical location, and consumption patterns. For instance, urban areas generally have a higher cost of living compared to rural areas due to differences in housing costs, transportation, and access to services.

Several factors contribute to the cost of living, making it a complex concept. Primary among these is inflation, often measured by the Consumer Price Index (CPI), which tracks the price changes for a fixed basket of goods and services representing average household spending, as noted by Bank Negara Malaysia [6]. However, the CPI may not fully reflect changes in individual costs of living due to varying spending patterns and different price changes across locations. Additionally, rising prices of everyday essentials like groceries and bills especially when these increases outpace household incomes, contribute to what is often referred to as a 'cost of living crisis'. Other significant factors include social security cuts, stagnating wages, tax increases, and global events like wars and pandemics, which can disrupt trade and production, further driving up costs, as highlighted by Patrick and Pybus [7].

Managing the cost of living crisis involves several strategies. Having a savings plan is fundamental, as savings can provide a financial buffer during hardships. Proper budget planning, which includes tracking income and expenses, setting financial goals, and prioritizing essential expenses, is also crucial, according to Universities UK [8]. Seeking additional income sources, such as part-time work or freelance gigs, and taking advantage of available financial assistance programs can help mitigate the impact of rising living costs. Developing coping strategies and fostering a sense of self-efficacy can also be beneficial in managing financial stress, as indicated by Freire *et al.,* [9].

The rising cost of living has significantly impacted households, especially those with low incomes. High inflation rates, driven by factors such as strong global demand for goods, supply chain disruptions, and soaring energy prices, have reduced the affordability of goods and services, as noted by Harari *et al.,* [10]. Low-income households experience higher-than-average inflation rates due to their spending patterns being more affected by high food and energy prices. Government measures, such as the Energy Price Guarantee and cost of living payments, have been implemented to support households, but challenges remain, especially for those with low incomes, according to Harari *et al.,* [10].

1.2.2 Cost of living visualization

Cost of living analysis assesses the affordability of necessities like housing, food, healthcare, and transportation within a specific area. It measures expenses and costs associated with living in a particular location and serves as a tool to compare economic situations across different regions or over time, based on Bank Negara Malaysia [6]. This analysis includes inflation tracking, which monitors changes in the prices of goods and services, directly impacting the cost of living. Data visualization of the cost of living translates this data into graphical formats such as charts, graphs, and maps, making the information more accessible and understandable. Such visualizations can depict changes in the Consumer Price Index (CPI) and other indices like the Everyday Price Index (EPI) and Perceived Price Index (PePI), helping individuals, policymakers, and researchers compare costs across locations and time periods, identify trends, and make informed decisions.

Various stakeholders benefit from cost of living visualization. Public individuals use this information to make decisions about budgeting, spending, and potentially relocating to areas with a more favorable cost of living, according to Latimaha *et al.,* [1]. Researchers analyze cost of living data to understand economic trends, the impact of inflation, and the effectiveness of policy measures, contributing to public debate and policy decisions, according to Latimaha *et al.,* [1]. Businesses need this data to set prices, forecast demand, and manage wages, ensuring their competitiveness and that their employees can afford to live where they operate, as noted by Latimaha *et al.,* [1]. Policymakers rely on accurate cost of living data to design and implement policies that stabilize prices, support economic growth, and protect vulnerable populations from the adverse effects of high living costs, as highlighted by Latimaha *et al.,* [1].

The benefits of cost of living visualization are significant for these stakeholders. For public individuals, it can influence lifestyle choices and help compare expenses across locations, based on Tiwari [11]. Researchers gain tools to better understand and predict the standard of living considering cost of living factors, according to Latimaha *et al.,* [1]. Businesses can use insights from these visualizations to understand the impact of inflation on costs, as noted by Ahmet Coibion Bozkurt *et al.,* [5]. Policymakers benefit by planning and implementing policies to protect communities from cost-of-living crises and address inequalities, according to Webster [2]. Data visualization helps transform data into actionable insights and captures decision-makers' attention, according to Lundkvist *et al.,* [12].

Several studies have explored the concept of the cost of living, focusing on indexes such as the Cost of Living Index, Rent Index, and Restaurant Price Index. These studies often rely on statistical models to describe economic trends and provide insights into living conditions in different countries or cities. While these analyses are effective for identifying patterns and relationships, they are typically static, meaning the data cannot be customized or explored further by the user. This limits their usefulness for individuals with unique questions, such as travelers planning a trip or researchers conducting targeted studies.

Interactive dashboards are a growing trend in data analysis but are still underutilized in cost-of-living research. Existing dashboards often present data in predefined formats, with limited opportunities for users to modify inputs. Additionally, the processes used to build these dashboards rarely involve Agile methodology, which focuses on continuous improvement and user feedback during development.

This research builds on these previous works by addressing their limitations. By combining Big Data Architecture with Agile practices, this study introduces a dashboard that allows users to interact with cost-of-living data in ways that were not possible before. The dashboard offers features like custom budget calculations and interactive data visualizations, making it more engaging and applicable to a wider audience. Unlike earlier studies, this work prioritizes user customization and accessibility, providing a practical tool that adapts to individual needs.

In doing so, this study contributes to the existing body of knowledge by creating a new way to analyze and present cost-of-living data. It moves beyond static models and traditional visualizations, offering a solution that is both innovative and practical. The Office for National Statistics notes that cost of living visualizations can explain changes in living costs, providing benefits to all stakeholders [13].

Analyzing the cost of living is crucial for several reasons. It provides predictive analysis, helping anticipate future economic conditions and enabling better planning, according to Latimaha *et al.,* [1]. It aids informed decision-making by revealing patterns and trends in living costs, offering valuable insights for individuals, businesses, and policymakers, based on the Office for National Statistics [13]. For policymakers, cost of living analysis is vital for creating policies to manage inflation and develop macro-economic plans to support vulnerable populations during high inflation periods, according to Ahmet Coibion Bozkurt *et al.,* [5]. Additionally, for researchers, it provides context-sensitive evidence to address complex issues faced by policymakers and helps understand factors influencing the cost of living, such as GDP per capita, population growth, unemployment rate, and economic openness, according to Latimaha *et al.,* [1].

1.2.3 Review of existing data visualization

Reviewing existing systems is crucial for several reasons. First, it provides insights into the strengths and weaknesses of current solutions, allowing identification of potential pitfalls and opportunities for improvement. This helps in refining project specifications to ensure the new solution stands out and addresses unmet needs or gaps in the market. Additionally, staying informed about emerging trends, best practices, and innovative approaches in the field can inspire and inform the development process. Conducting a comprehensive review of existing systems empowers informed decision-making, enhances project effectiveness, and maximizes its impact and success in addressing the identified problem or opportunity.

Based on Table 1, a comparison of existing systems reveals that four out of five systems offer real-time data insights, providing up-to-date information on the Consumer Price Index (CPI) and essential living costs. The COL ONE DEVON Dashboard is the exception. All systems provide comparative analysis, with Hargapedia focusing on food and item prices within Malaysian cities, while others compare the CPI between popular cities and countries worldwide. Only the Leeds Observatory Dashboard includes predictive analysis, showing trends and patterns to predict future cost of living changes. Despite its predictive capabilities, the Leeds Dashboard lacks interactive elements, presenting static information. In contrast, the other dashboards, except Leeds, offer interactive visualizations for enhanced user engagement and personalized data exploration. Features like search, filtering, and sorting in COL ONE DEVON Dashboard and Hargapedia further enhance user interaction and data exploration.

Table 1
Table comparison of existing data visualization

	COL ONE DEVON Dashboard	Leeds Observatory	Numbeo Dashboard	Ifar Creation's Cost of Living Application	Hargapedia Application
Real-time data insights	χ	√	√	√	√
Comparative analysis	√	√	√	√	√
Predictive analysis	χ	√	χ	χ	χ

Interactive visualization	√	χ	√	√	√
Variety features	√	χ	χ	χ	√

2. Methodology
2.1 Big Data Architecture

Big Data Architecture is a framework for managing and organizing vast amounts of data, or "big data," in a manner that makes it possible to extract value and hidden insights from it. It is designed to handle the ingestion, processing, and analysis of data that is too large or complex for traditional database systems, according to Rassam *et al.,* [14]. The components of Big Data Architecture, as shown in Figure 1 below, are obtained from Microsoft. They consist of nine components: data sources, data storage, real-time message ingestion, batch processing, machine learning, stream processing, analytical data store, analytics and reporting, and orchestration.

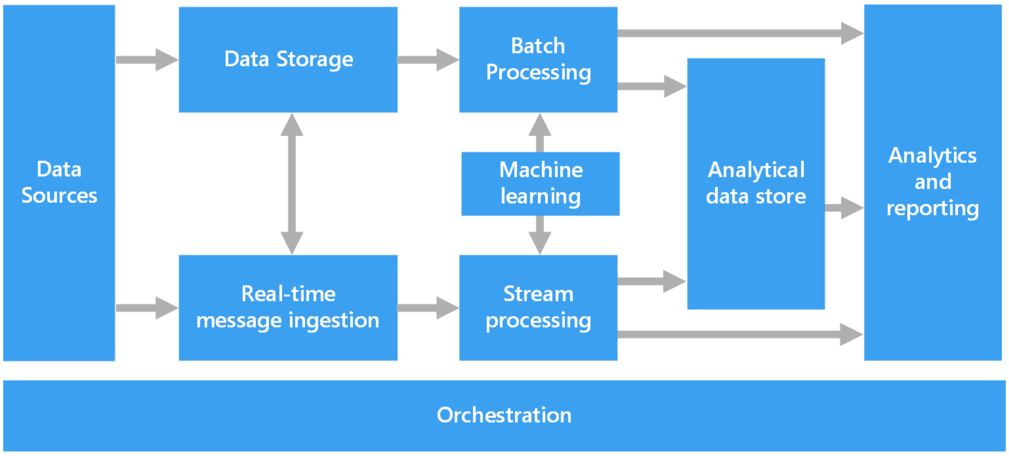

Fig. 1. Big Data Architecture from Microsoft Azure

The Big Data Architecture phases are revised and adapted to align with the data visualization development process. The components of Data Sources, Data Storage, Machine Learning, Data Processing, and Analytics and Reporting are closely aligned with the objectives and requirements of the project, as shown in Figure 2 below.

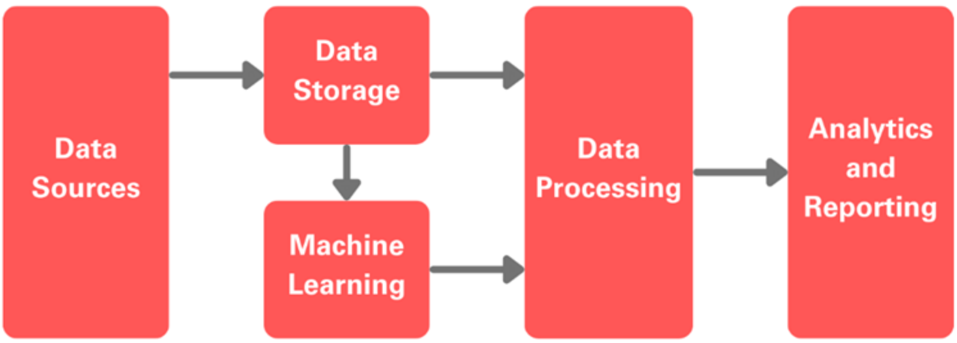

Fig. 2. Adapted Big Data Architecture for dashboard development

Beginning with Data Sources, the inclusion of both Kaggle's Cost of Living Index 2022 and Global Cost of Living datasets, spanning multiple countries worldwide, provides a robust foundation for analysis. The richness of these datasets facilitates insightful comparative analysis across regions, enabling a deep understanding of cost-of-living variations.

For Data Storage, Python programming in Jupyter Notebook is used for data cleansing and interpretation into a data warehouse, streamlining the preparation phase. This ensures that the data is structured and optimized for subsequent analysis.

The integration of Machine Learning algorithms from RapidMiner enhances the project's predictive capabilities, allowing for the identification of trends and patterns within the CPI indexes. As noted by Mizaini *et al.,* machine learning is an experience-based computational approach that uses past data to improve efficiency or make accurate predictions. Algorithms like regression and classification analyze structured or unstructured data to uncover hidden insights, trends, or future outcomes. This predictive analysis not only enriches the visualization but also provides stakeholders with valuable foresight into potential future economic trends, according to Mizaini *et al.,* [15]

For Data Processing, its inclusion underscores the importance of efficiently handling and preparing data for visualization, ensuring accuracy and relevance in the final output.

Finally, Analytics and Reporting serve as the culmination of the project's efforts. Power BI plays a pivotal role in transforming processed data into actionable insights and visually compelling reports. Together, these selected components form a cohesive and comprehensive framework, tailored to the project's objectives. They facilitate the creation of impactful visualizations that offer valuable insights into the global cost-of-living landscape.

2.2 Agile Methodology

The project incorporates Big Data Architecture alongside Agile methodology to ensure an iterative and efficient development process. Agile methodology, widely used in software development and big data visualization projects, emphasizes adaptability and continuous improvement throughout the project lifecycle. As illustrated in Figure 3, the Agile process for this dashboard development consists of five key phases: planning, designing, developing, testing, and reviewing. Each phase is completed in iterations, or sprints, with the goal of delivering functional features at the end of each sprint.

Fig. 3. Agile methodology for dashboard development

During the planning phase, the project requirements were outlined through a literature review and problem analysis to identify gaps in existing systems. Project objectives, scope, and features were defined, and datasets such as the "Cost of Living Index 2022" and "Global Cost of Living" were sourced to support development. The design phase focused on creating a user-friendly interface. This involved designing a storyboard for the dashboard, analyzing both functional and non-functional requirements, and cleaning datasets to ensure they were ready for visualization. In the development phase, visualizations were created independently using Microsoft Power BI. This process combined coding techniques, methods, and procedures to integrate various features into a cohesive dashboard. The Agile methodology facilitated flexibility, allowing for adjustments during development to accommodate feedback and resolve emerging challenges, such as integrating diverse datasets. The testing phase involved system testing on the Microsoft Fabric server to evaluate functionality. Usability testing was conducted using a questionnaire tool, and any bugs identified were resolved based on user feedback. Finally, in the review phase, user suggestions and testing results were incorporated to refine the dashboard, ensuring that it effectively met the project's objectives.

By using Agile methodology, the project maintained adaptability, allowing for iterative enhancements based on continuous feedback. This approach ensured the delivery of an interactive, user-focused dashboard tailored to meet user needs and address gaps in existing systems.

3. Results

3.1 Data Requirements

Two datasets from Kaggle, the "Cost of Living Index 2022" and "Global Cost of Living," were utilized to provide comprehensive insights into global cost-of-living variations. The "Cost of Living Index 2022" dataset contains 140 rows and eight columns, including indices such as Rent Index, Groceries Index, and Restaurant Price Index for 139 countries. This dataset was essential for comparing cost-of-living indices across countries but required cleaning due to incomplete and unstructured data. Python in Jupyter Notebook was employed to remove inconsistencies, standardize formats, and prepare the data for visualization.

The "Global Cost of Living" dataset offers detailed information on costs and prices in over 4,500 cities, comprising 58 columns and 4,875 rows. While it provides rich data on living expenses, such as transportation and accommodation costs, it also presented challenges. Many columns contained unnecessary details or redundant information, requiring consolidation into relevant categories to improve clarity and usability. Missing values were addressed to ensure accuracy, and transformations were applied to reduce the dataset's complexity for visualization.

A notable limitation of this approach is the reliance on these specific datasets, which may not account for real-time changes or regional disparities not captured in the data. While the datasets offer broad coverage, they represent snapshots from a specific timeframe and may not reflect current trends. To mitigate this, external validation and potential updates to the datasets were considered, ensuring the dashboard remains relevant and accurate.

3.2 Data Quality Assurance

To minimize potential biases in the data collection process, several steps were undertaken. First, the datasets were carefully sourced from reputable open platforms like Kaggle, ensuring a broad and diverse representation of cities and countries. This selection aimed to cover various income levels, geographic regions, and living conditions. Any inconsistencies or outliers in the data were identified and removed to prevent skewing the results.

Next, the data was thoroughly cleaned before analysis. Using Python in Jupyter Notebook, any missing or erroneous entries were addressed. This included applying imputation techniques for missing values or discarding rows with significant gaps in the data that could negatively impact the analysis. This step was crucial in ensuring the data used for predictions was as accurate and complete as possible.

To further strengthen the reliability of the data, a validation process was carried out. The collected data was cross-referenced with other reputable sources, including established cost-of-living indexes and existing dashboards, to verify its accuracy. Any discrepancies or inconsistencies between different sources were flagged and reviewed before proceeding with the analysis.

Finally, efforts were made to monitor and minimize any biases related to the data's origin. A diverse range of data points from multiple regions and categories was selected to prevent overrepresentation of specific countries or cities. This approach ensured that the predictions made by the dashboard were not unduly influenced by any one region or dataset, thus improving the fairness and reliability of the cost-of-living comparisons.

3.3 System Requirements

System Requirements refer to the specific conditions and capabilities that must be met for the successful development, deployment, and operation of a system. These requirements act as a blueprint, guiding the design and implementation of the project. System requirements are typically divided into functional and non-functional aspects, which detail the essential features of the system as well as its quality attributes.

Functional requirements define the core functionalities and behaviors of the system. They describe what the system must do to fulfill the intended purpose and meet user expectations. While, non-functional requirements outline the system's quality attributes, such as performance, usability, reliability, and security. These ensure that the system operates efficiently and securely, providing a seamless user experience.

Together, these requirements create a comprehensive framework to ensure the dashboard meets both user needs and project goals. Table 2 and Table 3 below list the functional requirements and non-functional requirements of the project.

Table 2
List of functional requirements

Functional Requirements	Description
Graphs and charts	The dashboard displays data in various graphs and charts for easy comprehension and analysis.
Data filtering	Users can refine their searches with filters, allowing them to sort and focus on specific data subsets or categories.
Interactive visualization	Users can interact with the dashboard by clicking on graphs to gain deeper insights.
Accessibility	The system is easily accessible from any location and at any time.

Table 3
List of non-functional requirements

Functional Requirements	Description
Performance and responsiveness	The dashboard quickly displays results after applying data filters, minimizing wait times.
Platform compatibility	Accessible via web browser, with included visualization and predictive model.
Usability	The system has an intuitive interface for easy interaction with the prediction system and visualization components.

3.4 Storyboard Concept

Designing a storyboard involves creating a detailed visual strategy for how the dashboard will be structured and what data will be presented. By illustrating this through an example, it becomes easier to understand how the scenario will play out in a real-world context. This approach helps users visualize how the dashboard will function and anticipate how they will interact with it. Figure 4 below provides an example of the storyboard, demonstrating the layout and user interaction flow within the dashboard.

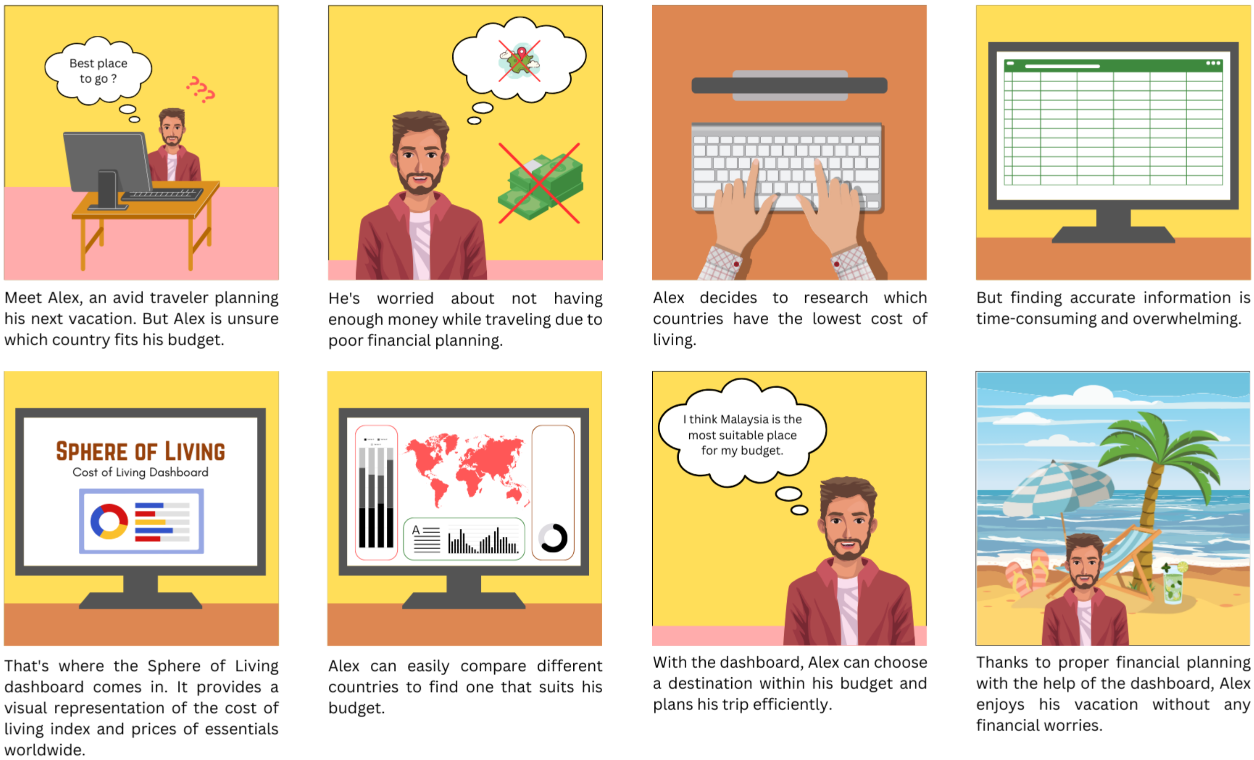

Fig. 4. Storyboard concept

3.5 Flowchart

A flowchart is a visual representation that outlines the sequential steps and decisions within a process. It uses various symbols and arrows to depict the flow of activities and their relationships. This tool is invaluable for visualizing the user journey through different pages of the dashboard, illustrating how users interact with the visualizations and access information related to the global cost of living.

The cost of living data visualization is designed to provide a comprehensive overview of global cost-of-living data, organized across five distinct pages, as shown in Figure 5 below. Each page presents unique insights and functionalities to help users understand and analyze various aspects of living costs worldwide.

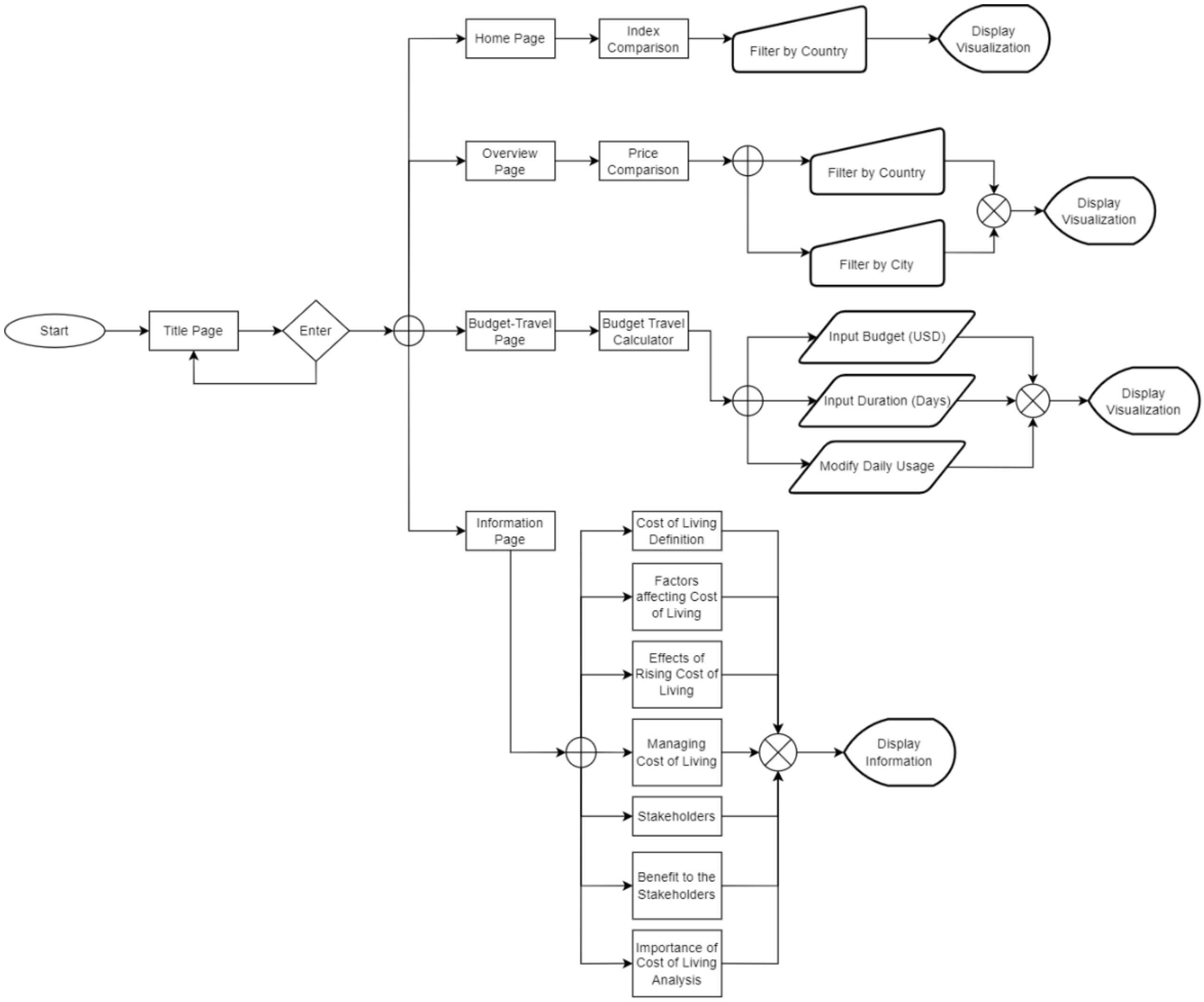

Fig. 5. Flowchart of the cost of living dashboard

The first page of the dashboard is the Title Page, featuring the dashboard title and an "Enter" button that directs users to the Home Page. On the Home Page, users are presented with a detailed visualization of the Cost of Living Index across 131 countries. This includes indices for Rent, Groceries, Restaurant Prices, and Local Purchasing Power, all compared to New York's index value of 100. Users can filter the data by country for more specific comparisons.

The Overview Page provides a comprehensive view of the cost of living in 2,408 cities worldwide. It displays key prices, including meals, drinks, groceries, local transport, fuel, education fees, rent, mortgage rates, and monthly net salaries, all in USD. This page also features a predictive analysis tool that compares current and predicted average monthly net salaries, with filters for city and country to tailor the data.

The Budget-Travel Page helps users find suitable travel destinations based on their budget and stay duration. Users can customize their daily usage preferences for transport, fuel, meals, drinks, and groceries, allowing the dashboard to calculate daily expenses for selected countries and provide a tailored travel cost estimate.

The Information Page educates users on the cost of living. It covers essential topics such as definitions, factors influencing cost, tips for managing living expenses, the effects of rising costs, and the importance of understanding these economic factors. This page aims to deepen users' understanding of the forces that drive living costs.

Together, these five pages provide a well-rounded view of global living costs. They enable users to compare expenses, plan budget-friendly travel, and enhance their understanding of the economic factors influencing the cost of living.

3.6 Data Design

Data design is a crucial aspect of the project, ensuring that data is structured, stored, and accessed efficiently to provide meaningful insights. The first dataset obtained from Kaggle, Cost of Living 2022, contains information about the Cost of Living Index across countries worldwide. This dataset requires transformation and cleaning, as it contains unclean data. Similarly, the second dataset, Global Cost of Living, offers information about various costs and prices in more than 4,500 cities across the world. This dataset also requires cleaning due to the presence of numerous columns containing unnecessary prices and costs for visualization. These columns will be reduced and combined into categories of relevant prices and costs. Additionally, the dataset contains missing values, which need to be addressed.

To accomplish the cleaning task for both datasets, the Python programming language in Anaconda Jupyter Notebook is utilized. The following steps outline the necessary data cleaning procedures.

Figure 6 below shows the necessary tasks for cleaning the datasets. Specific columns are identified for removal to streamline the dataset, eliminating unnecessary prices and costs that are irrelevant for visualizing the cost of living. The columns_to_drop list contains the names of columns to be removed. The command df.drop(columns=columns_to_drop, inplace=True) is used to drop these columns from the DataFrame in place, meaning the changes are directly applied to the df.

```
columns_to_drop = [
    'Unnamed: 0', 'x3', 'x4', 'x5', 'x23', 'x24', 'x25', 'x26', 'x27', 'x29', 'x30', 'x31', 'x32',
    'x34', 'x35', 'x36', 'x37', 'x38', 'x39', 'x40', 'x41', 'x44', 'x45', 'x46',
    'x47', 'x52', 'x53'
]
df.drop(columns=columns_to_drop, inplace=True)
```

Fig. 6. Drop column

Based on Figure 7 below, the code defines a function to calculate the row-wise average of specified columns while ignoring any NaN values. The function def row_mean(df, cols): takes a DataFrame and a list of column names as arguments. The line return df[cols].mean(axis=1, skipna=True).round(2) calculates the mean of the specified columns for each row, skipping NaN values, and rounds the result to two decimal places. New columns are created by averaging the specified columns and handling NaNs appropriately.

For example, df['Average Meals Price in Restaurants (USD)'] = row_mean(df, ['x1', 'x2']) creates a new column by averaging the values in columns x1 and x2, which contain the prices for Meals in Inexpensive Restaurants and Meals in Mid-range Restaurants. Similar commands create new columns for drinks (sum up as average for Cappucino, Coke and Water), groceries (sum up as average for Milk, Bread, Rice, Eggs, Cheese, Chicken Fillets, Beef Round, Tomato, Potato, Onion and Lettuce), fruits (sum up as average for Apples, Banana and Oranges), education fees (preschool and primary school), and apartment rent prices (1 bedroom in city, 1 bedroom outside of city, 3 bedroom in city and 3 bedroom outside of city).

```
# Function to calculate row-wise average ignoring NaN values
def row_mean(df, cols):
    return df[cols].mean(axis=1, skipna=True).round(2)

# Create new columns by averaging specified columns, handling NaNs
df['Average Meals Price in Restaurants (USD)'] = row_mean(df, ['x1', 'x2'])
df['Average Drinks Price in Restaurants (USD)'] = row_mean(df, ['x6', 'x7', 'x8'])
df['Average Groceries Price (USD)'] = row_mean(df, ['x9', 'x10', 'x11', 'x12', 'x13', 'x14', 'x15', 'x19', 'x20', 'x21', 'x22'])
df['Average Fruits Price (USD)'] = row_mean(df, ['x16', 'x17', 'x18'])
df['Average Yearly Education Fees (USD)'] = row_mean(df, ['x42', 'x43'])
df['Average Apartment Rent Price (USD)'] = row_mean(df, ['x48', 'x49', 'x50', 'x51'])

# Drop the old columns that were averaged
columns_to_drop_after_averaging = [
    'x1', 'x2', 'x6', 'x7', 'x8', 'x9', 'x10', 'x11', 'x12', 'x13', 'x14', 'x15',
    'x16', 'x17', 'x18', 'x19', 'x20', 'x21', 'x22', 'x42', 'x43', 'x48', 'x49', 'x50', 'x51'
]
df.drop(columns=columns_to_drop_after_averaging, inplace=True)
```

Fig. 7. Calculate and add new column as average prices

After averaging, the old columns that contributed to the new averages are no longer necessary. The columns_to_drop_after_averaging list specifies these columns. The command df.drop(columns=columns_to_drop_after_averaging, inplace=True) removes these columns from the DataFrame.

Figure 8 below illustrates how the presence of null values is checked and removed. The line null_values = df.isnull().sum() calculates the sum of null values in each column and stores the result in the null_values variable. The print(null_values) statement outputs the count of null values for each column. Any rows containing null values are then removed to ensure completeness. The command df.dropna(inplace=True) removes these rows, applying the changes directly to the DataFrame.

```
null_values = df.isnull().sum()
print(null_values)
```

```
city                                          0
country                                       0
x28                                        1473
x33                                         578
x54                                        1415
x55                                         980
data_quality                                  0
Average Meals Price in Restaurants (USD)    330
Average Drinks Price in Restaurants (USD)   233
Average Groceries Price (USD)               153
Average Fruits Price (USD)                  272
Average Yearly Education Fees (USD)         936
Average Apartment Rent Price (USD)         1074
dtype: int64
```

```
df.dropna(inplace=True)
```

Fig. 8. Check and remove null values

Figure 9 below shows the next step of merging the two datasets on the 'Country' column. The command df_combined = pd.merge(df_1, df_2, on='Country', how='inner') merges the datasets, keeping only the rows with matching 'Country' values. The how='inner' parameter ensures that only the intersection of the two datasets is retained, resulting in a DataFrame df_combined that contains data for countries present in both datasets.

```
# Merge the datasets on the 'Country' column, keeping only rows with matching countries
df_combined = pd.merge(df_1, df_2, on='Country', how='inner')
df_combined
```

Fig. 9. Merging dataset with matching 'Country' column

3.7 Predictive Analysis

Figure 10 below illustrates the predictive analysis process, which was developed using RapidMiner and Python to predict the 'Average Monthly Net Salary' based on the 'Rent Index.' The cleaned and merged dataset is loaded into RapidMiner's Auto Model feature, which automatically identifies the best prediction models and suitable predictors. The task is set to predict the "Average Monthly Net Salary," with predictors selected based on their relevance to the model. The "Percentage Difference" columns are excluded from the analysis, as they only represent index variations and do not contribute to the prediction.

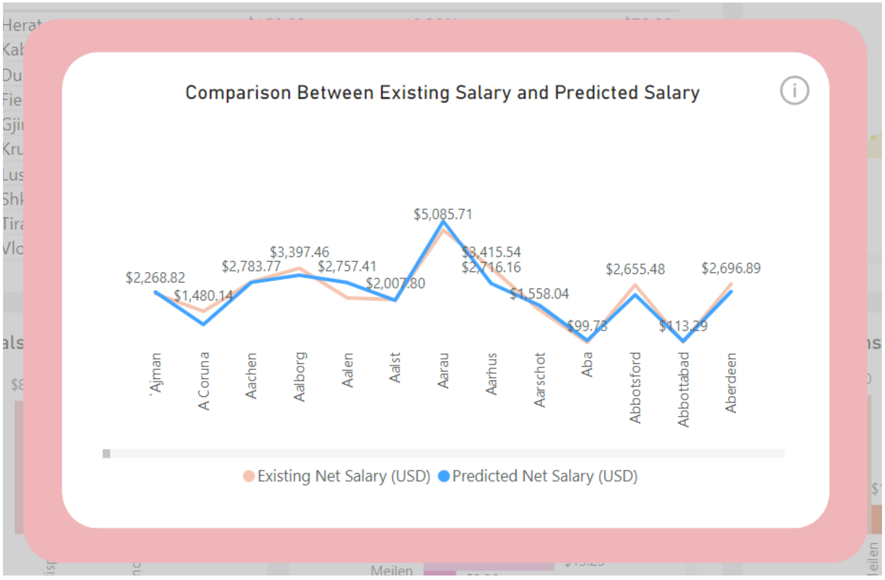

Fig. 10. Predictive analysis of average net salary

The Auto Model feature in RapidMiner identifies the Random Forest model as the most suitable for this analysis due to its low Root Mean Squared Error (RMSE) of 639.56. The Rent Index attribute, with a strong correlation of 0.871 to the target variable, is determined to be the most important predictor. This high correlation signifies a robust positive relationship between rent costs and salary, making it the optimal variable for prediction.

Following this, Python is used to implement the Random Forest model in Jupyter Notebook. The necessary libraries, including Pandas for data manipulation, scikit-learn for machine learning functions, and Matplotlib for visualization, are imported. The dataset is loaded into a Pandas DataFrame, and missing values are checked to ensure data completeness. Since the dataset includes categorical data, specifically the "City" column, it is encoded using LabelEncoder to ensure that the model can handle these labels numerically.

The features and target variable are then defined. The "Rent Index" and the encoded "City" data are used as independent variables (features), while the "Average Monthly Net Salary" serves as the dependent variable (target). The dataset is split into training and testing sets, with 80% of the data used for training and 20% for testing the model's performance. The Random Forest model is trained using 100 decision trees, which make predictions based on different subsets of the data.

Random Forest is an ensemble learning method that combines multiple decision trees to enhance prediction accuracy. Each tree is trained on a random subset of the data, and the final prediction is made by averaging the results from all the trees. This approach reduces overfitting, making the model more robust and reliable. After training, the model's performance is evaluated using the Mean

Squared Error (MSE) metric, which quantifies the difference between predicted and actual values. A lower MSE indicates better model performance.

Once the model's performance is evaluated, predictions for the entire dataset are generated. The predicted salary values are added to the dataset, which is then exported for use in the dashboard. The predicted net salary data is loaded into the dashboard, and a relationship is established with the existing dataset through the "City" column. Finally, a comparison between the actual and predicted salary data is visualized using a line chart, providing an interactive way for users to explore the predicted net salaries alongside the actual values.

This machine learning process not only predicts the Average Monthly Net Salary but also emphasizes the significant role of the "Rent Index" in influencing salary expectations. The use of Random Forest ensures a reliable and accurate prediction, which can be applied across different cities to help users make informed decisions regarding cost of living and salary expectations.

3.8 Dashboard Development

The dashboard is developed using Microsoft Power BI and serves as an innovative tool for analyzing and comparing cost-of-living data worldwide. This section highlights the dashboard's functionality, emphasizing its alignment with the research objectives of promoting financial literacy and enabling informed decision-making. Unlike traditional static reports, the dashboard incorporates interactive visualizations and predictive insights, enhancing user engagement and providing a dynamic data-driven experience.

The dashboard is designed with user interaction in mind, guiding users through an intuitive exploration of global cost-of-living data across five main pages: Title Page, Home Page, Overview Page, Budget-Travel Page, and Information Page.

Figure 11 below illustrates the Title Page of the dashboard, which introduces the system name, "Sphere of Living". The page is visually enriched with a description of the system, accompanied by a background image depicting countries worldwide. A navigation arrow button directs users to the next page, marking the beginning of their journey through comprehensive cost-of-living analysis. This design reflects the research objective of providing a user-friendly interface that invites users to explore various dimensions of global cost-of-living data.

Fig. 11. Title page

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The Home Page, as shown in Figure 12, offers an overview of cost-of-living indexes across different countries. This page is designed to facilitate a comparative analysis of key cost-of-living metrics globally, providing users with a clear understanding of how various countries rank in terms of their living costs. The page's features address the research goal of enabling users to make informed decisions by comparing geographic and economic contexts. It allows users to explore a variety of indices, such as Rent, Groceries, Restaurant Prices, and Local Purchasing Power, with all comparisons made against New York's index value of 100. Through interactive filters, users can easily focus on specific countries or regions, enhancing the analytical experience.

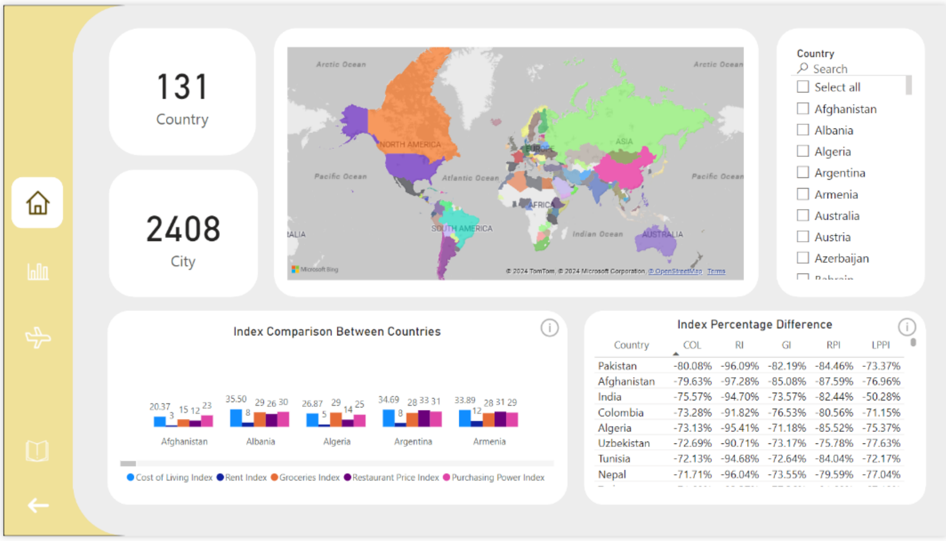

Fig. 12. Home page

The description for the components available on this page is further explained in Table 4 below.

Table 4
Table of descriptions for home page

Component	Description
Text Visualization	Displays the total number of countries and cities included, contextualizing the dataset's scope.
Filled Map	Visualizes the geographical distribution of the cost-of-living index, helping users identify regional trends.
Filter Option	Allows users to compare multiple countries by selecting from the available filters, ensuring personalized analysis.
Clustered Column Chart	Enables side-by-side comparison of indexes, aiding decision-making through visual insights.
Table View for Index Percentage Difference	Provides cost-of-living comparisons relative to New York, offering clarity on economic differences.

The page aligns with existing studies that emphasize the importance of data-driven comparisons in understanding global cost-of-living variations. It facilitates a broader comprehension of geographic and economic contexts, empowering users to analyze and compare cost-of-living indices worldwide effectively.

The Overview Page, depicted in Figure 13, provides a detailed breakdown of specific cost categories, such as meals, drinks, groceries, education fees, transport, and rent. This page delves into granular data, offering insights into everyday expenses across 2,408 cities worldwide. Its design prioritizes user interactivity, enabling users to filter and explore cost variations by city and country. This fosters a nuanced understanding of the diverse factors that influence living costs, supporting informed decision-making. The inclusion of predictive analysis tools further enhances this page by allowing users to compare current and forecasted salary data, adding a forward-looking perspective to the analysis.

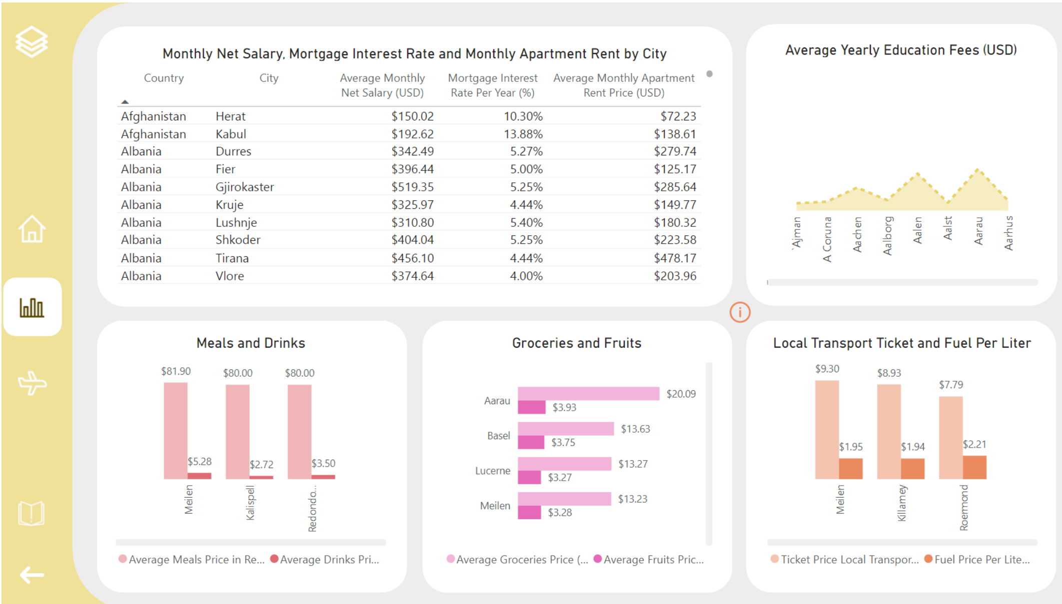

Fig. 13. Overview page

The description for the components available on this page is further explained in Table 5 below.

Table 5
Table of descriptions for overview page

Component	Description
Pop-Up Filter Option (Figure 14)	Accessible by clicking the button at the top left corner. Allows users to personalize data views by filtering countries and cities.
Table View	Displays detailed comparisons of average net salaries, rent prices, and mortgage interest rates by location.
Pop-Up Predictive Analysis Visualization (Figure 15)	Introduces predictive capabilities by comparing estimated net salaries to existing values, showcasing how the dashboard extends beyond static reports.
Area Chart	Displays average yearly education fees in USD. Helps users compare cities or countries with the lowest or highest yearly education fees.
Clustered Column Chart (Meals & Drinks)	Displays average meal prices in inexpensive and mid-range restaurants, and average drink prices (cappuccino, coke, and water) in USD. Helps users compare cities and countries with the lowest meal and drink prices.
Clustered Column Chart (Transport & Fuel)	Displays average local transport ticket prices and fuel prices per liter in USD. Helps users compare cities and countries with the lowest prices for local transport tickets and fuel.
Clustered Bar Chart (Groceries & Fruits)	Displays average grocery prices (milk, bread, rice, eggs, cheese, chicken fillets, beef round, tomato, potato, onion, lettuce) and average fruit prices (apples, banana, oranges) in USD. Helps users compare cities and countries with the lowest prices for groceries and fruits.

The integration of predictive analysis enhances the dashboard's innovation, filling gaps in previous cost-of-living studies that lacked such forward-looking insights.

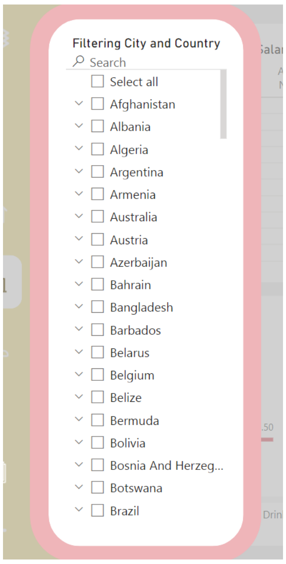

Fig. 14. Pop-up filter option

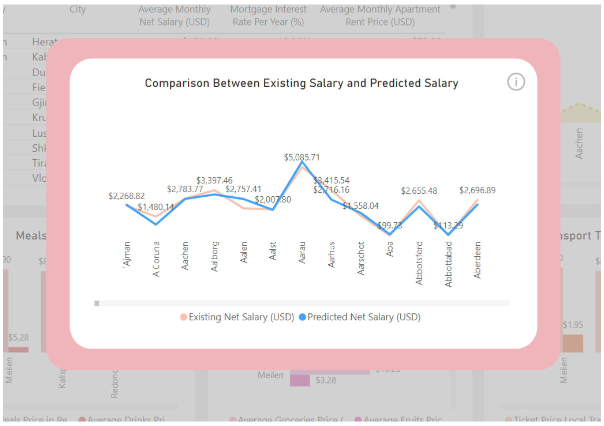

Fig. 15. Pop-up predictive analysis visualization

The Budget-Travel Page, illustrated in Figure 16, directly supports the research objective of aiding financial decision-making. It allows users to input their budget and travel duration to identify affordable destinations tailored to their preferences. Users can customize daily expenditure estimates for transport, fuel, meals, drinks, and groceries, enabling a comprehensive calculation of daily expenses. This interactive feature provides personalized recommendations for travel destinations, empowering users to plan budget-friendly trips efficiently. By offering this functionality, the page bridges the gap between financial planning and cost-of-living data, making it a valuable tool for practical decision-making.

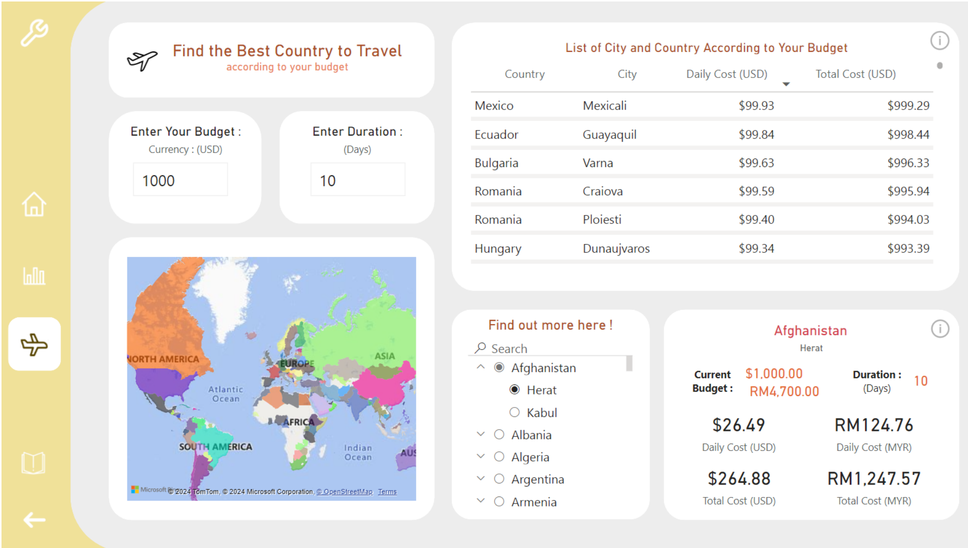

Fig. 16. Budget-travel page

The description for the components available on this page is further explained in Table 6 below.

Table 6
Table of descriptions for budget-travel page

Component	Description
Pop-Up Modifiers (Figure 17)	Accessible by clicking the button at the top left corner. Personalizes daily cost calculations by incorporating variables such as transport usage, meal consumption, and grocery expenses.
Budget and Duration Input	Allows users to determine which countries and cities fit their budget, calculated dynamically based on user inputs.
Table View	Lists affordable destinations, providing comparative cost breakdowns.
Location Display	Visualizes selected destinations on a map for geographic context.
"Find out more" Visualization	Enables users to explore unlisted destinations, supporting financial planning and highlighting unique features of each location.

This page demonstrates the dashboard's ability to simplify travel cost planning by providing tailored recommendations based on user inputs. It addresses a gap in existing tools, which often overlook personalized financial insights, by integrating cost-of-living data with user preferences. This functionality enhances the user experience, making travel planning more efficient and informed, while aligning with the objective of empowering users with actionable financial information.

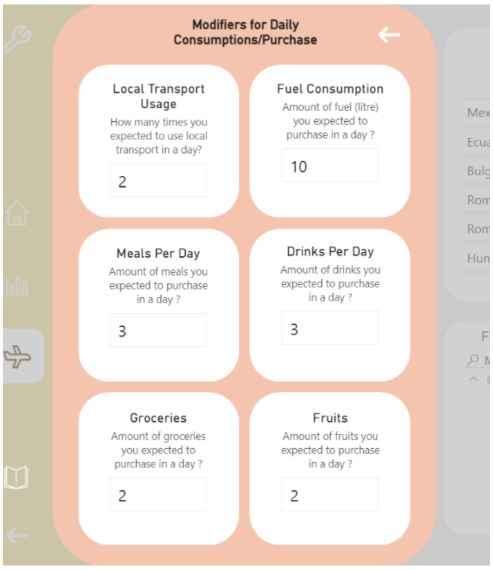

Fig. 17. Pop-up modifiers

The Information Page serves as an educational resource, offering valuable insights into cost-of-living issues and their broader implications. As illustrated in Figures 18 and 19, the page addresses key topics such as contributing factors, management strategies, and societal impacts. Additionally, it highlights the roles of stakeholders, the benefits of understanding living costs, and the significance of analyzing these metrics.

By integrating comprehensive contextual information, this page supports the research objective of fostering financial literacy. It ensures that users are equipped with the knowledge to interpret and utilize actionable data effectively, enhancing the dashboard's value as both an analytical and educational tool.

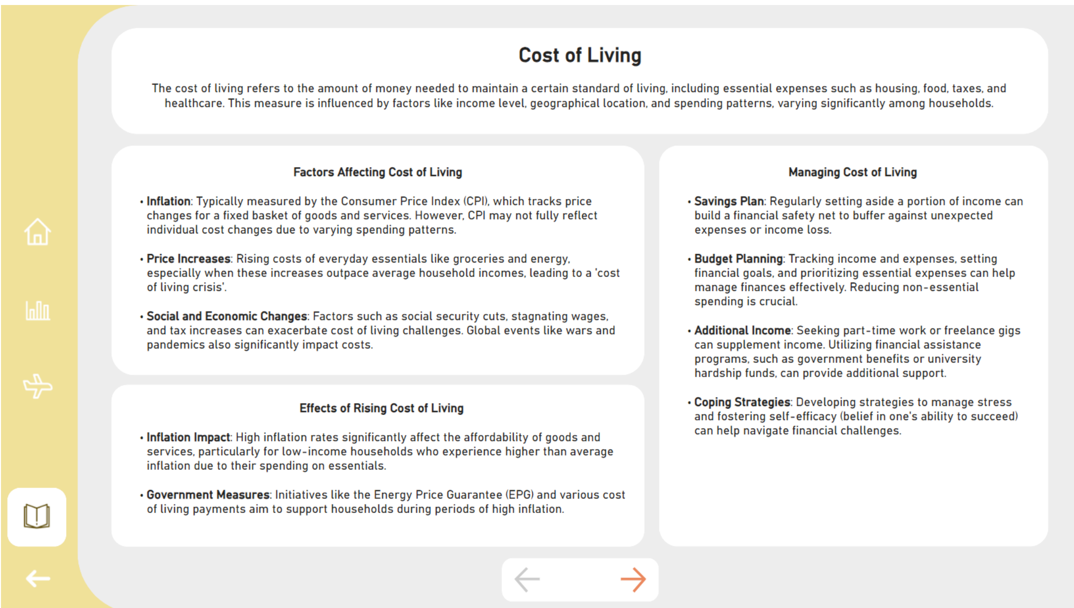

Fig. 18. First information page

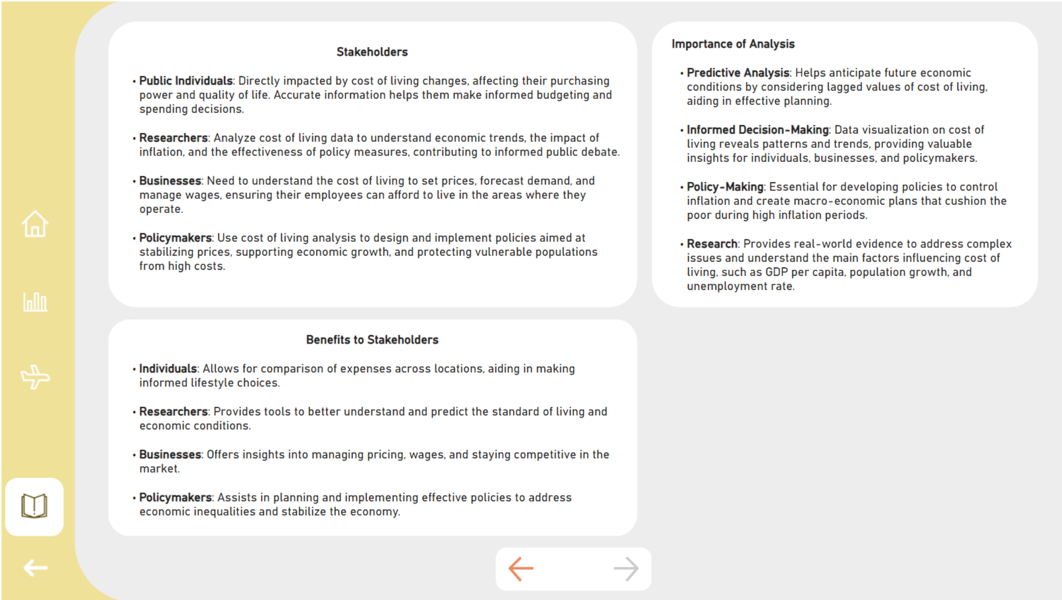

Fig. 19. Second information page

3.9 System Testing

The system testing phase was crucial in assessing the usability and functionality of the dashboard, ensuring it meets the research objectives of promoting financial literacy and enabling informed decision-making. Feedback was collected through a structured survey conducted via Google Form, where participants completed the System Usability Scale (SUS) questionnaire, as detailed in Table 7. This questionnaire includes 10 statements rated on a 5-point Likert scale, measuring user agreement or disagreement.

Table 7
SUS questions

No.	Question
1.	I think that I would like to use this dashboard frequently.
2.	I found the dashboard unnecessarily complex.
3.	I thought the dashboard was easy to use.
4.	I think that I would need the support of a technical person to be able to use this dashboard.
5.	I found various functions in this dashboard were well integrated.
6.	I thought there was too much inconsistency in this dashboard.
7.	I would imagine that most people would learn to use this dashboard very quickly.
8.	I found the dashboard very cumbersome to use.
9.	I felt very confident using the dashboard.
10.	I needed to learn a lot of things before I could get going with this system.

The survey garnered 12 responses, which provided valuable insights into user experiences. The calculated average SUS score, illustrated in Figure 20, was 88.96, categorizing the system as "Excellent" based on the SUS adjective rating scale shown in Table 8. This high score reflects the system's exceptional usability, indicating that users found the dashboard to be highly intuitive, responsive, and aligned with their needs for analyzing cost-of-living data.

Task	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
1	5	5	4	5	5	4	5	5	5	5	5	5
2	1	2	1	2	1	2	2	2	2	1	1	2
3	5	4	4	5	5	5	5	5	4	5	5	5
4	1	3	1	5	1	2	3	5	3	1	1	3
5	5	5	5	4	5	4	5	4	5	5	5	5
6	1	1	2	1	1	2	1	1	1	1	1	1
7	5	5	4	4	5	3	5	4	5	5	5	4
8	1	1	1	2	1	1	1	2	1	1	1	1
9	5	4	4	5	5	4	5	5	4	5	5	5
10	2	1	1	3	1	2	2	3	1	1	1	1
X = (Sum of Odd) - 5	**20**	**18**	**16**	**18**	**20**	**15**	**20**	**18**	**18**	**20**	**20**	**19**
Y = 25 - (Sum of Even)	**19**	**17**	**19**	**12**	**20**	**16**	**16**	**12**	**17**	**20**	**20**	**17**
SUS Score [(X + Y) * 2.5]	**97.5**	**87.5**	**87.5**	**75**	**100**	**77.5**	**90**	**75**	**87.5**	**100**	**100**	**90**

**Note: R in column title stands for respondent*

Average SUS Score (SUS Score/Number of Respondents)	**88.95833333**

Fig. 20. SUS calculation

Table 8
SUS score scale adjective rating [15]

SUS Score	Grade	Adjective Rating
> 80.3	A	Excellent
68 – 80.3	B	Good
68	C	Okay
51 – 68	D	Poor
< 51	E	Awful

The testing results confirm the dashboard's success in achieving its goals. Its interactive features and intuitive design allow users to perform tasks such as comparing indexes, predicting financial metrics, and identifying budget-friendly travel destinations. These functionalities empower users to make data-driven decisions, directly supporting the study's objectives.

The testing outcomes also highlight the system's superiority over traditional static cost-of-living tools, which often lack interactivity and user engagement. The dashboard's innovative design and predictive analysis capabilities set it apart, as evidenced by the "Excellent" SUS rating. This distinction underscores the system's contributions to advancing interactive visual analytics, offering users a functional and enjoyable platform for exploring cost-of-living data.

Overall, the system testing validates the dashboard's effectiveness as an analytical tool, affirming its potential to foster financial literacy and facilitate informed decision-making. By exceeding expectations, the dashboard establishes itself as a significant contribution to the domain of cost-of-living analytics.

4. Conclusion

This project successfully tackled the complex challenge of understanding global cost-of-living disparities and their far-reaching implications for individuals, businesses, and policymakers. The primary objective was to create an intuitive, interactive data visualization tool that simplifies the intricacies of cost-of-living data while providing actionable insights. The resulting dashboard facilitates comparative analysis across 131 countries and 2,408 cities, achieving the transformation of raw data into a user-centric resource. Key metrics, including rent, groceries, restaurant prices, and purchasing power, are effectively visualized, empowering users to make data-driven decisions.

The dashboard incorporates innovative features, such as predictive analysis tools, which enhance its utility by enabling users to compare current salaries with future projections based on cost-of-living indices. These features align with contemporary trends in cost-of-living analysis and address the limitations of traditional static methods by introducing interactivity and dynamic exploration. The project demonstrates that effective data visualization can promote financial literacy and support informed decision-making, meeting its core objectives of empowering diverse stakeholders.

Key findings reveal significant regional disparities in living costs, influenced by factors such as inflation, wage inequality, and economic policies. The project's broader implications extend to various stakeholders: individuals can leverage the tool for financial planning and relocation, businesses can utilize it for strategic decisions regarding market expansion and workforce planning, and policymakers can evaluate the impact of economic policies on purchasing power. These outcomes underscore the dashboard's potential as a tool for fostering equitable economic understanding and promoting informed decision-making.

System testing validated the dashboard's functionality and usability, with a high System Usability Scale (SUS) score of 88.96, placing it in the "Excellent" category. This strong performance confirms the dashboard's ability to meet both its technical and functional goals, delivering an accessible and effective tool for analyzing cost-of-living data. However, some limitations were identified. The lack of mobile optimization reduces accessibility for users on smaller devices, and the absence of temporal data restricts its capability to analyze trends or provide long-term forecasts. Additionally, reliance on 2022 data limits its relevance to current economic shifts.

To further enhance the dashboard's significance and utility, future improvements should focus on mobile optimization, the integration of historical data for trend analysis, and the implementation of automated systems for real-time data updates. These enhancements would ensure the dashboard remains relevant and indispensable in an evolving economic landscape.

In conclusion, this project successfully achieved its goal of developing a comprehensive and impactful data visualization tool to analyze global cost-of-living disparities. By addressing its limitations and implementing the proposed enhancements, the dashboard has the potential to become an even more valuable resource for individuals, businesses, and policymakers navigating financial challenges and striving for equitable economic outcomes.

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