JOURNAL OF MULTIDISCIPLINARY RESEARCH

VOLUME 4 ISSUE 2, JULY – DECEMBER, 2024

FACULTY OF POSTGRADUATE STUDIES

& PROFESSIONAL ADVANCEMENT

NSBM GREEN UNIVERSITY, SRI LANKA

JOURNAL OF MULTIDISCIPLINARY RESEARCH

VOLUME 4 | ISSUE 2 | JULY – DECEMBER, 2024

ISSN: ISSN 2815-0023

FACULTY OF POSTGRADUATE STUDIES & PROFESSIONAL ADVANCEMENT

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EDITORIAL

The Journal of Multidisciplinary Research (JMR) is an attempt to promote research excellence through collaborations and incorporation of multi discipline. In this issue of the forth volume ten articles have been selected for publication related to management, computing, science, and engineering.

In this second issue of the forth volume, the first article which is based on graph theory discusses proper lucky labeling of a generalized centerless wheel graph. The second article is a proof of concept for fashion industry addresses limitations of existing fashion recommendation systems. The third article is a discussion the industry 4.0 readiness on AI usage in Sri Lanka in accounting professionals' perspective. The next article is also focuses on management discipline and finds the impact on smart tourism technologies on destination loyalty with related to generation z travelers. The next article is suggesting a surveillance model for national security in Sri Lanka. The following article analyzes movie review using machine learning and the authors have used a naive Bayes approach. The last article in the issue is discusses global financial patterns from 1989 to 2021 and according to authors their study sheds light on the interplay between financial development trajectories and major regional or global shocks.

Dr. Rasika Ranaweera (Editor-in-Chief)

Journal of Multidisciplinary Research (ISSN 2815-0023)

ARTICLES IN THIS ISSUE

PROPER LUCKY LABELING FOR CENTERLESS DOUBLE WHEEL GRAPH AND CENTERLESS CONCENTRIC WHEEL GRAPH

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Abstract

Proper lucky labeling is a concept in graph theory. The labeling is said to be proper lucky labeling of the graph if the vertices of the graph are labeled by natural numbers that satisfy the condition that the labeling of adjacent vertices and the sum of the labeling of adjacent vertices are not equal. The least natural number that labels the graph is called the proper lucky number and is denoted by $\eta_p(G)$. This research aims to determine the proper lucky labeling of a generalized centerless wheel graph. For that, we consider n number of vertices and m number of concentric centerless wheels. Additionally, we examine a unique kind of centerless double-wheel graph in this work. When n is even, both graphs yield the proper lucky number of 2, and when it is not, the proper lucky number is 3. Also, we prove that centerless concentric wheel graph for infinite graph for even vertices in the cycle.

Keywords: Proper Lucky Labeling, Proper Lucky Number, Centerless Wheel Graph

1. Introduction

Graph labeling has many different ways to be used in the area of graph theory. There is an important connection between the number and the graph structure (Rosa 1967). A graph's edge, vertex, or both can have a number marked on them with a specific condition using the labeling function. Gallian presented a lively overview of graph labeling. Proper labeling is the method of graph labeling, which is to assign adjacent vertices alternative natural numbers (Karonski 2004). Lucky labeling for 3 colorable graphs was introduced and it compared with proper vertex coloring (Ahadi 2012 and Akbari 2013). The graph that fulfills the proper lucky labeling conditions is called the proper lucky graph, and it has a very close association with graph coloring. Mathematicians have studied proper lucky labeling on a variety of graphs like mesh graphs, duplicated triangular snake graphs, and quadrilateral snake graphs (Kings Yenoke and Antony Xavier 2017, P. Indira and B. Selvam 2020, T. V. Sateesh Kumar and S. Meenakshi 2021). In this research, we are introducing a general formula for vertex labeling in such a way that the whole labeling remains proper lucky labeling for a centerless double wheel graph (CDW_{2n}) and centerless concentric wheel graph (CDW_{mn}) and we prove that the proper lucky number is 2 where n is even and the proper lucky number of odd vertices in the cycle is 3.

1.1 Definition 1: (Proper lucky labeling)

Let $f: \mathrm{U}(G) \rightarrow \mathbb{N}$ be a function. If u and v are adjacent vertices in G such that $f(u) \neq f(v)$ and $S(u) \neq S(v)$ where S is the sum of the labeling of adjacent vertices, then f is called a proper lucky labeling graph. The least natural number labeled on the graph is the proper lucky number and is denoted by $\eta_p(G)$.

1.2 Definition 2: (Centerless concentric wheel graph)

Centerless concentric Wheel graph (CDW_{mn}) is the cartesian product of C_n and K_2, where $C_n$be cyclic graph with n vertices & m wheels and K_2 be a complete graph.

1.3 Definition 3: (Minimum degree (δ))

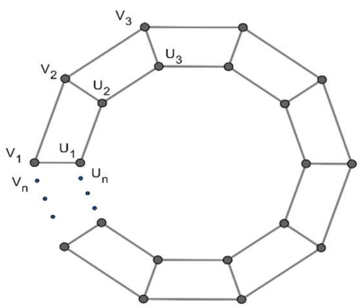
The minimum degree of a graph denoted by, is the degree of the vertex with the least number of edges incident to it.

2. Methodology

2.1 Theorem 01

Let G be a centerless double-wheel graph. If n is even, then the proper lucky number of G is 2 ($\eta_p(G) = 2$); otherwise, $\eta_p(G) = 3$.

Figure 1: CDW_{2n}



Proof

Let $u_1, u_2, \ldots, u_n$ be the vertex of the middle wheel and $v_1, v_2, \ldots, v_n$ be the vertices of the outside wheel, where n is a finite positive integer.

Case 1 (n is even)

Define a map $f: U(G) \to \{1,2\}$ a follow. Let $u_i \epsilon\, U \in$ & $v_i \epsilon\, U$ where $i = 1,2, \ldots, n$, then the vertex u_i is mapped to 1 or 2. If u_i is mapped to 1, its adjacent vertices are mapped to 2, and vice versa.

$$f(u_i) = f(v_{i+1}) = \begin{cases} 1; & i \text{ is odd} \\ 2; & i \text{ is even} \end{cases}$$

Now consider the sum of adjacent vertices,

$$S(u_i) = f(u_{i-1}) + f(u_{i+1}) + f(v_i) = 3f(v_i)$$

$$S(v_i) = f(v_{i-1}) + f(v_{i+1}) + f(u_i) = 3f(u_i)$$

$$S(u_i, v_i) = \begin{cases} 6, & \text{if } f(u_i),\ f(v_i) = 1. \\ 3, & \text{otherwise.} \end{cases}$$

Case 2 (n is odd)

Define a map $f: U(G) \longrightarrow \{1,2,3\}$. Let u_i , $v_i \epsilon\, U$ where i is a finite positive integer.

$f(u_2), f(u_4), \ldots, f(u_{2i}) = f(v_1) = 1$

$f(u_3), f(u_5), \ldots, f(u_{2i-1})$

$= f(v_2), f(v_4), \ldots, f(v_{2i}) = 2$

$f(u_1) = f(v_3), f(v_5), \ldots, f(v_{2i-1}) = 3$

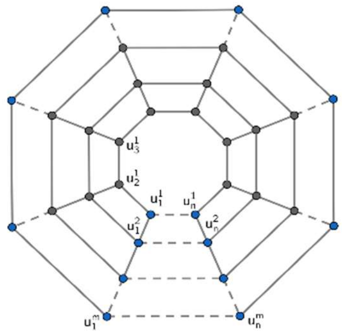
Now consider the sum of adjacent vertices,

$$S(u_i) = \begin{cases} 4, & \text{if } i = 1 \\ 5, & \text{if } i \text{ is odd} \\ 6, & \text{if } i \text{ is even} \\ 7, & \text{if } i = 2, n \end{cases} \qquad S(v_i) = \begin{cases} 5, & \text{if } i = 2, n \\ 6, & \text{if } i \text{ is odd} \\ 7, & \text{if } i \text{ is even} \\ 8, & \text{if } i = 1 \end{cases}$$

2.2 Theorem 02

A centerless concentric wheel graph is proper lucky with $\eta_p(G) = 2$ where n is even; otherwise, $\eta_p(G) = 3$.

Figure 2: CDW_{mn}



Proof

Case 1 (n is even)

Define a map $f: U(G) \to \{1,2\}$ a follow. Let $u_i^k \epsilon\, U$, where $i = 1,2, \dots, n$ and $k = 1,2, \dots, m$, then the vertex u_i^k is mapped to 1 or 2. If u_i^k is mapped to 1, its adjacent vertices are mapped to 2, and vice versa.

$$f(u_i^k) = \begin{cases} 1; \text{both } i \,\&\, k \text{ are odd or even} \\ 2; \text{otherwise} \end{cases}$$

Now consider the sum of adjacent vertices,

For $k = 1$ and $k = m$

$S(u_i^1) = 3f(u_{i+1}^k)$

$$S(u_i^k) = \begin{cases} 3; f(u_i^k) = 2 \\ 6; f(u_i^k) = 1 \end{cases}$$

For $1 < k < m$

$S(u_i^k) = 4f(u_{i+1}^k)$

$$S(u_i^k) = \begin{cases} 4; f(u_i^k) = 2 \\ \\ 8; f(u_i^k) = 1 \end{cases}$$

Case 2 (n is odd)

Define a map $f: U(G) \longrightarrow \{1,2,3\}$. Let $u_i^k \epsilon\, U$ where $i = 1,2,\dots,n$ and $k = 1,2,\dots,m$ (number of concentric wheels).

$$f(u_n^k) = f(u_{2i}^{2k}) = f(u_{2i-1}^{3k}) = 3$$
$$f(u_{2i}^k) = f(u_{2i-1}^{2k}) = f(u_n^{3k}) = 2$$
$$f(u_{2i-1}^k) = f(u_n^{2k}) = f(u_{2i}^{3k}) = 1$$

Now consider the sum of adjacent vertices,

For $m = 1$

$$S(v_i) = \begin{cases} 7, \text{ if } i = 1, n-1 \\ 5, \text{ if } i \text{ is even} \\ \\ 6, \text{ if } i \text{ is odd} \\ 4, \text{ if } i = n \end{cases}$$

For $m = 3k - 1$

$$S(u_n^{3k-1}) = \begin{cases} 8, \text{ if } i = 1 \\ 7, \text{ if } i \text{ is even} \\ \\ 10, \text{ if } i \text{ is odd and } i = n \\ 5, \text{ if } i = n-1 \end{cases}$$

For $m = 3k$

$$S(u_n^{3k}) = \begin{cases} 6, \text{ if } i = 1 \\ 11, \text{ if } i \text{ is even} \\ 5, \text{ if } i \text{ is odd} \\ 10, \text{ if } i = n-1 \\ 5, \text{ if } i = n \end{cases}$$

For $m = 3k$+1

$$S(u_n^{3k+1}) = \begin{cases} 10, \text{ if } i = 1 \\ 6, \text{ if } i \text{ is even and } i = n \\ \\ 9, \text{ if } i \text{ is odd} \\ 8, \text{ if } i = n - 1 \end{cases}$$

3. Results and Discussion

3.1 Theorem 01

Figure 3: CDW_{2n} with $n = 6$

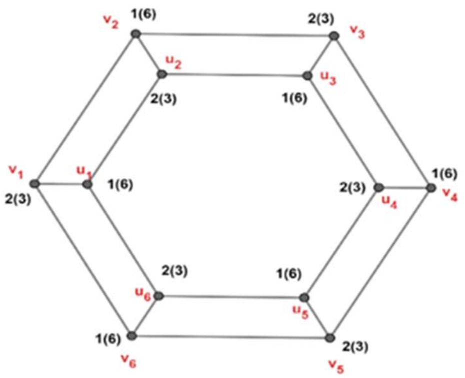
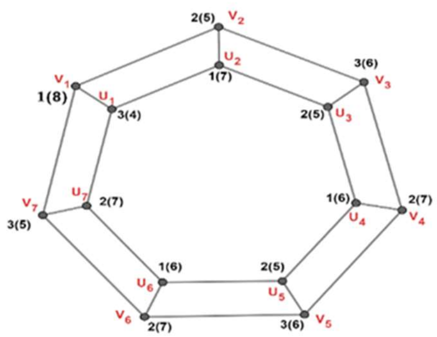


Figure 4: CDW_{2n} with $n = 7$



For Case 01:

Clearly, $f(u) \neq f(v)$ and $S(u) \neq S(v)$ for all $(u, v) \epsilon E(G)$. Therefore, the graph satisfies the conditions of the proper lucky labeling. i.e., the proper lucky number is 2 ($\eta_p(G) = 2$).

For Case 02:

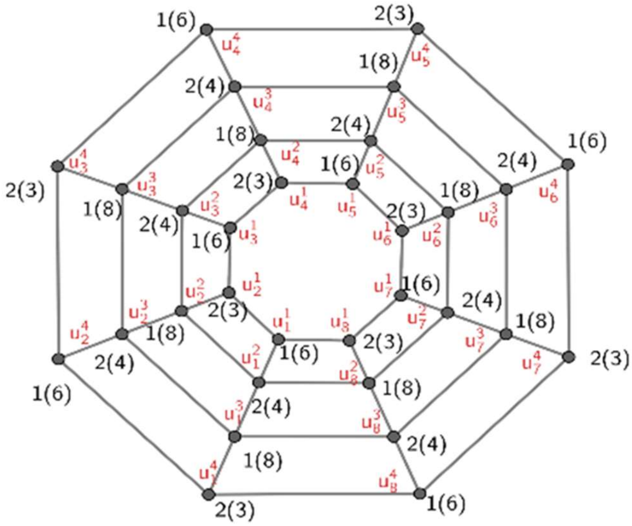
Clearly, $f(u) \neq f(v)$ and $S(u) \neq S(v)$ for all $(u, v) \epsilon E(G)$. Therefore, the graph satisfies the conditions of the proper lucky labeling. i.e., the proper lucky number is 3 ($\eta_p(G) = 3$).

3.2 Theorem 02

For Case 01:

These general formulas are valid for the infinite number of vertices and wheels where the number of vertices is even.

Figure 5: CDW_{mn} with $n = 8$ & $m = 4$



$$f(u_i^k) = \begin{cases} 1; \text{both } i \,\&\, k \text{ are odd or even} \\ 2; \text{otherwise} \end{cases}$$

$$S(u_i^1) = 3f(u_{i+1}^k);\ k = 1$$

$$S(u_i^k) = 4f(u_{i+1}^k);\ k > 1$$

Proof

Prove by Mathematical Induction.

Base case

For $k = 1$,

$$f(u_i^1) = \begin{cases} 1; \text{both } i \,\&\, 1 \text{ are odd or even} \\ 2; \text{otherwise} \end{cases}$$

For example, if i is even then $f(u_i^1) = 2$

Now consider $S(u_i^1) = 3f(u_{i+1}^1)$

If i is odd then $i + 1$is even.

Since $f(u_{i+1}^1) = 2;\ S(u_i^1) = 3 * 2 = 6$

If i is even then $i + 1$is odd.

Since $f(u_{i+1}^1) = 1;\ S(u_{i+1}^1) = 3 * 1 = 3$

Thus, $k = 1$ is valid.

For $k = 2$,

$$f(u_i^2) = \begin{cases} 1; \text{both } i \ \& \ 2 \text{ are odd or even} \\ 2; \text{otherwise} \end{cases}$$

Since 2 is even, $f(u_i^2)$ will be 1 if i is even and 2 if it is odd.

Now consider, $S(u_i^2) = 4f(u_{i+1}^2)$

If i is even, $f(u_{i+1}^2) = 2; S(u_i^2) = 4 * 2 = 8$

If i is odd; $f(u_{i+1}^2) = 1;\ S(u_i^2) = 4 * 1 = 4$

Thus, the statement is true for $k = 2$.

Induction step

Assume that the statement is true for $k = p$ Assume $S(u_i^p) = 4f(u_{i+1}^p)$ where $p \in \mathbb{N}$

and p is an odd number

Now we want to prove that

$S(u_i^{p+1}) = 4f(u_{i+1}^{p+1})$ for $p \in \mathbb{N}$

For $k = n + 1$

If $k = n + 1$, then $S(u_i^{p+1})$ should follow the given pattern $S(u_i^{p+1}) = 4f(u_{i+1}^{p+1})$

When $i + 1$ and $n + 1$ are both odd or both even, then $f(u_i^{p+1}) = 1$ and $f(u_{i+1}^{p+1}) = 2$.

So, $S(u_i^{p+1}) = 4 * 2 = 8$

When $i + 1$ and $n + 1$ are not both odd or both even, then $f(u_i^{p+1}) = 2$ and $f(u_{i+1}^{p+1}) = 1$.

So, $S(u_i^{p+1}) = 4 * 1 = 4$

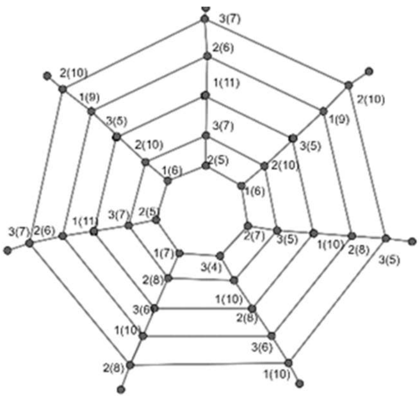
Thus, $S(u_i^{p+1}) = 4f(u_{i+1}^{p+1})$ holds as long as $k = n + 1$

We verified the base case for $k = 1,\ k = 2$, and assuming if $k = n,$ it is also true that If $k = n + 1$.

By mathematical induction, the formula $S(u_i^k) = 4f(u_{i+1}^k)$ is true for all $k \geq 2$.

For Case 02:

Figure 6: CDW_{mn} with $n = 7$ & $m = 5$



Here both cases satisfied proper lucky labeling conditions. So, the proper lucky number for case 1 is 2 and the other case we get the proper lucky number is 3.

4. Conclusion

In this paper, we compute the proper lucky number of the centerless double wheel graph and centerless concentric wheel graph for odd and even numbers of vertices in one wheel. The proper lucky number of even vertices is 2, and the proper lucky number of odd vertices is 3. Also, we prove that centerless concentric wheel graph with even vertices is true for an infinite graph. Additionally, for both the centerless double wheel graph and centerless concentric wheel graph, the proper lucky number is equal to $\delta(CDW_{2n}) - 1$ for even n and $\delta(CDW_{2n})$ for odd n where δ is the minimum degree of a graph.

In the present study, the rainbow connection number of symmetric and non-symmetric of the higher order extension of Sandat graph was established. In both symmetric and non-symmetric higher order extension of Sandat graph is three only when the number of petals greater than or equal to 2. Moreover, the rainbow connection number of the above graph has discussed when the number of petals equal to 1. A new algorithm has introduced which can use to have the rainbow coloring of the above graph.

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REVOLUTIONIZING FASHION WITH AI: THE DEVELOPMENT AND IMPACT OF THE 'WEAR ME' APPLICATION

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Abstract

The fashion industry is undergoing a significant transformation fueled by advancements in artificial intelligence (AI) and machine learning (ML), highlighting an increasing need for personalized fashion recommendations. This paper introduces the "Wear Me" application, designed to provide customized clothing suggestions tailored to individual attributes such as body type and skin tone. Leveraging advanced computer vision and deep learning algorithms, "Wear Me" analyzes user-uploaded images to deliver real-time outfit recommendations that enhance personal appearance and align with the user's unique identity. The application is structured around a robust three-tier architecture, including the client, logic, and data tiers, ensuring efficient image processing and seamless user interaction. Key functional features include user registration, secure image uploads, analysis of body type and skin tone, and feedback mechanisms. Non-functional requirements prioritize usability, performance, scalability, and data security to protect user information. The logic tier integrates Convolutional Neural Networks (CNN) and YOLO (You Only Look Once) models for accurate image recognition, enabling precise body segmentation and highly personalized recommendations. The paper details the methodologies and technologies employed in the application's development while focusing on the process of its implementation in terms of testing and evaluation. A thorough literature review identifies gaps in existing systems, particularly their limited incorporation of diverse user characteristics into cohesive recommendation models. Findings demonstrate that "Wear Me" addresses these challenges by offering innovative, user-focused solutions that improve the personalization and satisfaction of styling recommendations. This research highlights the transformative potential of AI-driven technologies in redefining the fashion industry, delivering tailored shopping experiences that cater to individual preferences and identities.

Keywords: Artificial Intelligence, Machine Learning, Fashion Recommendation Systems, Fashion Industry, Convolutional Neural Networks (CNN), Body Type Analysis, Skin Tone Analysis

1. Introduction

1.1 Introduction to the Fashion Industry

The fashion industry is a dynamic global sector generating billions in revenue (Lu, 2021). Traditionally, it has been divided into haute couture and the garment industry, but with technological advancements, AI-driven fashion solutions are redefining the landscape. AI and machine learning (ML) enable automated decision-making, influencing personalized recommendations, trend analysis, and consumer engagement.

1.2 Co-relation between Consumers and Fashion

Fashion plays a crucial role in self-expression and social perception. Studies highlight that clothing reflects personality, mood, and confidence (Kwon, 1991; Stolovy, 2021). While individuals seek outfits that align with their identity, challenges arise due to body type mismatches, social expectations, and lack of fashion knowledge. Many users struggle with choosing the right outfit, increasing the demand for AI-powered recommendations.

1.3 Feedback and Recommendation

Existing fashion recommendation systems rely on social media trends, rule-based matching, or body-type analysis but often lack comprehensive personalization (Zhang & Caverlee, 2019; Chang et al., 2018). While social media-based suggestions are popular, they focus on general trends rather than individual preferences. Intelligent systems like virtual fitting rooms (Chong et al., 2021) have limitations in body type classifications, and existing ML models do not integrate multiple attributes such as skin tone and personal style cohesively.

1.4 Significance of the Study

The significance of this study lies in its potential to bridge the gap between traditional fashion industry practices and emerging technological advancements. As the industry evolves, integrating innovative solutions becomes essential to enhance efficiency, sustainability, and consumer experience. This research addresses a critical need by exploring AI-driven technologies in fashion industry and its implications for personalized consumer requirements. By providing insights into the practical application of these technologies, this study contributes to both academic literature and industry practices, offering a foundation for future research and real-world implementations.

2. Literature Review

Fashion recommendation systems have evolved over time, moving from basic rule-based models to complex algorithms integrating big data and AI. These systems are categorized into three main types: fashion pairing software, social media-based recommendation systems, and intelligent systems.

2.1 Fashion Pairing Software

Fashion pairing systems are designed to combine different garments with varying styling techniques. These systems leverage knowledge-based fashion coordination by using both verbal and visual inputs, which allow them to retrieve clothing items with similar attributes. Neural networks and genetic algorithms (GA) are commonly employed in the development of such systems (Chakraborty et al., 2021).

One example of a fashion feedback system is the Natural Language Feedback for Fashion: Producing Diverse and Informative Feedback (Fritz et al., 2019), which focuses on outfit pairing and fashion feedback generation. This technology provides text-based comments and suggestions for improving an outfit. The researchers developed two distinct models for generating two types of feedback: GOOD and TIP. Images are first processed using Convolutional Neural Networks (CNN) to extract visual features, which are then converted into text to provide detailed feedback on the outfit. This method represents a significant upgrade to fashion recommendation systems, offering comprehensive insights into outfit coordination. Furthermore, a specialized algorithm is employed to enhance the system's accuracy, enabling users to receive tailored advice on how to improve their clothing choices.

2.2 Social Media-Based Software

Social media-based recommendation systems are among the most widely used techniques for fashion suggestions today (Chakraborty et al., 2021). These systems monitor user behavior on platforms like Facebook, Instagram, and Pinterest by analyzing interactions such as likes, shares, and bookmarks to generate personalized recommendations.

Fashion recommendation systems typically draw from three main sources:

1. The user's social network
2. The user's clothing preferences
3. A coordinated clothing set that ensures style consistency

These technologies provide retailers with valuable consumer insights, enhancing the online shopping experience (Chakraborty et al., 2021). For instance, Instagrammers, Fashionistas, and Me (Zhang & Caverlee, 2019) analyzes data from fashion influencers to recommend styles based on popular hashtags like #OOTD. However, such systems often lack deep personalization, as they rely on general trends rather than individual preferences.

To address this, models using Recurrent Neural Networks (RNNs) have been developed to incorporate social media trends into recommendations. Visual Influence-Aware RNNs assess the impact of fashion bloggers to refine suggestions. Zheng et al. (2021) proposed a metric learning framework that analyzes trends in users' selfies to recommend outfits based on personal style preferences. However, selfie-based methods often focus on upper-body clothing, limiting full wardrobe coordination.

Similarly, Buy Me That Look (Abhinav et al., 2021) utilizes human key point detection to recommend outfits based on posture. This system identifies full-body images, matches fashion items, and retrieves products from databases. While accurate for t-shirts, it lacks the ability to deliver broader, customer-specific recommendations.

2.3 Smart or Intelligent Systems

One of the most promising areas in AI research is the development of expert systems, particularly in fashion, where consumer attributes like physical characteristics and clothing preferences are analyzed to provide tailored recommendations (Zhou et al., 2013). "Wear Me" exemplifies such advancements by integrating multiple user-specific attributes.

The study Which Outfit Best Suits Me? (Chang et al., 2018) explored body-type-based recommendations, developing a dataset, a body shape determination model, and a statistical framework. Despite its innovative CNN-based approach, its reliance on celebrity measurements and a 54.3% accuracy rate highlighted the need for contextual elements like skin tone to enhance usability.

In ViBE: Dressing for Diverse Body Shapes (Grauman & Hsiao, 2020), researchers used K-means clustering and ResNet-50 to match clothing to various body types. However, the study excluded key factors like limb length and shoulder width, limiting its classification accuracy.

Skin-Tone and Occasion-Oriented Outfit Recommendation System (Dhake et al., 2019) tailored suggestions based on skin tone and event using decision trees and K-means. While innovative, it lacked broader contextual integration and faced accuracy issues.

SmartFit (Chong et al., 2021) introduced virtual fitting rooms, using SURF and k-NN for body type recognition. It improved efficiency but categorized users into only four body types and lacked sufficient training data.

Fashion Is Taking Shape (Moll et al., 2019) utilized the SMPL body model to assess how outfits alter appearances but was limited by a dataset biased towards average-sized users and the requirement for multiple photos.

These studies highlight the progress and challenges in AI-driven fashion systems. Many lack integration of diverse user attributes into cohesive models. "Wear Me" addresses this gap by combining body type, skin tone, and other characteristics, advancing personalized fashion recommendations.

3. Methodology

The development of the "Wear Me" application followed a systematic approach, combining user-centric design with advanced AI and machine learning techniques. This section outlines the research philosophy, data collection methods, development approach, and evaluation strategy.

3.1 Research Philosophy and Approach

The project adopted a pragmatic research philosophy, which balanced theoretical insights with practical outcomes. A deductive approach was employed, starting with the hypothesis that fashion choices could be optimized by analyzing user attributes such as body type and skin tone. This approach guided the formulation of research questions and the design of the application, ensuring that the system addressed real-world challenges in personalized fashion recommendations. The flexibility of the pragmatic philosophy allowed for a combination of quantitative and qualitative methods, tailored to the project's requirements (Martin, 2022).

3.2 Data Collection Methods

Data collection was conducted through primary and secondary sources to inform both technical requirements and user-centric features. Primary data was gathered through interviews with ten fashion industry experts, who provided professional insights into styling based on body types and skin tones. These interviews helped identify common fashion challenges, such as mismatched outfits and the lack of personalization in existing systems. Additionally, questionnaires were distributed to hundred and fifty potential users to understand their fashion preferences and interest in AI-driven recommendations. The survey revealed that 75% of respondents struggled with choosing outfits for their body type, 82% expressed interest in AI-driven recommendations, and 65% desired a system that considered both skin tone and body shape.

Secondary data was collected through a comprehensive literature review of previous research on fashion recommendation systems, particularly those using Convolutional Neural Networks (CNNs) and k-Nearest Neighbors (k-NN). This review helped identify gaps in existing systems, such as the lack of personalized recommendations based on multiple user attributes. Public image datasets containing images of various body shapes, clothing types, and skin tones were also analyzed and used to train and validate the AI models (Zhang & Caverlee, 2019; Chang et al., 2018).

3.3 Data Analysis

The collected data was systematically analyzed using a combination of qualitative and quantitative methods. Thematic analysis was applied to expert interview responses, categorizing them into key themes such as challenges in outfit selection and the impact of body type on styling. These insights shaped the functional requirements for the AI-driven outfit recommendations. Descriptive statistics were used to analyze user survey responses, identifying dominant trends such as the demand for personalized recommendations. Correlation analysis was employed to determine the relationship between user demographics (e.g., age, gender, fashion preferences) and their AI recommendation needs. Sentiment analysis was also applied to open-ended questionnaire responses to assess user sentiment toward AI-generated outfit suggestions.

For the secondary data, performance evaluation of machine learning models was conducted using image datasets for body type classification and outfit recommendations. Accuracy metrics such as precision, recall, and F1-score were used to measure model effectiveness. Benchmarking against existing systems was performed to evaluate the performance of "Wear Me" in terms of personalization, accuracy, and real-time analysis speed.

The analysis of primary and secondary data was instrumental in defining the functional and non-functional requirements of the system. For example, the thematic analysis of expert interviews highlighted the need for accurate body type and skin tone analysis, which became core functional requirements. Similarly, user survey results emphasized the importance of usability and real-time performance, which were incorporated as non-functional requirements.

3.4 Development Methodology

An Agile development methodology was chosen for its iterative structure, which allowed for continuous testing and refinement. The System Development Lifecycle (SDLC) in Agile included several stages. During the planning phase, requirements for the "Wear Me" app were defined in collaboration with stakeholders, based on findings from interviews and questionnaires. Initial designs were created in the design phase, covering both system architecture and user interface. The app was developed in stages, with each iteration focusing on specific core functionalities, such as body type identification and clothing analysis. Early prototype testing helped identify areas for improvement, and each iteration allowed the team to refine algorithmic accuracy and UI intuitiveness. After each sprint, the app was tested by users to gather feedback for future improvements, ensuring that the system evolved in response to real-time evaluations (Martin, 2022).

3.5 Design Methodology

The system was designed using Object-Oriented Analysis and Design (OOAD), which structured the system around modular components for easier implementation and testing. Class diagrams were used to represent objects such as User, BodyType, and

RecommendationEngine, enabling efficient management of each user's personal data and the recommendation model's outputs. Sequence diagrams illustrated interactions within the system, such as the sequence of steps involved in uploading an image, processing user attributes, and generating recommendations. Wireframes and user interface (UI) designs were developed to enhance user experience, prioritizing simplicity and accessibility to ensure users could upload photos and view recommendations effortlessly. The use of OOAD ensured that the system was modular, scalable, and easy to maintain, while the focus on user-centered design principles resulted in an intuitive and accessible interface (Amanda, 2022).

3.6 Evaluation Methodology

The evaluation methodology was designed to test the app's accuracy in providing personalized recommendations and to measure user satisfaction with the system's functionality. Benchmarking was conducted to compare "Wear Me" with similar recommendation systems, focusing on metrics such as recommendation accuracy and user satisfaction. Functional testing confirmed that the system performed each core function as expected, such as uploading images, processing features, and providing recommendations. Non-functional testing assessed the app's usability, reliability, and speed in delivering recommendations, with usability testing involving feedback from end-users to ensure ease of navigation and understanding. Performance testing focused on ensuring the system could handle the computational load of real-time image processing and recommendation generation with minimal delay. The evaluation process ensured that the system met both functional and non-functional requirements, delivering a high-quality user experience (Martin, 2022).

4. Implementation

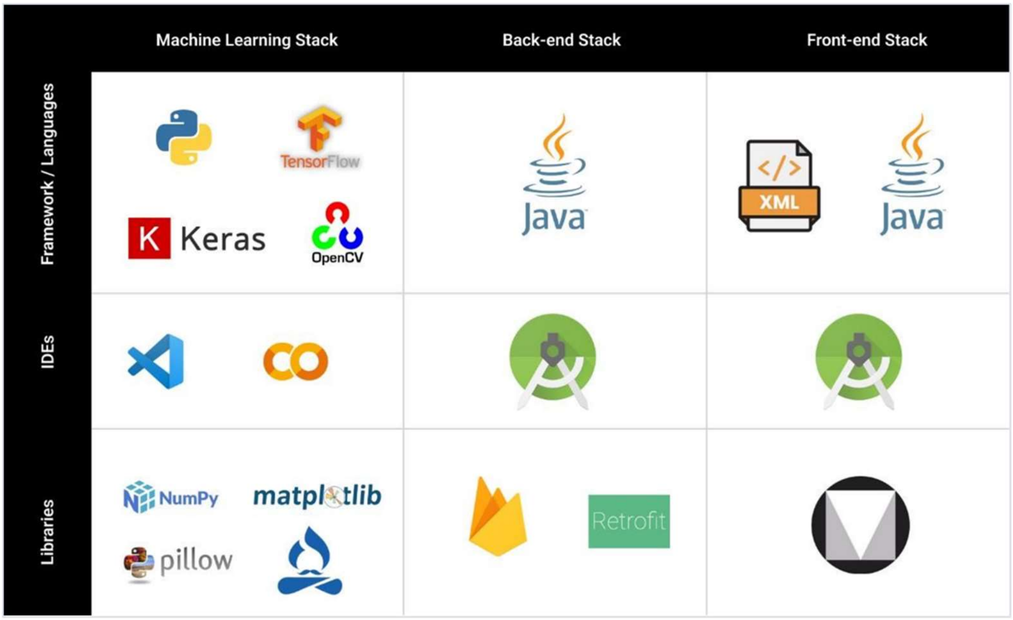
4.1 Technology Selection

4.1.1 Selection of Technology Stack

The following were the technologies, IDEs, frameworks, and libraries chosen for the project's various ML, backend, and frontend components. Python has been chosen as the primary language for ML programming. The frameworks for the ML stack include Tensor Flow, Keras, and OpenCV. Numpy, matplotlib, pillow, and body-pix libraries were used to train and test the model. It was decided to use the Android Studio IDE for front-end development. The IDEs chosen for the implementation of the ML stack are VS Code and Google Colab.

Figure 1: Technologies Used in the Application

Source: Authors



4.1.2 Data Selection

Project data selection in data science is essential to the model's success. (Costrounis, n.d.) The images serve as the project's data source for "Wear Me". For training and testing purposes, the author has created two different types of data sets to identify the user's body type and outfit. To train and test the model, the author has only created one dataset, the clothing dataset. There are now 44 classes for different sorts of clothes. The dataset was then updated with 30 new images, one for per class. From the acquired photos, 25 images were used for the train data and five images were used for the test data. The identical procedure was followed in every class. Similarly, 1320 images of clothing were used to create the initial dataset.

The secondidatasetiwasiuseditoiidentifyitheifiveidifferentibodyitypes. Recognized and assigned their own classifications were bodies with the shapes of an apple, a pear, an hourglass, a triangle, and a rectangle. Each class's related body images have been included.

4.1.3 Selection of Development Framework

The main deep learning frameworks used for the ML part of the research were Keras, TensorFlow, and OpenCV. For body segmentation, Tensor Flow and Open CV were used, and the TensorFlow framework was once more used for garment categorization. It was decided to use Keras because it is an easy-to-use Python framework that works well with TensorFlow. (Read the Docs, n.d.) As Keras is user-friendly for beginners, it is suitable for projects with a strict deadline (Guru99, 2022). . Another aspect that influenced our choice to adopt Keras was the "Wear Me" project's relatively small dataset. The author selected Keras as one of the frameworks because of all these advantages. OpenCV is primarily used for computer vision and image processing tasks. The author utilized OpenCV to segment the body for this project. As a result, the system can distinguish between the person's body and the image and recognize the image. Bootstrap is a free and open-source CSS (Cascading Style Sheet) framework. It is simple to create responsive user interfaces with Bootstrap. The bootstrap framework can be used to make the project's mobile application responsive without the need for pure CSS or media queries. Additionally, bootstrap is a compact framework that aids in enhancing system performance.

4.1.4 Selection of Programming Language

ML Stack

Python, Java, and R were the languages that were taken into consideration for creating the ML stack for the system "Wear Me." The author has decided to use Python to construct the "Wear Me" solution after weighing the advantages and disadvantages of several programming languages. Python boosts productivity because it requires no compilation and is simple to learn since this is a little job (Stempniak, n.d.).

Backend Stack

The author then made Java his choice for the backend development among a range of options, which also included C++. Powerful, approachable, and versatile are all words that describe Java. We're looking at options for front-end development like Android and flutter. Among those, Java is the preferred programming language. As the application is being created for Android smartphones, Java is an easy language to learn.

Table 1: Comparison of MLs

Source: Authors

Comparison	Java	Python	R
Interpreted language	Low	High	High
Has low entry points	Low	High	Low
User-friendly	Low	High	Medium
Takes less time to get started	No	Yes	No
OOP supported	Yes	Yes	Medium
Required more code	Yes	No	Yes

4.1.5 Libraries

The libraries chosen and used for the prototype's development were Numpy, Pillow, Matplotlib, and BodyPix. The Numpy library was used to do the mathematical operations, such as locating the image's pixels and putting their values in an array. The pillow library has also been used for managing images. Additionally, it works with picture pixels when putting the idea into practice and supports image formats, just like Numpy. The following comes Matplotlib. In this system, "Wear Me,"ithe Matplotlib library was used for testing reasons, including printing a photo in a plot to test it. The human body was worked with using the "BodyPix" library.

4.1.6 IDE

The training procedure was carried out using Google Colab IDE, which needs a lot of GPU and CPU power. Additionally, it makes it simple to train a sizable dataset without lagging. The application's author used Google Colab to train the NN by including image processing. After weighing various IDEs, including PyCharm and Visual Studio Code, the ML stack was implemented using VS Code as the primary IDE. The reason VS Code was chosen is because it is simple to use and includes all the functionality of the PyCharm IDE. Writing the ML algorithm by including the trained data has been completed using Visual Studio Code. This is the algorithm which is used to take against the captured image from the mobile camera.

The author has used Android Studio IDE in addition to the ML stack for both the backend and frontend development. The "Wear Me" android mobile application is the primary justification for using the Android Studio.

4.1.7 Summary of Technology Selection

Table 2: Summary of Technology Selection

Source: Authors

Component	Tool
Programming Language	Python, Java
Development Framework - Body Segmentation	TensorFlow, OpenCV
Development Framework - Cloths Classification	TensorFlow
Libraries	Numpy, Pillow, BodyPix, Matplotlib
UI Framework	XML, Material Design
IDE - Training	Google Colab
IDE - Product	VS Code
IDE (Backend and Frontend)	Android Studio
Version Control	Git

4.2 Implementation of Core Functionalities

Code snippets that used in the project are showing the core functionalities of the system "Wear Me" are explained below.

4.2.1 Identification of Cloths and Body Types

The image path is obtained and read using Cv2.imread(). After being read, the image is in BGR format, which the author here converts to RGB. The input image is then downsized to 416 by 416 pixels. The image data is split by 255 so that it can operate on 0 and 1 values. This makes working with little values easier than working with large numbers. The author switches the model to TensorFlow lite using FLAGS. framework. Utilizing TensorFlow lite will speed up the application. Identification of the image and feature extraction are therefore becoming quicker. Yolo is the model in use here, and TensorFlow is the underlying framework.

4.2.2 Draw the Boundary Box

The border box surrounding the image should be drawn and the program will compare and determine what the image is about, what kind of clothing that person is wearing, or what kind of body type they have by using the boundary box.

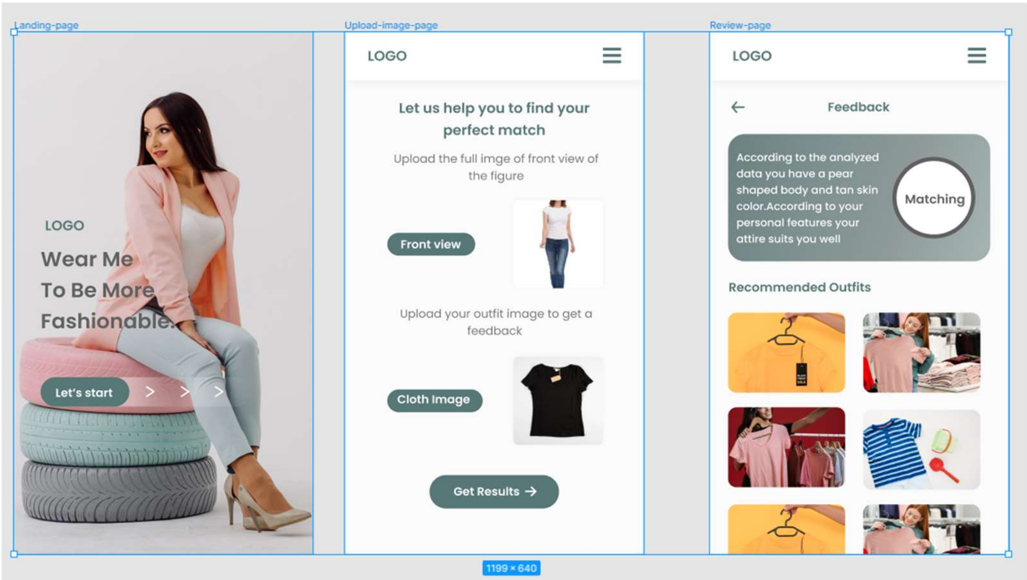
4.2.3 Skin Color Selection and Identification

To obtain the skin tone as an RGB value, the method get Color Name () was created. The draw function () method allows the model to choose and recognize the human color from the provided pixels. To determine the human face's skin tone, the x and y values are set. Then both algorithms are invoked via a while loop, allowing for the extraction and identification of the skin tone.

2.1 4.3 Mobile app User Interfaces

Figure 2: App Interfaces

Source: Authors



5. Testing

The testing phase of the "Wear Me" application was designed to ensure that the system met both functional and non-functional requirements. This section outlines the goals, testing criteria, model testing, benchmarking, and evaluation of the system's performance.

5.1 Goals and Objectives of Testing

The primary goal of testing was to validate that the system complied with the specified functional and non-functional requirements. The testing process aimed to ensure that the application performed as expected, with a focus on accuracy, usability, and performance. Specific objectives included validating the system's ability to identify body types, classify clothing items, and analyze skin tones, as well as assessing the user experience and real-time processing capabilities.

5.2 Testing Criteria

The testing process was divided into functional testing and non-functional testing. Functional testing focused on verifying that the core functionalities of the system, such as image upload, body type identification, and recommendation generation, performed as expected. Non-functional testing assessed the system's usability, reliability, and performance under various conditions. The testing criteria were designed to ensure that the application met the needs of end-users while maintaining high levels of accuracy and efficiency.

5.3 Model Testing

The machine learning models used in the "Wear Me" application underwent rigorous testing to ensure their accuracy and effectiveness. The clothing classification model, trained on a dataset of 44 clothing categories, was tested using the YOLO framework. The model achieved a Mean Average Precision (MAP) score of 83.85%, indicating high accuracy in detecting and classifying clothing items. The body type identification model, trained on a dataset of five body types, was also tested for accuracy and real-time performance. The results demonstrated that the model could accurately identify body types and generate personalized recommendations within seconds

```
IOU threshold 50 %, used Area-Under-Curve for each unique
Recall mean average precision (mAP@0.50) 0.83 8528, or 83.85
Total Detection Time: 3 Seconds
```

5.4 Benchmarking

The "Wear Me" application was benchmarked against similar fashion recommendation systems to evaluate its performance. The benchmarking process compared the application's accuracy, personalization capabilities, and real-time processing speed with those of existing systems. The results showed that "Wear Me" outperformed many existing systems in terms of recommendation accuracy and user satisfaction, achieving an MAP score of 83.85% compared to the 53% accuracy of the Style4BodyShape dataset (Hidayati et al., 2018) and the 80.17% accuracy of the Chictopia dataset (Sattar et al., 2019). These results highlight the effectiveness of the application's AI-driven approach to personalized fashion recommendations.

5.5 Functional Testing

Functional testing confirmed that the system performed each core function as expected. For example, the system successfully identified body types and skin tones from user-uploaded images, classified clothing items, and generated personalized recommendations. The testing process also verified that the system could handle various file formats and reject invalid inputs, such as images with incorrect file extensions. User feedback during functional testing indicated that the application was intuitive and easy to use, with most users expressing satisfaction with the accuracy and relevance of the recommendations.

5.6 Non-Functional Testing

Non-functional testing focused on assessing the system's usability, reliability, and performance. Usability testing involved gathering feedback from end-users to ensure that the application was intuitive and easy to navigate. Performance testing evaluated the system's ability to handle real-time image processing and recommendation generation, with a focus on minimizing delays and ensuring smooth operation under heavy computational loads. The results of non-functional testing demonstrated that the application was highly usable and reliable, with minimal latency in generating recommendations.

5.7 Limitations of Testing

While the testing process was comprehensive, certain limitations were identified. The dataset used for training and testing the models, although diverse, was relatively small, with 44 clothing categories and 30 images per category. A larger and more diverse dataset could further improve the accuracy and relevance of the recommendations. Additionally, the testing process was conducted under controlled conditions, and further testing in real-world scenarios would provide additional insights into the system's performance and usability.

6. System Evaluation

The evaluation of the "Wear Me" application was conducted to assess its effectiveness in providing personalized fashion recommendations and to measure user satisfaction with the system's functionality. This section outlines the evaluation methodology, criteria, and results, as well as the limitations of the evaluation process.

6.1 Evaluation Methodology and Approach

The evaluation process employed a combination of quantitative and qualitative methods to assess the system's performance and user satisfaction. Quantitative methods included benchmarking the application against similar systems and analyzing performance metrics such as accuracy, processing speed, and user satisfaction scores. Qualitative methods involved gathering feedback from end-users, fashion industry experts, and technical evaluators to assess the system's usability, relevance, and overall impact. The evaluation was designed to ensure that the system met both functional and non-functional requirements while providing a high-quality user experience.

6.2 Evaluation Criteria

The evaluation criteria were designed to assess the system's performance, usability, and suitability for consumers. Key criteria included:

- **Selection of Project Domain and Concept**: The relevance and timeliness of the research topic were evaluated to ensure that the study addressed a significant gap in the fashion industry.
- **Research Gap and Depth**: The depth of the research and its contribution to the field were assessed to determine the study's academic and practical significance.
- **Research Approach and Methodology**: The appropriateness of the research approach and methodology was evaluated to ensure that the study was conducted in a rigorous and systematic manner.
- **System Design and Architecture**: The design and architecture of the system were assessed to ensure that they met industry standards and supported the system's functionalities.
- **User Interface and User Experience**: The usability and accessibility of the system were evaluated to ensure that it provided a seamless and intuitive user experience.
- **Suitability for Consumers**: The system's ability to meet the needs of end-users in their day-to-day lives was assessed to determine its practical applicability.

6.3 Self-Evaluation

The authors conducted a self-evaluation of the research to assess its strengths and weaknesses. The evaluation focused on the selection of the research domain, the depth of the research, the appropriateness of the methodology, and the system's design and usability. The self-evaluation revealed that the research successfully addressed a significant gap in the field of AI-driven fashion recommendations, with the "Wear Me" application demonstrating high accuracy and user satisfaction. However, the evaluation also identified areas for improvement, such as the need for a larger and more diverse dataset and further optimization of real-time processing speeds.

6.4 Selection of Evaluators

The evaluation process involved feedback from three groups of evaluators: fashion industry experts, technical experts, and end-users. Five fashion industry experts with over two years of experience in the field were selected to provide insights into the system's relevance and impact on the fashion industry. Five technical experts, including data scientists and researchers in image processing, were chosen to evaluate the system's technical performance and accuracy. Six end-users, who were keen on fashion and likely to use the application, were selected to assess the system's usability and suitability for everyday use.

6.5 Evaluation Results and Expert Opinions

The evaluation results demonstrated that the "Wear Me" application was highly effective in providing personalized fashion recommendations. The system achieved an accuracy of 83.85% in clothing detection, with users expressing high levels of satisfaction with the relevance and quality of the recommendations. Fashion industry experts praised the system's ability to address a significant gap in the market, while technical experts highlighted the effectiveness of the AI models and the system's real-time processing capabilities. End-users found the application intuitive and easy to use, with many expressing interest in using it as part of their daily fashion routine.

6.6 Limitations of Evaluation

The evaluation process was not without limitations. The ongoing political and COVID-19-related challenges in the country limited the ability to conduct in-person user testing. As a result, much of the evaluation had to be conducted remotely, which reduced opportunities for direct user interaction and feedback. Additionally, the relatively small dataset used for training and testing the models may have affected the accuracy and diversity of the recommendations. Future evaluations should aim to incorporate larger-scale user testing and a more diverse dataset to ensure a more comprehensive assessment of the system's performance.

7. Discussion

The findings from this study demonstrate that the "Wear Me" application successfully addresses the limitations of existing fashion recommendation systems by integrating body type and skin tone analysis into a cohesive AI-driven solution. This section discusses the key findings, compares them with existing work, and highlights the practical implications, limitations, and future research directions.

7.1 Comparison with Existing Work

Prior research in AI-based fashion recommendations has primarily focused on social media-based suggestions, body type-based recommendations, and virtual fitting rooms. Social media-based systems, such as those analyzed by Zhang and Caverlee (2019), rely on trends from platforms like Instagram and Pinterest but often lack deep personalization. Body type-based systems, such as the one developed by Chang et al. (2018), use convolutional neural networks (CNNs) to classify body shapes but achieve limited accuracy (54.3%) and fail to integrate additional attributes like skin tone. Virtual fitting rooms, such as SmartFit (Chong et al., 2021), classify users into only four body types, limiting their ability to cater to diverse user populations.

In contrast, the "Wear Me" application combines multiple user-specific attributes, including body type and skin tone, into a single cohesive recommendation system. By leveraging YOLO-based image recognition and real-time feedback mechanisms, the application addresses the limitations of previous studies, achieving an accuracy of 83.85% in clothing detection and high user satisfaction. This represents a significant advancement in the field of AI-driven fashion recommendations.

7.2 Practical Implications

The "Wear Me" application has several practical implications for the fashion industry and consumers. For consumers, the system provides personalized fashion recommendations that enhance confidence and satisfaction by aligning with their unique attributes. This is particularly beneficial for individuals who struggle with outfit selection due to body type mismatches or lack of fashion knowledge. For retailers and designers, the application offers valuable insights into consumer preferences, enabling them to tailor their offerings and improve customer engagement. Additionally, the system's real-time processing capabilities make it suitable for integration into e-commerce platforms, allowing online shoppers to make more informed fashion choices.

7.3 Limitations of the Study

Despite its successes, the "Wear Me" application has certain limitations. The dataset used for training and testing the models, although diverse, was relatively small, with 44 clothing categories and 30 images per category. A larger and more diverse dataset could further improve the accuracy and relevance of the recommendations. Additionally, the system's real-time processing capabilities, while effective, require further optimization to reduce latency and improve performance under heavy computational loads. Finally, the current model does not account for cultural or seasonal fashion trends, which could limit its applicability in different regions or during specific times of the year.

7.4 Future Research Directions

Future research can explore several avenues to enhance the "Wear Me" application and address its limitations. Expanding the dataset to include more diverse clothing styles, body types, and cultural fashion preferences would improve the accuracy and relevance of the recommendations. Incorporating additional user attributes, such as hair color, height, and facial features, could further personalize the recommendations. Developing a multilingual user interface would enhance the application's accessibility across different markets. Finally, integrating user feedback loops would enable continuous refinement of the AI models, ensuring that the system remains up-to-date with evolving fashion trends and user preferences.

8. Conclusion

The "Wear Me" project represents a significant advancement in AI-driven fashion recommendations, offering a personalized and inclusive solution for users seeking tailored outfit suggestions. By integrating body type and skin tone analysis into a cohesive recommendation system, the application addresses the limitations of existing systems and demonstrates the transformative potential of AI in the fashion industry.

8.1 Achievement of Research Objectives

The primary research objectives of the study were successfully achieved. The "Wear Me" application leverages advanced machine learning techniques, including YOLO for object detection and TensorFlow for skin tone analysis, to deliver highly accurate and personalized recommendations. The system achieved an accuracy of 83.85% in clothing detection, as validated through rigorous testing and benchmarking. Additionally, the application's intuitive user interface and seamless integration of frontend and backend components ensured a high-quality user experience, meeting the goal of providing effortless and accessible fashion advice.

8.2 Key Challenges

Despite its successes, the study faced several challenges. The relatively small dataset used for training and testing the models limited the diversity of clothing styles and body types available for recommendation. This constraint may have affected the accuracy and relevance of the suggestions. Additionally, the system's real-time processing capabilities, while effective, require further optimization to reduce latency and improve performance under heavy computational loads. The evaluation process was also impacted by external factors, such as COVID-19 restrictions and political instability, which limited opportunities for in-person user testing and feedback.

8.3 Contribution to the Field

The "Wear Me" project contributes to the evolving field of AI-driven fashion recommendations by introducing an advanced system that personalizes style advice based on multiple user-specific factors. Unlike conventional recommendation systems that rely solely on trends or general fashion preferences, this application integrates machine learning techniques to deliver highly individualized suggestions. By combining object detection and skin tone analysis, the system sets a new standard for personalized fashion recommendations. The study highlights how AI can be leveraged to enhance consumer experiences in the fashion industry, paving the way for future developments in intelligent recommendation systems.

8.4 Closing Remarks

The "Wear Me" application demonstrates the potential of AI to revolutionize personal styling, making fashion more accessible, inclusive, and tailored to individual preferences. Despite certain limitations, the study lays the groundwork for future improvements and expansions. With further refinements in dataset diversity, processing efficiency, and personalization capabilities, "Wear Me" has the potential to become a leading tool for fashion-conscious users. By harnessing the power of AI, this project showcases how technology can transform the fashion industry, offering innovative solutions that enhance user confidence and satisfaction.

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THE IMPACT OF INDUSTRY 4.0 READINESS ON ARTIFICIAL INTELLIGENCE USAGE IN SRI LANKA: ACCOUNTING PROFESSIONALS PERSPECTIVE

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Abstract

Sri Lanka stands at a crossroads in its journey towards becoming a globally competitive AI enabled digital economy. This transformation may be gradual, but it demands concerted and focused collective action and urgency. Industry 4.0 is focused on creating "Smart working'' environment which is a new level of organization and control over the entire value chain of the life cycle of products and is geared towards increasingly individualized customer requirements. Employees are more likely to adopt Artificial Intelligence (AI) within their jobs if they see it as beneficial for their productivity and if they find it easy to use. Therefore, it is obvious that technology, particularly AI and industry 4.0 have significantly impacted accounting and auditing worldwide and the use of these technologies has become critical to the efficacy and efficiency of accounting and auditing operations. Just as computer skills became more important a few years ago, AI skills are becoming more relevant today. This set of skills includes using, applying, or interacting with AI and is called "AI literacy". Therefore, this research has examined Sri Lankan accounting professionals' perspective on AI and Industry 4.0 along with their AI literacy. The findings reflect that AI usage intention is significantly affected by industry 4.0 and it moderates the relationship between AI literacy and Intention to use AI. The study's conclusions can help companies effectively use AI advancements to enhance their accounting and auditing processes. The results may be used by policymakers to develop frameworks and rules that facilitate the integration and uptake of artificial intelligence in the field.

Keywords: Artificial Intelligence, Industry 4.0, Technology Acceptance Model, Accounting and Auditing

1. Introduction

According to Hashid & Almaqtari (2024), Artificial Intelligence (AI) has brought forth various benefits and transformations in the accounting profession by automating monotonous procedures, simplifying data analysis, making better decisions, and streamlining auditing processes. Further it highlights that Industry 4.0 has had a significant impact on the field of accounting and auditing worldwide. The features of Industry 4.0 are horizontal, vertical, and digital integration of the entire system (Crnjacet al., 2017). As explained by Vaidya et al., (2018) Industry 4.0 converted the regular machines to self-aware and self-learning machines which is automation to enhance the performance and to increase the productivity. Thus, AI is a prominent trend created by industry 4.0 in the modern world.

In the field of accounting the term Artificial Intelligence (AI) refers to the implementation of machine learning, natural language processing, and robotic process automation to simplify accounting processes (Naqvi, 2020). According to research findings, AI improves the accuracy and efficiency of financial reporting and facilitates automating routine tasks (Odonkor et al., 2024). However, challenges such as the need for skilled personnel adept in AI, data privacy concerns etc. are notable (Odonkor et al., 2024). Even though there are some challenges; to make quick and timely decisions in today's fast-paced business environment, it can be a competitive advantage (Odonkor et al., 2024). While the use of technology in accounting and auditing has been extensively researched in developed countries, research in developing countries is scarce (Hashid & Almaqtari, 2024). Sri Lanka is currently ranked 95th out of 193 countries in the Oxford Insights' 2023 Government AI Readiness Index, marking a ten-place improvement since 2022. This progress is largely attributed to the government's commitment to formulating an AI Strategy by fiscal 2024. The government's commitment to this objective is reflected in the planned creation of the National AI Center, the development of a comprehensive National AI Strategy with an associated 5-year roadmap supported by a LKR 1.5 billion allocation in the 2024 National Budget for initial AI initiatives. These measures aim to accelerate the responsible development and use of AI, fostering a digitally empowered Sri Lanka that champions innovation, inclusivity, and sustainable growth (CFSAI, 2024)

It also highlights that while there is a growing body of literature on AI's potential, there is a lack of comprehensive studies covering all Industry 4.0 technologies, including the Internet of Things, big data analytics, and cloud computing. Further, as automation and collaboration with AI will occur in many jobs including accounting, an individual's current level of AI literacy might predict if they can adapt to new technologies and if implementing AI-reliant workflows will be successful. A comprehensive study linking these technologies to AI in accounting and auditing could help understand the synergies and challenges of these technologies in the financial sector. Therefore, this study will focus on examining the industry 4.0 readiness and accounting professionals AI literacy on AI usage intention in Sri Lanka.

2. Literature Review

2.2 AI literacy

There are various definitions to AI literacy and according to Ng et al. (2021) it comprises four concepts such as Know and comprehend AI, Use & Apply AI, Evaluate & Create AI, and AI ethics. They believe that someone is considered to be AI literate if they understand the fundamentals of AI, are able to utilize AI applications, use their knowledge of AI in various contexts, assess, evaluate, forecast, and create AI applications, and are able to think ethically.

2.1.1. Know and Understand AI (UA)

According to study by Kokina and Davenport (2017), understanding artificial intelligence can help accounts to minimize the time-consuming tasks with high accuracy like, data entries, fraud detection, data analysis and transaction analysis. This will enhance the productivity and decision making of the accountants. Since, the AI tools are a main component in this industry, it is essential to accounting professions to have a fundamental knowledge about AI to stay competitive in the industry. AI knowledge in accounting consists of several areas, including machine learning (ML), robotics, natural language processing (NLP). These tools can analyse repetitive tasks and analysis numbers (Kokina & Davenport, 2017). Having better understanding of these AI components accounting professions can prevent from fraud as the system bills automatically and the digital footprints can be tracked (Bako & Tanko, 2022).

Moreover, it enhances the quality of the information and productivity by providing accounting software to auditors. So that it will save the time and detect the errors automatically (Bako & Tanko., 2022). There might be limitations to acquire knowledge in AI due to lack of resources and trainings. In summary having better understanding about artificial intelligence will significantly enhance accountants' quality of the service to its clients and reduce the time consumption and spending (Bako & Tanko, 2022).

2.1.2. Evaluate and create AI (CA)

Evaluating AI in accounting and auditing focusing on the latest trends, opportunities, and challenges (Zemankova, 2019). Hence this field is always changing, major companies are investing heavily in AI to expand its use in these areas. All the AI tools and applications developed by the big four companies, which are the leading companies in the industry (Zemankova, 2019). The most used AI technologies in this field are genetic algorithms, fuzzy systems, neural networks, and hybrid systems (combinations of these technologies) (Zemankova, 2019). The combination of expert systems and neural networks is the most successful (Zemankova, 2019). According to Zhao et al. (2004) traditional auditing faces threats and challenges from the prevailing application of real-time accounting (RTA), XBRL, Electronic Data Interchange (EDI), and AI. Tools like EDI, EFT, and CAATs support continuous auditing. According to Zhang et al. (2020) key AI technologies identified, including NLP, Machine Learning, and Cloud Computing, all of which are becoming essential in modern business. Big data, Blockchain, and AI are further enhancing workplace efficiency.

2.1.3. Apply AI (AI)

According to Davenport and Ronanki (2018), before starting an AI project, companies need to understand which technologies are suitable for different tasks and the strengths and limits of each. Rule based systems and robotic process automation are transparent but cannot learn or improve (Davenport and Ronanki, 2018). There are several challenges that could slow down AI projects such as difficulties in integrating with existing systems, excessive costs, and a shortage of skilled talent (Davenport and Ronanki, 2018). According to Haan (2023), businesses are using artificial intelligence (AI) in many ways to work more efficiently and effectively by saving time and reducing costs. With the improvements and developments in AI technology, it is becoming a valuable tool for companies in different fields (Haan, 2023). Businesses are increasing the usage of AI to improve their operations in many areas. A survey shows that the most common AI uses are in customer service (56%) and cybersecurity (51%). AI is also widely used in areas like managing customer relationships (46%), digital assistants (47%), and managing inventory (40%), creating content (35%), suggesting products (33%), handling accounting (30%) and more (Haan, 2023).

2.3 Industry 4.0

The fourth industrial revolution is known as the "Industry 4.0" which is a new level of organization and control over the entire value chain of the life cycle of products and is geared towards increasingly individualized customer requirements (Vaidya et al., 2018). Industry 4.0 is focused on creating "Smart working'' environment (Crnjac et al., 2017). As stated by Yang and Gu (2021) the idea of industry 4.0 arose from the Hannover fair in 2011. From the launch of Industry 4.0 in 2011, to the current day it has influenced almost all sectors (Yang and Gu,2021). The nine pillars of industry 4.0 are cyber-physical systems, internet of things, big data, 3D printing, robotics, simulation, augmented reality, cloud computing and cyber security (Yang and Gu,2021).

Primarily industry 4.0 is the IT driven changes and these developments do not only have technological but also versatile organizational implications (Lasi et al.,2014). Hence it has created smart factories where manufacturing will completely be equipped with sensors and autonomous systems and new systems in distribution and procurement where it is individualized (Lasi et al.,2014). The features of Industry 4.0 are horizontal, vertical, and digital integration of the entire system (Crnjac et al.,2017). By applying Industry 4.0 the changes are focused on the life cycle of a product instead of focusing on the production process (Crnjac et al.,2017). As explained by Vaidya et al., (2018) Industry 4.0 converted the regular machines to self-aware and self-learning machines which is automation to enhance the performance and to increase the productivity. AI is a prominent trend created by industry 4.0 in the modern world.

There are also few challenges faced when shifting from manual process to an automation process such as embedment, predictability, flexibility to unexpected conditions (Wang et al.,2016, cited in Vaidya et al.,2018). Despite the challenges faced, industry 4.0 is still in its infancy aiming to bring many advanced and integrating evolving technologies (Yang and Gu,2021). Yang and Gu (2021) also stated that many governments have adapted policies to support this technological revolution.

2.4 Intention to use Artificial Intelligence

In the field of accounting the term Artificial Intelligence (AI) refers to the implementation of machine learning, natural language processing, and robotic process automation to simplify accounting processes (Naqvi, 2020). According to research findings, AI improves the accuracy and efficiency of financial reporting and facilitates to automate routine tasks. Peer influence and leadership support are other factors that influence employees to use AI (Luhana et al., 2023). However, challenges such as the need for skilled personnel adept in AI, data privacy concerns etc. are notable (Odonkor et al., 2024). Even though there are some challenges, to make quick and timely decisions in today's fast-paced business environment, it can be a competitive advantage (Odonkor et al., 2024). For accounting professionals to effectively accept AI, increasing AI literacy is crucial (Nomura et al., 2019).

According to Eftimov and Kitanovikj (2023), to enhance the quality of the accountants work or service, AI based software and technologies can potentially help. Further to understand how AI can help or hinder repetitive work, accountants should be aware of its potential, opportunities, and challenges. Tasks such as comparing financial statements, and memorizing financial reports data etc. can be done by using AI technology easily, without utilizing much time on them and focusing on more humanized tasks such as strategic financial planning, and relationship building with clients etc. This would increase the efficiency and effectiveness of the workforce as well as the AI literacy of individuals (Carolus et al., 2022).

3. Methodology

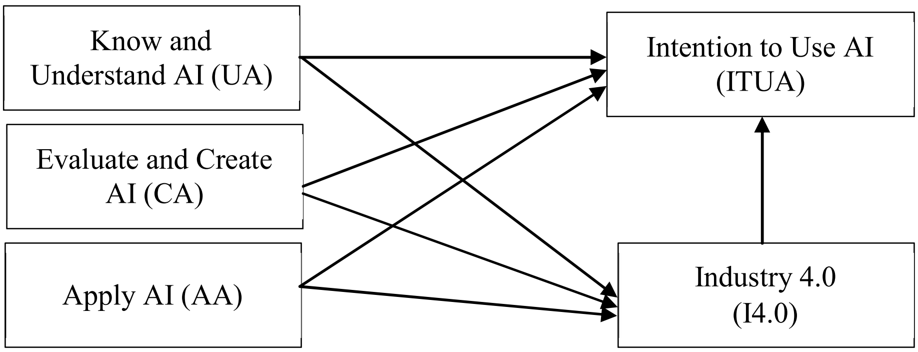
This study utilized the positivistic approach where the theory has been identified as Theory of Planned Behavior (TPB) as it was a well-accepted and supported by empirical evidence to test the association between beliefs and behavior. Outside the theory of the planned behavior framework, it was also shown that the subjective assessment of one's competencies is central to the intention to use AI (Kwak et al., 2022). According to

Carolus et al., (2022), an instrument for measuring AI literacy to predict and prepare AI use in a professional context should, from a psychological point of view, primarily focus on the subjective assessment of one's competencies (i.e., behavioral control or self-efficacy). Thus, they have used a56 items for the self-assessments in different domains of AI literacy which has been used in this study in three domains; Know and Understand AI (UA), Evaluate and Create AI (CA) and Apply AI (AA). A structured questionnaire was given to sixty (60) employees at one of the Big Four Accounting firms operating in Sri Lanka which are the four largest professional services networks in the world by revenue. The questionnaires were distributed physically, divided into two sections, where the first section gathers the demographic information of employees including gender, age, educational level, work experience and their perspective on artificial intelligence in the workplace, while the second section of the questionnaire focuses on specific statements rated on a 5-point scale to collect data on topics such as the employee's intention to using AI, their Industry 4.0 readiness and AI literacy.

The proposed conceptual model is given in figure 1.

Figure 1: Proposed Model

Source: Author



The completed questionnaires were analyzed using Smart PLS for structural equation modeling (SEM) analysis using partial least squares (PLS). Smart PLS was used to evaluate not only the eleven hypotheses but the relationships between the variables as well. The study conducted in 2024 November and quantitative data analysis was used. All the items related to the conceptual framework measured in the constructs used 5-point Likert scale ranging from (1) Strongly Disagree to (5) Strongly Agree.

4. Analysis and Discussion of Results

4.1. Measurement Model

Validity and reliability are two metrics used to assess this research's quality. In terms of the model's dependability, assessed the internal consistency reliability and the reliability of the model's indicators using the composite reliability (CR)/Cronbach's alpha (CA) values and outer loadings values, respectively (Table 1). The outer loadings values of all indicators exceeded Hulland's (1999) lower limit of 0.700, ranging from 0.794 to 0.949 in value. Furthermore, CR and CA values exceeded lower limit of 0.700 (Bagozzi and Yi, 1988). The aforementioned results indicated high internal consistency, confirming outer model's reliability.

Table 1: Measurement Model's Reliability and Convergent Validation

Variables	Indicator	Outer Loading	CR	CA	AVE
UA _ Know and Understand AI	UA1	0.760	0.955	0.839	0.746
	UA2	0.924			
	UA3	0.899			
CA _ Evaluate and Create AI	CA1	0.921	0.986	0.890	0.812
	CA2	0.907			
	CA3	0.875			
AA _ Apply AI	AA1	0.816	0.903	0.860	0.780
	AA2	0.893			
	AA3	0.936			
I4.0 _ Industry 4.0	I4.01	0.754	0.879	0.849	0.772
	I4.02	0.949			
	I4.03	0.921			
ITUA _ Intention to Use AI	ITUA1	0.910	0.967	0.855	0.764
	ITUA2	0.885			
	ITUA3	0.824			

Regarding the validity of the model, we assessed its convergent and discriminant validity using the square root of the AVE values and the Average Variance Extracted (AVE) values, respectively (Table 2). A good measurement requires AVE values to be more than 0.500, according to Chin and Todd (1995) convergent validity was confirmed by the AVE values for all constructs, which ranged from 0.746 to 0.812, much higher than 0.500 (Table 1).

According to Fornell and Larcker (1981), a measure of the discriminant validity of the model can be obtained by computing the square root of AVE for each construct and comparing its value to that of the other variables. Each variable's square root of AVE was found to be bigger than the other variables' correlation values.

Table 2: Measurement Model's Discriminant Validation

	AA	CA	I4.0	ITUA	UA
AA	0.883				
CA	0.335	0.901			
I4.0	0.546	0.290	0.879		
ITUA	0.224	-0.013	0.449	0.874	
UA	0.405	0.134	0.341	0.222	0.864

4.2. Structural Model

The structural model reflects the paths hypothesized in the research framework. The structural model is assessed based on the R square value and the significance of paths. The goodness of the model is determined by the strength of each structural path determined by R square value of the independent variables. The value of R square should be equal to or over 0.1 (Falk & Miller, 1992). The results in Table 3 shows that all R square values are over 0.1 hence predictive capability is established. SRMR is below the required value of 0.10, indicating acceptable model fit (Hair et al; 2016). As per the hypothesis testing/path coefficients the only two hypothesis accepted was the Apply AI on Industry 4.0 and the ($\beta = 0.448$, $p = 0.002$) and Industry 4.0 on Intention to use AI ($\beta = 0.475$, $p = 0.001$).

Figure 2: Proposed Structural Model

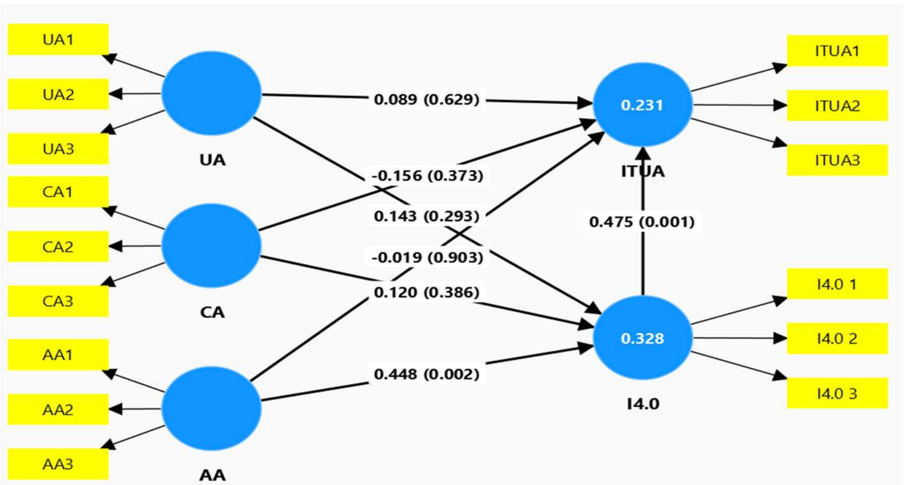


Table 3: Hypothesis Testing and Structural Model Fit

Hypothesis	Path	Beta coefficient	T statistics	P values	Supported
H1	Understand AI-> Intention to Use AI	0.089	0.484	0.629	No
H2	Understand AI -> Industry 4.0	0.143	1.052	0.293	No
H3	Create AI -> Intention to Use AI	-0.156	0.891	0.373	No
H4	Create AI -> Industry 4.0	0.120	0.868	0.386	No
H5	Apply AI -> Intention to Use AI	-0.019	0.122	0.903	No
H6	Apply AI -> Industry 4.0	0.448	3.149	0.002	Yes
H7	Industry 4.0 -> Intention to Use AI	0.475	3.293	0.001	Yes
Intention to Use AI	**0.231**				
Industry 4.0	**0.328**				
	SRMR 0.093				

4.3. *Mediation Analysis*

The mediation analysis was conducted to analyze how Industry 4.0 would impact the accountants' perception to use AI. The results (Table 4) revealed that there is a partial mediation between AI literacy domain; Apply AI and Intention to Use AI through Industry 4.0 readiness.

Table 4: Mediation Analysis

Relationship			Direct Effect	Sig.
Understand AI – Intention to Use			0.157	0.398
Understand AI – Industry 4.0			0.143	0.293
Specific Indirect Effects			Beta	Sig.
Understand AI -> Industry 4.0 -> Intention to Use AI			0.068	0.332
Relationship	**Total Effect**	**Sig.**	**Direct Effect**	**Sig.**
Create AI – Intention to Use			-0.156	0.373
Create AI – Industry 4.0			0.120	0.386
Specific Indirect Effects			Beta	Sig.
Create AI -> Industry 4.0 -> Intention to Use AI			0.057	0.398
Relationship	**Total Effect**	**Sig.**	**Direct Effect**	**Sig.**
Apply AI – Intention to Use			0.213	0.020
Apply AI – Industry 4.0			0.448	0.002
Specific Indirect Effects			Beta	Sig.
Apply AI -> Industry 4.0 -> Intention to Use AI			0.213	0.020

5. Conclusion

In conclusion, employees in accounting and auditing are willing to incorporate AI and Industry 4.0 technologies into their work, demonstrating that AI literacy—such as the ability to apply AI within the context of Industry 4.0—significantly influences their intention to use AI. This finding challenges the common perception that accounting professionals are reluctant to adopt AI, instead highlighting their openness to technological advancements. The implications of these findings are substantial for organizations aiming to integrate AI applications into their workflows. By fostering AI literacy and facilitating exposure to Industry 4.0 technologies, businesses can enhance efficiency, optimize decision-making, and increase overall productivity. Moreover, organizations should invest in targeted training programs to equip employees with the necessary AI skills, ensuring a smoother transition into AI-augmented roles.

Additionally, the study underscores the moderating role of Industry 4.0 in the relationship between AI literacy and employee intention to adopt AI. This suggests that companies should not only focus on AI education but also on creating an ecosystem where AI-driven tools and digital transformation are seamlessly integrated into accounting and auditing processes. Future research should explore this moderating effect further, incorporating additional variables from established theoretical frameworks such as the Theory of Planned Behavior (TPB) or other relevant models. Understanding the interplay of factors influencing AI adoption will provide deeper insights into how organizations can design effective strategies for digital transformation in the accounting profession.

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IMPACT OF SMART TOURISM TECHNOLOGIES ON DESTINATION LOYALTY: PERSPECTIVE OF GENERATION Z TRAVELERS

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Abstract

Smart Tourism Technologies (STT) has been a popular topic in tourism research among Generation Z (Gen Z), digital natives, who are known to possess unique psychological and behavioral patterns of consumption and are particularly influenced by smart technologies and social media marketing activities. Although smart technologies are widely used to enhance tourist experiences at smart tourism destinations, research in this area remains limited. Most prior studies have primarily focused on describing smart tourism technologies (STTs), with relatively few exploring their impact on overall tourist experiences, satisfaction, and related outcomes. Hence, this concept paper investigates the impact of STT on tourist satisfaction through the mediation of memorable experiences which denote the novelty of the conceptualization. Considering the gap identified, this concept paper suggests employing a quantitative research method and specifically Structural Equation Modeling (SEM) will be employed to examine the effects of STT on in-bound tourists' satisfaction mediated by memorable experience where the findings will be generalized for the population. This concept paper contributes to the existing literature on STT by explaining the mechanism on how memorable experience could affect the tourist satisfaction of Gen Z. Moreover, significant practical implications are provided for marketers, policymakers, and other decision-makers to increase the utilization of STT to enhance tourist satisfaction.

Keywords: Smart Tourism Technologies, Destination Loyalty, Generation Z

1. Introduction

Smart tourism technologies (STTs) are significantly impacting tourist satisfaction, particularly from the perspective of Generation Z travelers (Ionescu & Sârbu, 2024).

These technologies are recognized for enhancing tourist satisfaction and memorable experiences, which are crucial for fostering destination loyalty.

Further, STTs significant effect on tourists' experiences and satisfaction is leading to increased word-of-mouth recommendations and revisit intentions (Pai, Liu, Kang, & Dai, 2020; Jeong, & Shin, 2019; Ionescu & Sârbu, 2024; Zhang, Sotiriadis, & Shen, 2022; Azis, Amin, Chan, & Aprilia, 2020). Moreover, on a more contemporary note, Generation Z (Gen Z) travelers, being digital natives, are particularly influenced by smart technologies and social media marketing activities value interactivity and personalization and are more likely to pay a premium for enhanced experiences (Pricope et al., 2023; Liu et al., 2022). In addition, they are influenced by travel influencers and tend to share their experiences, which can further enhance tourist satisfaction (Pricope et al., 2023). Therefore, it is evident that destinations that effectively integrate STTs and cater to Gen Z's preferences can expect increased visitor satisfaction, revisit intentions and positive recommendations.

However, it is discussed in literature that there is a lack of sufficient research exploring tourists' perspectives on smart tourism, as its development is still in its early stages, and empirical studies on this subject are limited (Tavitiyaman et al. 2021). Moreover, according to Kahraman and Cifci (2022) further investigation in memorable experience is required in different destinations inclusive of small islands focusing on in-bound tourism as well as to measure dimensions affecting tourist satisfaction. Further, there is limited research on consumers' preferences regarding STTs, particularly concerning the adoption and use of specific technologies (Tavitiyaman et al., 2021). According to Hunter, Chung, Gretzel, and Koo (2015) cited in (Tavitiyaman et al., 2021), the authors suggest that it is imperative to study how impactful these STTs can be on attaining tourist satisfaction of Gen Z travelers.

Research Objectives

RO1: To determine the impact of accessibility, informativeness, interactivity and personalization ability of STTs on tourist satisfaction.

RO2: To determine the mediating impact of memorable experiences on the relationship between STTs and tourist satisfaction.

RO3: To determine the impact of memorable experiences on tourist satisfaction.

2. Literature Review

3.1 Overview of Smart Tourism Technologies (STTs)

Smart tourism is defined as the integration of new technologies into travel-related services, such as booking accommodations, transportation, restaurants, recreational activities etc. According to Cornejo Ortega & Malcolm (2020), in recent years, many travel destinations have adopted the "smart" concept, leveraging it to gain a competitive edge over other destinations by offering unique and differentiated products and services (Tavitiyaman et al., 2021).

Drawing from these definitions of smart tourism, this study defines STTs as the application of ICTs in tourism activities to improve tourists' travel experiences within a specific destination. Therefore, researchers Huang et al., (2017); Lee et al., (2018); No and Kim, (2015) have categorized STTs based on four key attributes: accessibility, informativeness, interactivity, and personalization, as measures of their effectiveness in tourism destinations, as cited in (Jeong & Shin, 2020; Hailey, Jeong, & Cho, 2021).

Further, STTs include general and specific technological applications designed to enhance tourists' experiences and provide added value to the holistic value proposition, according to Neuhofer et al., in (2015) as cited in (Jeong & Shin 2020). Examples of STTs include computing, the Internet of Things (IoT), cloud computing, Wi-Fi-enabled connectivity, near-field communication (NFC), radio-frequency identification (RFID), sensors, smartphones, mobile connected devices, beacons, virtual reality (VR), augmented reality (AR), mobile apps, integrated payment systems, smart cards, and social networking platforms, according to Gretzel et al., (2015); Huang et al., (2017); Wang, Li, and Li., (2013) as cited in (Jeong & Shin, 2020).

3.2 Know and Understand AI (UA)

The first attribute of the STT, Accessibility refers to the concept of information being readily available at a location (Jeong & Shin, 2019) and how simple it is to access and use online travel information sources and services (Paliwal et al., 2022) to improve their travel experiences and feel satisfied with the travel destinations. Further, accessibility has been identified as an enabler for cocreating experiences, becoming a significant predictor of memorable tourism experience (Tussyadiah & Fesenmaier, 2009).

Informativeness has been identified as quality and trustworthiness of the information provided to tourism destinations using STT (Huang et al. 2017; No & Kim 2015). Further, information quality and trustworthiness could enhance the tourist's experience (Jeong & Shin, 2019). The increasing amount of rich information stimulates individuals to enrich their travel experience in smart tourism destinations. Hence, it is evident that there is a relationship between informativeness and memorable tourist experience.

The third attribute of the STT, interactivity, is identified as the repeated communication among the stakeholders. In addition, interactivity promotes communication among stakeholders when individuals use STT (Jeong & Shin, 2019). Further, it is highlighted that when consumers are interacting with STT, it facilitates more relevant and applicable information for their requirements. Hence, it is noteworthy that higher level of interaction leads to more positive perception of information technology and user experience (Jeong & Shin, 2019).

The final attribute of the STT, Personalization refers to providing a unique tailored experience to individuals based on their interests, personal traits, and requirements (Song, 2024) and has been widely studied in recent years. Further, personalization satisfies the tourists travel experience with the help of smart tourism destinations (No & Kim 2015). As per the previous findings, it is evident that personalized experiences can enhance consumer engagement and emotional connectedness (Lou & Xie, 2021). Furthermore, the importance of personalization is highlighted with the reduction of time spent during the information search (Schaupp & Bélanger 2005; Ball, Coelho, & Vilares 2006). Hence, it has been identified that both interactivity and personalization allow STTs to provide the most relevant information to the tourists and enhance tourists' memorable experiences. Based on the above arguments, below propositions have been derived,

P1: Accessibility significantly impacts Memorable Experience

P2: Informativeness significantly impacts Memorable Experience

P3: Interactivity significantly impacts Memorable Experience

P4: Personalization significantly impacts Memorable Experience

3.3 Know and Understand AI (UA)

In the tourism context, satisfaction is defined as the positive evaluation of their psychological state resulting from travel experience (Jeong & Shin, 2019). According to previous literature, it has been identified that tourists feel satisfied when they have a positive experience with activities, they participate in at tourist destinations (Jeong & Shin, 2019). Further, it has investigated how technology is impacting the memorable experience and satisfaction of the consumers (Carbonell & Escudero 2015; Ozturk & Hancer 2015; X. Wang et al. 2016). Moreover, it is noteworthy that negative technological experience has a significant negative effect on their satisfaction and intentions to use the technology again. Furthermore, memorable experiences are recognized as the driving factor affecting decision making. Additionally, customers' experience appears to have a strong positive relationship with their satisfaction with the use of technology (Ozturk & Hancer 2015). Hence, it is evident that when tourists perceive their experience as memorable, attractive, and valuable they tend to be satisfied. Accordingly, the below proposition has been derived.

P5: Memorable Experience significantly impacts Tourist Satisfaction

According to the previous literature, it is noteworthy that there is a relationship between attributes of STT and memorable experiences (Jeong & Shin, 2019), while memorable experiences have a significant impact on tourist satisfaction (Carbonell & Escudero 2015; Ozturk & Hancer 2015; X. Wang et al. 2016). Based on the above relationships, it is noteworthy that there could be a relationship developed on the mediating effect of memorable experience on the STT and tourist satisfaction. Accordingly, the below propositions has been derived.

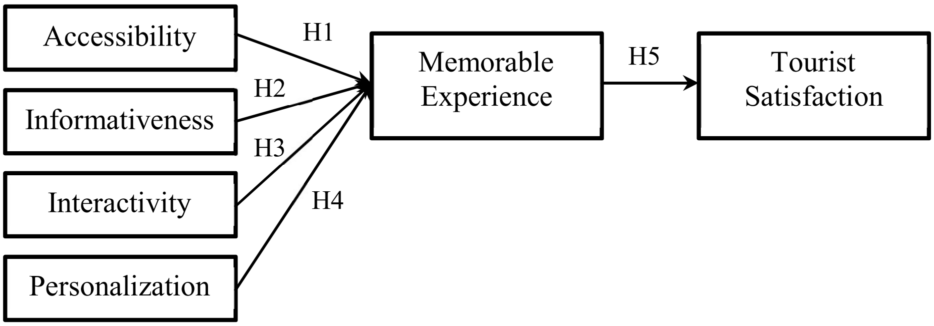
P6: Memorable Experience mediates the relationship between STT and Tourist Satisfaction

3. Methodology

A quantitative approach is recommended to measure the impact of STTs on tourist satisfaction by creating a memorable experience in the minds of the travelers. Surveys can be designed to capture quantitative data on the experiences and satisfaction of Gen Z regarding the STTs dimensions such as accessibility, informativeness, interactivity and personalization and their impact on overall traveler's satisfaction (Zhang, Sotiriadis, & Shen, 2022; Jeong, & Shin, 2019).

Figure1: Conceptual Framework

Source: Authors



Moreover, utilizing Structural Equation Modeling (SEM) can help in understanding the complex relationships between smart tourism technology attributes and tourist satisfaction as it is identified as a robust method for exploring the influence of smart technology use behavior on tourist satisfaction and revisit intention. It is particularly useful when the research model is complex and involves multiple constructs as denoted in the conceptual framework built by the authors.

In terms of studies in the fields of tourism and hospitality marketing and management, sample sizes ranging from 360 to 600 participants often have been used to ensure statistical significance and generalizability of the findings (Zhang, Sotiriadis, & Shen, 2022; Azis, Amin, Chan, & Aprilia, 2020). Given the focus on Generation Z travelers, it is crucial to ensure that the sample is representative of this demographic. This may involve targeting specific age groups (e.g., 18-25 years old) and ensuring a balanced representation of gender and geographic location (Pricope, Băltescu, Brătucu, Tecău, Chițu, & Duguleană, 2023).

As per the sampling techniques, convenience sampling technique which involves selecting participants who are easily accessible and willing to participate, has been often used in online surveys where respondents are recruited through social media platforms and other digital channels frequented by Generation Z (Pricope, Băltescu, Brătucu, Tecău, Chițu, & Duguleană, 2023). Snowball sampling technique too can be useful for reaching a wider network of Generation Z travelers by leveraging existing participants to recruit additional respondents. This approach has been identified particularly effective in digital communities and social media networks (Pricope, Băltescu, Brătucu, Tecău, Chițu, & Duguleană, 2023).

4. Implications

5.1 Theoretical Implications

The adoption of STTs are expected to accelerate rapidly in the coming years, further transforming the landscape of destination management (Femenia-Serra et al., 2019). Hence, this concept paper contributes to the growing body of literature on STTs and its impact on travelers especially the Gen Z travelers addressing the population gap. STTs have been identified as integral in enhancing tourist satisfaction by providing personalized and interactive experiences. Hence, the attributes of STTs, such as accessibility, information quality, and personalization, are recognized as crucial in studying of the influence on tourist satisfaction and their intentions to visit destinations and revisit intention as well (Pai, Liu, Kang, & Dai, 2020; Jeong, & Shin, 2019). Moreover, researchers have identified these as technologies facilitating both explorative and exploitative uses, which significantly impact the overall travel experience and tourist satisfaction (Huang, C., Goo, J., Nam, K., & Yoo, C. 2017; Zhang, Y., Sotiriadis, M., & Shen, S. 2022).

5.2 Managerial Implications

Generation Z travelers exhibit unique behaviors in their interaction with STTs, heavily relying on digital platforms and social media for travel planning and decision-making (Pricope, Băltescu, Brătucu, Tecău, Chițu, & Duguleană, 2023). Hence, this concept paper focuses on the to deal with the application of STTs to navigate complexities in tourism and hospitality industry related processes, logistics and most importantly marketing of its services. For Generation Z, the memorable experiences facilitated by STTs are pivotal in shaping their travel narratives and recommendations to peers, thereby the authors amplify the impact of these technologies on tourism marketing and management strategies (Yoo, Goo, Huang, Nam, & Woo, 2017; Torabi, Shalbafian, Allam, Ghaderi, Murgante, & Khavarian-Garmsir, 2022). Further, such kind of positive experiences and satisfaction associated with STTs can lead to increased word-of-mouth recommendations and a willingness to pay a premium for enhanced services (Zhang, Sotiriadis, & Shen, 2022). Hence, the need for continuous innovation and adaptation of STTs to meet the evolving expectations of this tech-savvy generation is essential for sustaining their engagement and satisfaction (Ye, & Law, 2020; Yoo, Goo, Huang, Nam, & Woo, 2017).

5. Conclusion

This concept paper aims to contribute to the existing knowledge of STT on tourist satisfaction. Further, it focuses on understanding how STT leads to memorable experiences and thereby to tourist satisfaction. According to the previous literature, the direct relationships of STT and memorable experience towards tourist satisfaction along with a mediating impact of memorable experience have been developed. Further, this concept paper contributes to the growing body of literature on STT while providing significant practical implications for marketers, policymakers, and other decision-makers to increase the utilization of STT to enhance tourist satisfaction. Hence, it is noteworthy that initiations to enhance the discussion on STT, memorable experience and thereby the relationship towards tourist satisfaction.

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INTEGRATED SENSOR NETWORK FOR SURVEILLANCE AND RESPONSE MODEL FOR NATIONAL SECURITY OF SRI LANKA

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Abstract

Sri Lanka is increasingly becoming a pivotal state therefore interests towards this country by world powers is growing. These interests create threats as well as opportunities. An effective surveillance, situation analysis and response mechanism to counter internal and external threats whilst maximizing benefits of opportunities is of utmost importance to safeguard national security and sustained development. It is a tedious task to deal with nationwide information with manual systems. Time taken to arrive at decisions using manual procedures result obsolete solutions due to slowness in manual systems against rapid conflict transformations and technology advancements, hence the state must have a system to predict such possible disturbances and respond effectively with minimum aftereffects. National security in Sri Lankan perspective depends mainly on the survival of economy, territorial integrity, peace, political stability, favorable foreign relations, energy, environment and natural resources. To safeguard these aspects, we need to continuously monitor land, sea, air, global trends and cyberspaces through surveillance systems plus monitor government and private sector financial and social aspects trough e-governance. Then derive the best options of responses and implement them effectively. This study proposes a basic architecture of in which all the blocks are derived from already developed and tested systems by developed countries, but we need to customize them to suit for Sri Lankan needs and culture.

Keywords: National Security, Surveillance, Real-time Monitoring, Decision Support Systems.

1. Introduction

1.1 National Security

Prior to planning how to protect national security, we must define what it is. National security has been defined in many ways and definition has been evolving with the world order (U.S. Navy, 2012) (Victoria, 2018) and interpreted depending upon the states' perception of national and foreign policies. Hence the definition of national security has been modified to suit the states' requirements, policies and their threat perceptions. To be focused on to Sri Lankan perspective, generic definition need be considered with modifications to suit us. Generic definition is "National security is the requirement to maintain survival of the state through use of economic, diplomacy, power projection and political power" (Victoria, 2018). Now it encompasses a broad range of facets, all of which impinge on the nonmilitary or economic security of the nation and the socio-cultural values. In these lines, to uphold national security, a nation like Sri Lanka primarily needs to possess economic security, military security, political security, environmental security, energy and natural resources security. Security threats involve not only conventional foes such as other nation-states but also non-state actors such as violent non-state actors (Yon, 2009), narcotic cartels, and non-governmental organizations. Natural disasters too need to be considered in this category. In contemporary world Information is a key asset and information security also must be considered as one of the most important components of the national security.

By encompassing all above aspects, national security in Sri Lankan perspective can be defined as 'National security is to survival of national economy, territorial integrity, peace, political stability, favorable foreign relations, energy, environment, Information and natural resources against natural disasters, violent non state actors, and diplomatic, political, military power projections of external actors. There are various definitions to AI literacy and according to Ng et al. (2021) it comprises four concepts such as Know and comprehend AI, Use & Apply AI, Evaluate & Create AI, and AI ethics. They believe that someone is considered to be AI literate if they understand the fundamentals of AI, are able to utilize AI applications, use their knowledge of AI in various contexts, assess, evaluate, forecast, and create AI applications, and are able to think ethically.

1.2 Monitoring Surveillance and Decision Making in Sri Lankan Perspective

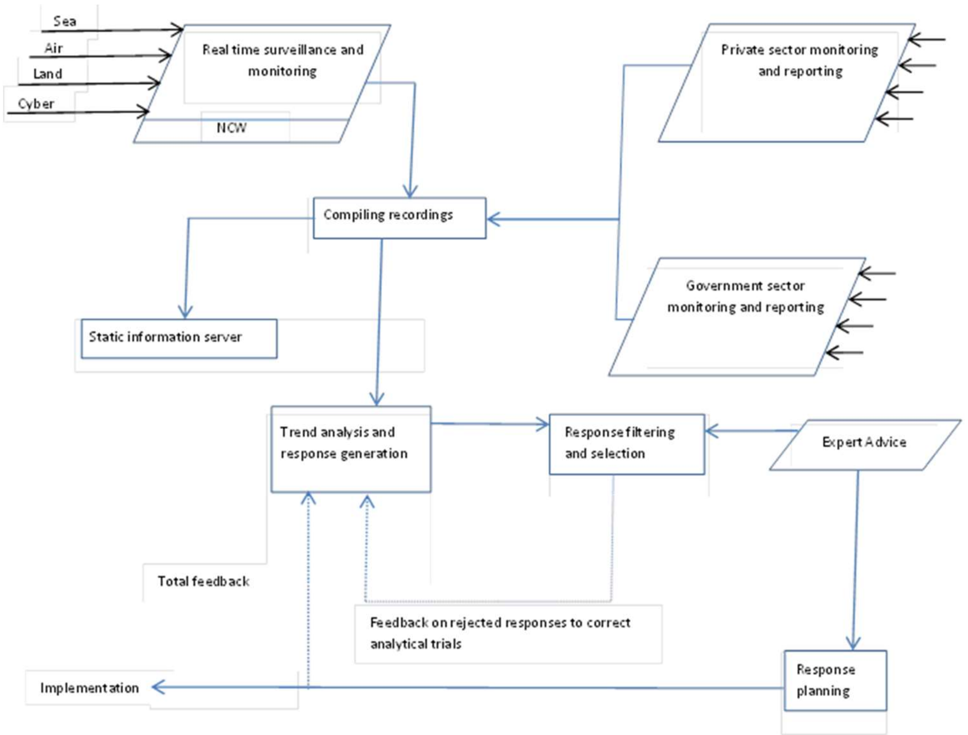
In contemporary competitive geopolitical arena, a correct, accurate and timely response to any social, political, environmental and technological change is prudent to maintain stability and durable peace of the country. Therefore, surveillance and response system backed by professional Decision Support System (DSS) is mandatory for Sri Lanka to safeguard national security. Network Centric Warfare (NCW) pioneered by United States Department of Defense, in late nineties as a military doctrine (Alberts, Garstka, & Stein, 1997). They used multiple sensor surveillance system and enables rapid sharing of information gathered by geographically dispersed sensors through ICT enabled networks. Further provides (Decision Support System) DSS for decision makers, providing high competitive advantage over adversaries and to have preparedness against natural disasters/ changes. Therefore, NCW approach is proposed to cover the real time surveillance/ monitoring, storing data, processing and for easy interpretations. This approach combined with e-governance enabled, private and government sector monitoring and reporting is ideal to deal with huge amount of information by means of pictorial and graphical presentations. Live information and stored information availability enables the decision makers to have total picture of the operational domain, and also to disseminate relevant information to relevant units for fast and unambiguous situational awareness and responses. In military this is known as Common Operating Picture (COP) (Gunasekara ,2012). Availability of live information enables analysis of effect of a live engagement helping to plan next Effect Based Operation (EBO) (McCrabb, 2001) that maximizes efficiency of effort and effectiveness of engagements.

1.3 IT Based Situational Influence Assessment

Situational Influence Assessment Model (SIAM) developed by US (Hayes & Sands, 1997) is an analysis model and it is found to be a suitable guide line to develop necessary analytical tool for the proposed system for Sri Lanka. SIAM has initially published by Centre for Naval Warfare Studies at US. Naval Warfare College 1996 (U.S. Navy, 2012) and later development project was undertaken by Joint Warfare Analysis Centre funded by Command Control Computing Communication Intelligence and Surveillance (C4IS) Research Program (Hayes & Sands, 1997).

Figure 1: Situational Influence Assessment Model (SIAM)

Source: Author



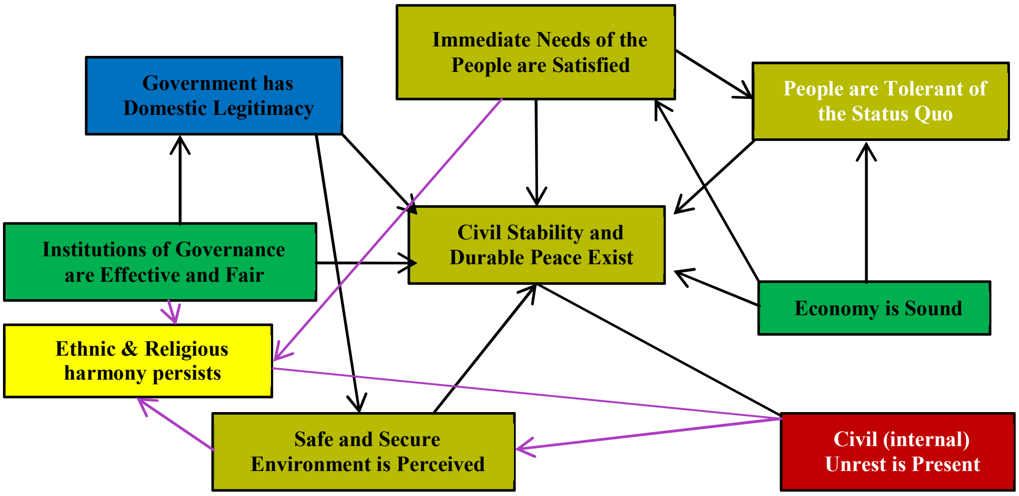
In the SIAM, the analyzing model, situations are depicted by nodes and inter-nodal influences are depicted by the links. Figure 2 shows a sub net with the situation under consideration (civil stability and durable peace exists) which is named as a root node. The nodes influencing the root node are named as causal nodes. This subnet is a part of a large network with many nodes. For actual use full net need to be used because, even remote nodes may have reverberation on the root node. Finally, the proposed model displays the total probabilistic risk levels for decision makers. This provides windows based graphical user interphone and Bayesian functions are used to interpret data/ information to derive outputs. Therefore, this system provides probabilistic, rather than deterministic, answers keeping room to select best as per the vision of the national apex.

2. *Methodology for Implementation*

Current ICT infrastructure and availability of latest hardware and software as "Commodity Off The Shelf" (COTS) items plus high standard of Sri Lankan knowledge base proves ability of Sri Lankans to build own surveillance, analyzing and response system. The complete national system will consist of a cluster of networks as of Fig.2, each covering appropriate area, integrated together. The analyzing tools need to be developed and aligned with information obtained from experts of relevant fields such as military, treasury (finance), ministries, ICT professionals and departments. The literature available on, how the SIAM was developed (Hayes & Sands, 1997) gives a good insight for planning the development of a system suited to our requirements.

Figure 2: Subnet of Root-node "Civil Stability and Peace Exists"

Source: Author



This paper selects "sea" component indicated at Fig 1, as pilot to explain the method of implementation. "Maritime hub is one out of five hubs out lined for sustainable economy and its components run in all parts of the proposed model. At the "sea" input at Fig 1, surveillance is done by following means.

a. AIS (Automatic Identification System) provides live information of merchant vessels.

b. RADAR for monitoring, tracking, plotting and correlating objects detected by other means.

c. VTMS (Vessel Traffic Management System) mainly used for track and control vessels and craft in the ports vicinity and restricted areas.

d. VMS (Vessel Monitoring System) to locate and track licensed fishing vessels beyond 200 nautical miles, by Fisheries Corporation.

e. Surveillance cameras from short, ships and air.

The inputs relevant to maritime hub for government sector monitoring and reporting should come from, Ministry of Fisheries, Department of Metrology, Sri Lanka Ports Authority, and Coast conservation etc. They will give their surveillance, finance and human resource management data for analyzing and compilation of records. It is recommended facilities for transmission of relevant information be incorporated when e-based reporting under e-governance is planned to avoid duplication of infrastructure. The external and global trends related to each department are expected to be fed from the relevant departments. The private sector entities also such as ship and maritime builders, repairers and service providers should be made to update their information regularly similar to the government sector.

The current situations are fed to the response development tool for analysis and to generate possible response options. Though in Fig 1, the analysis takes place after the compilation and recording, required data, protocols, and influence weight ages need to be determined first to architect the system. Following sequence is suggested for the implementation.

a. Form a task group.
b. Identify entities needed to be incorporated for surveillance, monitoring and reporting, in order of priority and start corresponding to select suitable representatives.
c. Plan and conduct a series of workshops to build primary infrastructure for information exchange and also to develop initial cause effect models.
d. Prepare following for government approvals.
    i. COP architecture for operations room arrangements consulting operational managers and ICT experts of relevant entities.
    ii. Draw preliminary flowcharts consulting relevant professionals of said entities.
e. Finalize the prototype of the system to be implemented.
f. Hire ICT professionals as required to develop the system. Maximum possible efforts to be taken to use in house developed software and COTS equipment to overcome threats of embargos.

3. Conclusion

National security is vital for a country and need no elaborations. Real time monitoring, surveillance and reporting on threats, opportunities and trends influencing national security is to be analyzed and most effective responses need to be derived promptly surpassing the speed of adversaries and situational transformations, safe guarding the aspects encompassed in above coined definition of national security. For that network centric surveillance system backed by a suitable decision support system is mandatory. Sri Lanka has professionalism, expertise and resources to develop and implement such system.

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SENTIMENT ANALYSIS OF MOVIE REVIEWS USING MACHINE LEARNING: A NAIVE BAYES APPROACH

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Abstract

Sentiment analysis, a subfield of natural language processing (NLP), has gained significant attention for its ability to automatically classify text data into positive or negative sentiments. This study focuses on sentiment analysis of movie reviews using the IMDb Movie Reviews dataset, a widely used benchmark in NLP research. The goal is to classify reviews as positive or negative using the Naive Bayes algorithm, a probabilistic classifier known for its simplicity and effectiveness in text classification tasks. The text data underwent preprocessing steps, including text cleaning, stopword removal, and tokenization, before being converted into numerical features using Term Frequency-Inverse Document Frequency (TF-IDF). The model was trained on 40,000 reviews and evaluated on a test set of 10,000 reviews, achieving an accuracy of 85.02%. Precision, recall, and F1-scores were also 0.85 for both positive and negative classes, indicating balanced performance. The results demonstrate the effectiveness of Naive Bayes in sentiment analysis, while also highlighting challenges such as handling ambiguous language and sarcasm. This study provides a foundation for future research into more advanced sentiment analysis techniques and their applications in understanding audience perceptions.

Keywords: Sentiment Analysis; Movie Reviews; Naive Bayes; Machine Learning; Text Classification; IMDb Dataset; TF-IDF; Natural Language Processing (NLP); Sentiment Classification; Audience Perception

1. Introduction

Sentiment analysis, also known as opinion mining, is a subfield of natural language processing (NLP) that focuses on identifying and extracting subjective information from text data. It plays a critical role in understanding public opinion, customer feedback, and social media sentiment, making it a valuable tool for businesses, researchers, and policymakers (Liu, 2012). With the exponential growth of online content, particularly user-generated reviews, sentiment analysis has become increasingly important for automating the process of gauging public sentiment at scale (Pang et al., 2014).

Movie reviews, in particular, provide a rich source of data for sentiment analysis. Platforms like IMDb and Rotten Tomatoes host millions of reviews, offering insights into audience perceptions of films. Analyzing these reviews can help filmmakers, studios, and streaming services understand audience preferences, improve content, and make data-driven decisions (Taboada et al., 2011). However, the sheer volume of reviews makes manual analysis impractical, necessitating the use of automated sentiment analysis techniques.

Machine learning has emerged as a powerful approach for sentiment analysis, enabling the classification of text into positive or negative categories with high accuracy (Medhat et al., 2014). Among the various algorithms, Naive Bayes has gained popularity due to its simplicity, efficiency, and effectiveness in text classification tasks (Zhang et al., 2016). Despite its simplicity, Naive Bayes often performs competitively with more complex models, making it an ideal choice for baseline sentiment analysis (Wang et al., 2012).

This study focuses on sentiment analysis of movie reviews using the IMDb Movie Reviews dataset, a widely used benchmark dataset in NLP research. The goal is to classify reviews as positive or negative using the Naive Bayes algorithm and evaluate its performance. By leveraging machine learning techniques, this research aims to demonstrate the feasibility of automating sentiment analysis for large-scale text data while identifying challenges and areas for improvement.

The remainder of this paper is organized as follows: Section 2 provides a review of related work in sentiment analysis and machine learning. Section 3 details the methodology, including data preprocessing, feature extraction, and model training.

Section 4 presents the data analysis and results, followed by a discussion of the findings in Section 5. Finally, Section 6 concludes the paper and suggests directions for future research.

2. Literature Review

Sentiment analysis has emerged as a critical area of research in natural language processing (NLP), driven by the increasing availability of user-generated content on social media, review platforms, and other online forums (Liu, 2012). The goal of sentiment analysis is to automatically identify and extract subjective information, such as opinions, emotions, and attitudes, from text data. This capability has broad applications, including market research, customer feedback analysis, and social media monitoring (Pang et al., 2014).

2.1 Sentiment Analysis Techniques

Early approaches to sentiment analysis relied on lexicon-based methods, which use predefined lists of words associated with positive or negative sentiments (Taboada et al., 2011). While these methods are simple and interpretable, they often struggle with context-dependent language, sarcasm, and nuanced expressions (Medhat et al., 2014). To address these limitations, machine learning-based approaches have gained prominence, leveraging labeled datasets to train models that can automatically classify text into sentiment categories (Zhang et al., 2016).

2.2 Machine Learning in Sentiment Analysis

Machine learning algorithms, particularly supervised learning methods, have been widely adopted for sentiment analysis due to their ability to learn patterns from labeled data (Wang et al., 2012). Among these algorithms, Naive Bayes has been particularly popular for text classification tasks. Naive Bayes is a probabilistic classifier that assumes independence between features, making it computationally efficient and effective for high-dimensional text data (Zhang et al., 2016). Despite its simplicity, Naive Bayes often performs competitively with more complex models, especially in scenarios with limited training data (Wang et al., 2012).

2.3 Applications of Sentiment Analysis

Sentiment analysis has been applied to various domains, including product reviews, social media, and movie reviews. In the context of movie reviews, sentiment analysis can provide valuable insights into audience perceptions, helping filmmakers and studios make data-driven decisions (Taboada et al., 2011). For example, Pang, Lee, and S. Vaithyanathan (Pang et al., 2002) demonstrated the effectiveness of machine learning techniques in classifying movie reviews as positive or negative, achieving accuracies comparable to human performance. Their work laid the foundation for subsequent research in this area, highlighting the potential of automated sentiment analysis for large-scale text data.

2.4 Challenges in Sentiment Analysis

Despite its successes, sentiment analysis faces several challenges. One major challenge is the handling of ambiguous language, such as sarcasm, irony, and mixed sentiments (Liu, 2012). These linguistic nuances are difficult for traditional bag-of-words models to capture, often leading to misclassifications (Medhat et al., 2014). Additionally, the performance of sentiment analysis models can vary significantly across domains, necessitating domain-specific adaptations (Zhang et al., 2016).

2.5 Recent Advances

Recent advances in deep learning have further improved the performance of sentiment analysis models. Techniques such as recurrent neural networks (RNNs) and transformers (e.g., BERT) have demonstrated state-of-the-art results by capturing contextual information and long-range dependencies in text (Devin et al., 2019). However, these models often require large amounts of labeled data and computational resources, making them less accessible for certain applications (Zhang et al., 2016). In contrast, traditional machine learning models like Naive Bayes remain popular for their simplicity and efficiency, particularly in resource-constrained settings (Wang et al., 2012).

2.6 Gaps in the Literature

While significant progress has been made in sentiment analysis, there is a need for more research on improving the interpretability and robustness of models, particularly in handling ambiguous and context-dependent language (Liu, 2012). Additionally, the performance of traditional machine learning models like Naive Bayes in comparison to deep learning models warrants further investigation, especially in domain-specific applications such as movie reviews (Zhang et al., 2016).

3. Methodology

3.1 Sentiment Analysis Techniques

This study employs a supervised machine learning approach to perform sentiment analysis on the IMDb Movie Reviews dataset. The methodology encompasses data preprocessing, feature extraction, model training, and evaluation. The goal is to classify movie reviews as either positive or negative using the Naive Bayes algorithm, a probabilistic classifier well-suited for text classification tasks.

3.2 Data Processing

The raw text data underwent a series of preprocessing steps to ensure optimal model performance:

3.2.1 Text Cleaning:

- Removal of HTML Tags: HTML tags and other non-textual elements were removed using regular expressions to eliminate noise.
- Removal of Special Characters and Numbers: Punctuation, special characters, and numerical values were removed to focus on textual content.
- Lowercasing: All text was converted to lowercase to ensure uniformity and reduce the complexity of the feature space.

3.2.2 Stopword Removal:

Common stopwords (e.g., "the," "and," "is") were removed using the Natural Language Toolkit (NLTK) library. This step reduces the dimensionality of the feature space and focuses the analysis on meaningful words.

3.2.3 Tokenization:

The cleaned text was tokenized into individual words or tokens, which serve as the basic units for feature extraction.

3.3 Feature Extraction

To convert the preprocessed text into a numerical format suitable for machine learning, the Term Frequency-Inverse Document Frequency (TF-IDF) technique was employed:

- Term Frequency (TF): Measures the frequency of a word in a review.
- Inverse Document Frequency (IDF): Measures the importance of a word in the entire dataset.
- TF-IDF: Combines TF and IDF to emphasize words that are discriminative for sentiment classification. The TfidfVectorizer from the scikit-learn library was used to generate a sparse matrix of TF-IDF features, with a maximum of 5,000 features to balance computational efficiency and model performance.

3.4 Model Selection

The Naive Bayes algorithm was selected for this study due to its simplicity, efficiency, and effectiveness in text classification tasks. Specifically, the Multinomial Naive Bayes variant was used, as it is well-suited for discrete data such as word counts or TF-IDF features. The model was implemented using the MultinomialNB class from the scikit-learn library.

3.5 Model Training and Evaluation

- Data Splitting: The dataset was split into training and testing sets using an 80:20 ratio. Specifically, 40,000 reviews were used for training, and 10,000 reviews were reserved for testing.
- Model Training: The Naive Bayes model was trained on the TF-IDF features of the training set. The model learns the probability distribution of words for each sentiment class (positive and negative) during this phase.
- Model Evaluation: The trained model was evaluated on the test set using the following metrics:
  - Accuracy: The proportion of correctly classified reviews.
  - Precision: The proportion of correctly predicted positive/negative reviews out of all predicted positive/negative reviews.
  - Recall: The proportion of correctly predicted positive/negative reviews out of all actual positive/negative reviews.

- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of model performance.

A confusion matrix was also generated to provide a detailed breakdown of true positives, true negatives, false positives, and false negatives.

3.6 Implementation Tools

The following tools and libraries were used for implementation:

- Python: The primary programming language for data preprocessing, model training, and evaluation.
- scikit-learn: For feature extraction (TfidfVectorizer), model implementation (MultinomialNB), and evaluation metrics.
- NLTK: For stopword removal and text preprocessing.
- pandas: For data manipulation and analysis.
- matplotlib and seaborn: For data visualization, including confusion matrix heatmaps and word clouds.

3.7 Ethical Considerations

- The dataset used in this study is publicly available and does not contain personally identifiable information (PII).
- The study adheres to ethical guidelines for data usage and machine learning research, ensuring transparency and reproducibility.

The methodology encompasses data preprocessing, feature extraction, model training, and evaluation. The goal is to classify movie reviews as either positive or negative using the Naive Bayes algorithm, a probabilistic classifier well-suited for text classification tasks.

4. Data Analysis

4.1 Dataset Description

The IMDb Movie Reviews dataset consists of 50,000 movie reviews, evenly balanced with 25,000 positives and 25,000 negative reviews. Each review is represented as a raw text string, and the sentiment labels are binary, with 1 denoting positive sentiment and 0 denoting negative sentiment.

4.2 Theoretical Implications

After preprocessing the data, an exploratory analysis was conducted to gain insights into the dataset:

- Class Distribution: The dataset is perfectly balanced, with an equal number of positive and negative reviews. This balance ensures that the model is not biased toward either class during training.
- Word Frequency Analysis: Word clouds were generated to visualize the most frequent words in positive and negative reviews. Positive reviews prominently featured words such as "excellent," "wonderful," and "amazing," while negative reviews included words such as "bad," "worst," and "terrible." This analysis confirmed that the dataset contains distinct lexical patterns for each sentiment class.

4.3 Impact of Preprocessing

The preprocessing steps, particularly stopword removal and text cleaning, significantly reduced noise in the dataset. This reduction allowed the model to focus on meaningful words, improving its ability to distinguish between positive and negative reviews. The TF-IDF feature extraction further emphasized discriminative words, enhancing the model's performance.

5. Results

5.1 Model Performance

The sentiment analysis model was evaluated on a held-out test set comprising 10,000 reviews. The evaluation metrics are summarized below and shown in Figure 1.

Figure 1: Results of the Model performance

Source: Authors

```
Accuracy: 0.8502
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.85      0.85      4961
           1       0.85      0.85      0.85      5039

    accuracy                           0.85     10000
   macro avg       0.85      0.85      0.85     10000
weighted avg       0.85      0.85      0.85     10000

Confusion Matrix:
 [[4201  760]
 [ 738 4301]]
```

Accuracy: The model achieved an overall accuracy of 85.02%, indicating that it correctly classified 85% of the reviews in the test set.

Precision, Recall, and F1-Score: The model's performance was evaluated using precision, recall, and F1-score for both positive and negative sentiment classes. The results demonstrate balanced performance across both classes, as shown in Table 1:

Table 1: Precision, Recall, and F1-Score

Source: Authors

Metric	Negative Reviews (Class 0)	Positive Reviews (Class 1)	Macro Average	Weighted Average
Precision	0.85	0.85	0.85	0.85
Recall	0.85	0.85	0.85	0.85
F1-Score	0.85	0.85	0.85	0.85

Interpretation:

- Precision: 85% of the predicted negative and positive reviews were correct.
- Recall: 85% of the actual negative and positive reviews were correctly predicted.
- F1-Score: The harmonic mean of precision and recall was 0.85 for both classes, indicating balanced performance.
- Macro and Weighted Averages: Both averages were 0.85, further confirming the model's consistency across classes.

Confusion Matrix: The confusion matrix shown in Figure 1 provides a detailed breakdown of the model's predictions:

- True Negatives (TN): 4201 (correctly predicted negative reviews).
- False Positives (FP): 760 (negative reviews incorrectly predicted as positive).
- False Negatives (FN): 738 (positive reviews incorrectly predicted as negative).
- True Positives (TP): 4301 (correctly predicted positive reviews).

5.2 Visualization of Results

To enhance the interpretability of the results, the following visualizations were created:

- Confusion Matrix Heatmap: A heatmap of the confusion matrix was generated to visually represent the distribution of true positives, true negatives, false positives, and false negatives, as shown in Fig 2.
- Word Clouds: Word clouds for positive and negative reviews were constructed to highlight the most frequent words in each class, providing insights into the lexical patterns associated with each sentiment. The result is shown in Fig 3.

Figure 2: Confusion Matrix Heatmap

Source: Authors

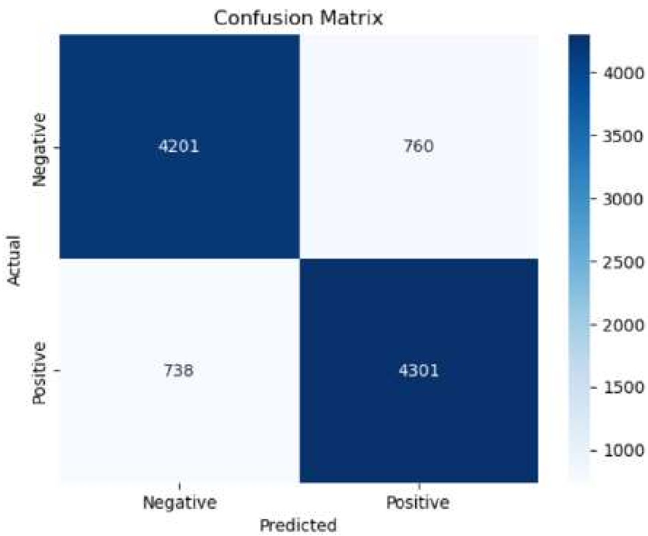
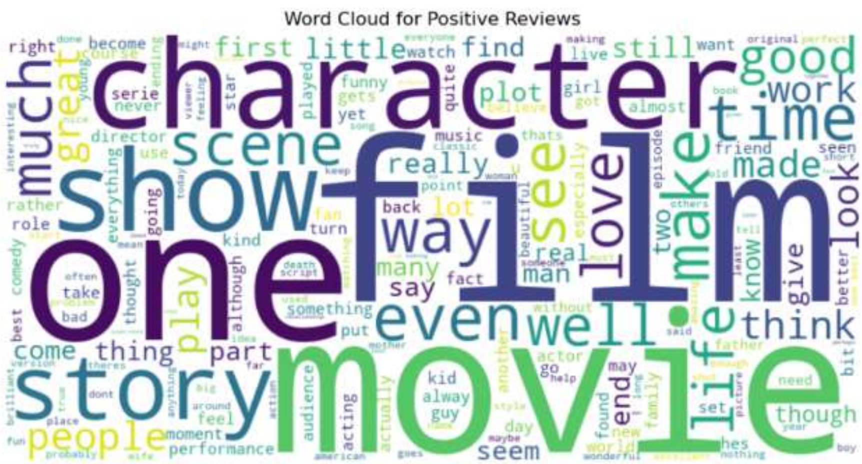


Figure 3: Word Cloud

Source: Authors



5.3 Error Analysis

A qualitative analysis of misclassified reviews was conducted to identify common sources of error. Key findings include:

- Ambiguous Language: Reviews containing mixed sentiments (e.g., "The movie was not bad, but it wasn't great either") were frequently misclassified, as the model struggled to interpret conflicting cues.
- Sarcasm and Irony: Sarcastic reviews (e.g., "Oh, great, another masterpiece... not!") were often misclassified due to their contradictory nature, which poses a challenge for traditional bag-of-words models.
- Contextual Nuances: Words with multiple meanings (e.g., "flat" could mean "boring" or "smooth") sometimes led to incorrect predictions, underscoring the limitations of lexical-based approaches.

6. Discussion and Conclusion

The results indicate that the Naive Bayes model performs well in classifying movie reviews, achieving an accuracy of 85%. The model demonstrates balanced performance across both sentiment classes, as evidenced by the equal precision, recall, and F1-scores for positive and negative reviews. This balance suggests that the model does not exhibit bias toward either class and is equally effective at identifying both sentiments.

The confusion matrix reveals that the model makes a similar number of errors for both classes (760 false positives and 738 false negatives). This symmetry in misclassifications further confirms the model's unbiased performance. However, the presence of misclassified reviews highlights areas for improvement, particularly in handling ambiguous or nuanced language.

The Naive Bayes model achieved an accuracy of 85% on the IMDb Movie Reviews dataset, demonstrating its effectiveness in sentiment analysis. The balanced precision, recall, and F1-scores indicate that the model performs equally well for both positive and negative reviews. However, challenges such as ambiguous language, sarcasm, and contextual nuances highlight areas for future improvement. These results provide a solid foundation for further research into more advanced sentiment analysis techniques, including the use of deep learning models and contextual embeddings.

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GLOBAL FINANCIAL PATTERNS (1989–2021): A STATIONARITY ASSESSMENT AND K-MEANS CLUSTER ANALYSIS OF ASIAN COUNTRIES USING THE IMF FINANCIAL DEVELOPMENT INDEX

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Abstract

This paper investigates financial development patterns among 24 Asian countries from 1989 to 2021, focusing on the IMF Financial Development Index (FD Index) as the primary metric. We first applied the Augmented Dickey-Fuller (ADF) test to assess whether these time series exhibit stationarity. Most countries show p-values above the 0.05 threshold, indicating non-stationary data and necessitating a detrending procedure. We then employ k-means clustering to identify (1) key time periods associated with historical financial shocks and (2) clusters of countries sharing similar financial development trajectories. Our time-domain clustering highlights pivotal eras such as the Dot-Com Bubble (1999–2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020–2021). Meanwhile, the year 1997 emerges as a standalone cluster, coinciding with the onset of the Asian Financial Crisis. In cross-country clustering, we find two primary groups distinguishing countries with relatively advanced, diversified financial systems from those in earlier stages of financial development, often characterized by higher volatility, lower FD Index scores, and greater external vulnerability. These findings underscore that while Asia's financial systems often respond similarly to major global shocks, structural disparities persist. Countries with higher FD Index scores typically demonstrate stronger resilience, underscoring the importance of deep and inclusive financial institutions and markets. Policymakers, investors, and scholars may leverage these insights to design region-specific reforms, enhance macroprudential surveillance, and bolster collaborative strategies for sustainable financial growth.

Keywords: Stationarity, Augmented Dickey-Fuller, K-Means Clustering, IMF Financial Development Index, Asian Financial Markets, Global Financial Crises

1. Introduction

Over the past several decades, Asia has evolved into one of the most influential regions in the global economy, displaying remarkable growth rates, expanding trade networks, and increasingly sophisticated financial systems. This transformation has been facilitated by factors such as trade liberalization, large-scale foreign direct investment, and technological advancements that have enabled countries to diversify beyond traditional sectors (Arlinghaus & Nachreiner, 2014; Sahay et al., 2015). Notwithstanding these opportunities, Asian economies have also faced financial instability on multiple occasions, most notably during the 1997 Asian Financial Crisis and the 2007–2009 Global Financial Crisis. Both events underscored how international capital flows, unregulated market innovations, and limited oversight can trigger volatility, contagion, and recessions that derail years of progress (Anicich et al., 2015; Davis et al., 1999). Understanding the underlying drivers of these upheavals—and the conditions that facilitate recovery—requires robust analytical tools that distinguish short-term disruptions from longer-term shifts in financial structures.

1.1 Role of the IMF in Fostering Asian Financial Development

The International Monetary Fund (IMF), established in 1944 at the Bretton Woods Conference, has played an integral role in promoting global monetary cooperation, ensuring financial stability, and facilitating international trade (IMF, 2020). While its mandate is global, the IMF's interventions have been particularly notable in Asia, where countries have frequently turned to the institution for policy advice, financial support, and technical assistance during times of crisis and reform. During the 1980s and 1990s, many Asian nations embarked on economic liberalization initiatives, relaxing capital controls and welcoming foreign investment. These efforts, though beneficial for economic expansion, exposed structural weaknesses in banking systems and regulatory frameworks (Johnson, 1993). The IMF's guidance encompassing the introduction of prudential regulations, exchange rate adjustments, and fiscal consolidation often influenced how these nations implemented market-oriented policies.

The 1997 Asian Financial Crisis stands out as a key example of the IMF's involvement. Initially triggered by speculation against the Thai baht, the crisis spread to Indonesia, South Korea, Malaysia, and the Philippines, revealing vulnerabilities in currency pegs, corporate governance, and financial supervision. The IMF provided emergency lending packages tied to structural reforms, aiming to restore investor confidence and stabilize currencies (IMF, 2020). Although some critics argued that the Fund's prescriptions exacerbated short-term economic pain, many Asian countries subsequently strengthened their oversight bodies, accumulated foreign reserves, and diversified their financial sectors, demonstrating a long-term shift toward more robust financial systems (Barker, 1993; Sahay et al., 2015).

1.2 The Importance of Studying Asian Economies

Today, Asia is home to both high-income financial hubs (e.g., Japan, Singapore) and emerging or frontier markets (e.g., Bangladesh, Myanmar), making the region's financial landscape extraordinarily diverse (Davis et al., 1999). Some countries have developed deep capital markets and rank among the largest in the world, while others rely on commodity exports, inward remittances, or external borrowing to sustain growth. This diversity not only affects individual countries' economic trajectories but also shapes regional and global financial stability. For instance, disruptions in one major Asian market can reverberate across supply chains and investment networks worldwide, as evidenced by contagion effects during both the 1997 crisis and the 2007–2009 turmoil (Anicich et al., 2015).

Focusing on 24 Asian countries offers a holistic vantage point for analyzing cross-country variations in financial structures. These nations collectively account for a significant share of global population and gross domestic product (GDP), and their development pathways illustrate how factors like regulatory quality, institutional capacity, political stability, and geopolitical alliances interact to influence financial outcomes (Svirydzenka, 2016). Moreover, the rise of regional bodies, such as the Association of Southeast Asian Nations (ASEAN) and initiatives like the Belt and Road, underscore Asia's evolving role in shaping international trade flows, investment patterns, and capital mobility (IMF, 2020).

1.3 Non-Stationarity in Macroeconomic and Financial Data

A core analytical challenge in examining financial systems is non-stationarity. the phenomenon whereby statistical properties (such as mean, variance, and autocorrelation) of a time series change over time. In macroeconomic contexts, non-stationarity often arises from technological progress, institutional reforms, demographic shifts, and policy changes (Bank & Wheelwright, 1983). For instance, an emerging economy liberalizing its capital account may see a persistent upward trend in financial indicators, rather than cyclical fluctuations around a stable mean (Barker, 1993). If these underlying trends are not accounted for, empirical analyses risk spurious correlations and misleading inferences (Davis et al., 1999).

Researchers generally address non-stationarity by conducting unit root tests, such as the Augmented Dickey-Fuller (ADF) test, to determine whether a variable follows a stationary or non-stationary process (Arlinghaus & Nachreiner, 2014). When the ADF test indicates the presence of a unit root, transformation methods—like detrending or first-differencing—become necessary before applying conventional econometric models. This step is crucial to ensure that subsequent analyses—such as regressions, causality tests, or clustering algorithms—reflect genuine relationships and periodic shifts, rather than long-run growth paths or secular trends (Johnson, 1993).

1.4 The IMF Financial Development Index (FD Index)

While traditional measures of financial sector depth (e.g., private credit-to-GDP) or access (e.g., bank branches per capita) have provided partial insights, the IMF recognized the need for a more comprehensive metric, leading to the creation of the Financial Development Index (FD Index) (Svirydzenka, 2016). This index captures six broad dimensions:

- Financial Institutions' Depth (e.g., private credit, insurance, pension funds, mutual funds)
- Financial Institutions' Access (e.g., bank branches, ATMs, account ownership)
- Financial Institutions' Efficiency (e.g., net interest margin, overhead costs)
- Financial Markets' Depth (e.g., stock market capitalization, bond market capitalization)
- Financial Markets' Access (e.g., ease of listing, foreign listings)
- Financial Markets' Efficiency (e.g., price impact, transaction costs)

Each sub-dimension is scored and combined into a single FD Index value, facilitating cross-country comparisons and tracking changes over time (Svirydzenka, 2016). For emerging markets that are rapidly transforming, the FD Index can uncover structural vulnerabilities (e.g., insufficient diversification), identify gaps in access (e.g., low rates of financial inclusion), or highlight inefficiencies (e.g., high lending spreads) that undermine resilience to external shocks (Sahay et al., 2015). Meanwhile, for more mature markets, it reveals whether growth in sophistication (e.g., complex derivatives, algorithmic trading) aligns with robust regulatory capacity.

1.5 Why the FD Index Matters for Studying 24 Asian Countries

Asia's heterogeneity in financial development underscores why the FD Index is particularly suited to an in-depth analysis of this region. Countries such as Japan and Singapore are often considered global financial hubs, boasting advanced equity, bond, and money markets. By contrast, nations like Myanmar or Bangladesh have historically lower FD Index scores, reflecting limited financial access, nascent capital markets, and challenges with regulatory enforcement (Svirydzenka, 2016). Yet, these emerging economies also demonstrate high growth potential, often introducing digital finance innovations (e.g., mobile banking) that can rapidly boost inclusion.

Examining how each of the 24 Asian countries evolves in terms of the FD Index from 1989 to 2021 can reveal common turning points, such as the period following the 1997 crisis, when countries reformed banking systems, or the post-2008 landscape, when quantitative easing in advanced economies affected capital flows into Asia (Davis et al., 1999). It also shows whether economies converge toward similar levels of development or maintain wide disparities over time, crucial for policy coordination and crisis prevention at the regional level (Arlinghaus & Nachreiner, 2014).

1.6 Objectives and Research Focus

Given the potential for non-stationary dynamics in long-run financial indicators, particularly those capturing structural changes—and the multi-dimensional nature of the FD Index, this study adopts two main objectives:

Time-Based Analysis: Identify distinct historical periods in Asia's financial development, using k-means clustering on aggregated or transformed FD Index data for each year. The hypothesis is that specific crisis windows (e.g., the 1997 Asian Financial

Crisis, the 2007–2009 Global Financial Crisis) will manifest as unique clusters, reflecting synchronized dips or volatility in FD Index scores.

Cross-Country Classification: Group the 24 Asian countries by their FD Index trajectories over the 1989–2021 window. We anticipate a cluster of highly developed financial systems (e.g., Japan, Singapore), a cluster of moderately advanced markets (e.g., Malaysia, Thailand), and a cluster of lower FD Index countries (e.g., some South Asian and Middle Eastern states). However, we remain open to the possibility that certain nations—due to unique reforms or resource wealth—may not align neatly with regional peers (Barker, 1993; Sahay et al., 2015).

To address non-stationarity, Augmented Dickey-Fuller (ADF) tests are applied to the FD Index series for each country, and transformations (detrending or differencing) are performed where necessary (Arlinghaus & Nachreiner, 2014). These preprocessing steps help ensure that subsequent clustering captures meaningful short- and medium-term fluctuations, rather than mere long-run ascents in financial maturity (Johnson, 1993). By combining robust stationarity checks with k-means clustering, we aim to elucidate how Asia's financial landscape has evolved, how crises reshape the development pathway, and why certain economies appear more resilient or vulnerable in the face of global shocks.

1.7 Structure of This Journal Article

The remainder of this article proceeds as follows:

Section 2 (Literature Review) contextualizes existing research on financial development, crisis contagion, and clustering algorithms. It summarizes key findings on how advanced metrics, such as the FD Index, enhance our understanding of macro-financial stability in emerging markets.

Section 3 (Methodology) outlines the data sources, including a detailed overview of the IMF FD Index construction, stationarity testing procedures, and the k-means clustering framework. Specifics on variable definitions, sample coverage, and data transformations are provided.

Section 4 (Findings and Discussion) presents the empirical results. We first reveal the outcomes of the ADF tests, discussing how many countries show evidence of non-stationary FD Index series. Then, we detail the time-based clusters, highlighting critical years of financial turmoil or reform, and the cross-country clusters, describing shared financial characteristics among groupings of nations.

Section 5 (Limitations and Recommendations) acknowledges potential constraints, such as the use of annual data, the exclusion of certain macroeconomic variables, and the rigid partitioning of k-means. We suggest avenues for future research, such as higher-frequency data and enhanced incorporation of institutional factors.

Section 6 (Conclusion) synthesizes the study's key insights, reiterates the relevance of the FD Index for capturing multidimensional financial development, and proposes implications for policymakers, investors, and international stakeholders aiming to strengthen Asia's financial resilience.

Through this approach, we intend to contribute a comprehensive, data-driven understanding of Asia's financial development trajectories, revealing how the IMF's broader mission and metrics (like the FD Index) align with evolving realities on the ground.

2. Literature Review

2.1 Financial Development and Its Measurement

Financial development entails the expansion and efficient functioning of financial institutions and markets. A well-developed financial sector promotes savings mobilization, effective risk management, and resource allocation to productive activities, thereby contributing to sustainable economic growth (Sahay, Čihák, & others, 2015). However, quantifying financial development can be challenging. Common proxies—such as private credit-to-GDP or stock market turnover—capture only partial dimensions. Recognizing this limitation, the International Monetary Fund introduced the Financial Development Index (FD Index) to integrate multiple dimensions, encompassing both financial institutions (banking sector) and financial markets (equity, bond markets), as well as measures of depth, access, and efficiency (Svirydzenka, 2016).

2.2 Global Shocks and Regional Implications

Asia's financial trajectory cannot be examined in isolation from global upheavals:

- 1997 Asian Financial Crisis: Sparked by a speculative attack on the Thai baht, the crisis exposed vulnerabilities in currency pegs and weak banking sectors. Countries with lower FD Index scores at the time had difficulty containing contagion (Barker, 1993; Johnson, 1993).
- Dot-Com Bubble (1999–2001): Although centered in the U.S. tech sector, the crash affected Asian equity markets, particularly those reliant on foreign portfolio inflows (Arlinghaus & Nachreiner, 2014).
- Global Financial Crisis (2007–2009): Demonstrated how even advanced economies could experience systemic breakdowns, with repercussions for trade-dependent Asian markets (Davis et al., 1999).
- COVID-19 Pandemic (2020–2021): While distinct from previous crises, the pandemic led to unprecedented fiscal and monetary responses worldwide, testing the capacity of financial systems, especially those with lower FD Index values to handle sudden stops in economic activity.

2.3 Why Stationarity Matters

Empirical studies in macro-finance show that time series often exhibit unit roots, implying that shocks can have lasting effects rather than dissipating over time (Bank & Wheelwright, 1983; Davis et al., 1999). When analyzing FD Index scores particularly in rapidly evolving economies non-stationarity may arise from secular trends (e.g., progressive financial liberalization). Applying the ADF test helps researchers ascertain whether differencing or detrending is needed, reducing the risk of spurious correlations (Barker, 1993).

2.4 Clustering in Financial Development Research

Clustering algorithms systematically group observations based on similarity, offering valuable insights in two ways:

- Temporal Clustering: By treating each year as an observation (with aggregated or median FD Index data across countries), researchers can highlight sub-periods of convergence or divergence in financial development. For instance, prior work shows that major crisis years may cluster separately from stable expansion phases (Arlinghaus & Nachreiner, 2014).

- Cross-Country Clustering: Each country is represented by its FD Index values (over time or averaged), revealing which nations share similar structural characteristics. In Asia, highly developed financial hubs—like Japan and Singapore—often contrast with frontier markets in terms of access, efficiency, and depth (Johnson, 1993).

2.5 Financial Development in Asia: Key Themes

Studies focusing on Asia underscore several recurring themes:

- Institutional Quality: Effective legal frameworks, prudent regulations, and political stability correlate with higher FD Index scores (Sahay et al., 2015).
- Rapid Growth vs. Vulnerability: While quick expansion of credit and capital markets can boost short-term growth, insufficient oversight can lead to asset bubbles and banking crises.
- Integration vs. Contagion: Deeper integration with global capital markets can yield efficiency gains and risk-sharing benefits but may also import external shocks, as seen in 1997 and 2008 (Barker, 1993).

2.6 Contributions of This Study

Although existing literature establishes the significance of the FD Index and the propensity for shocks to trigger volatility, relatively few papers combine stationarity testing with k-means clustering to capture both temporal and cross-country financial development patterns in Asia. By applying the ADF test to FD Index series for 24 Asian countries over a 32-year span, this paper addresses:

- How major crises are reflected in regional financial development data.
- Which subsets of countries follow similar FD Index trajectories and how cluster assignments shift (or remain stable) through crises.
- To What Extent the FD Index signals resilience or vulnerability across different Asian markets.

The integrated framework advanced here clarifies how and when Asia's financial structures converge, diverge, or remain segmented in the face of external or internal disruptions.

3. Methodology

3.1 Selection of Countries

Asia is home to 48 recognized sovereign states, each at varying levels of economic development and financial sophistication (United Nations, 2023). While the goal of this study was to offer a comprehensive regional analysis using the IMF Financial Development Index (FD Index) for all Asian nations, data constraints proved a limiting factor. In reviewing the FD Index coverage from 1989 to 2021, we found that many countries lacked continuous, reliable data for the full time span due to reporting gaps, incomplete historical records, or recent geopolitical changes.

Consequently, to ensure methodological consistency and robustness of our statistical analyses, we restricted our sample to 24 Asian countries—those for which the FD Index and supporting macroeconomic variables (e.g., GDP, inflation) were consistently available throughout the 1989–2021 period. This subset includes both high-income financial hubs (e.g., Japan, Singapore) and emerging/frontier markets (e.g., Bangladesh, Myanmar), providing significant heterogeneity in terms of financial systems and economic structures. Below summarize the 24 countries retained in the final sample.

i.	Kingdom of Bahrain	ii.	Islamic Rep. of Iran	iii.	Malaysia
iv.	Bangladesh	v.	Israel	vi.	Maldives
vii.	China, P.R: Hong Kong	viii.	Japan	ix.	Myanmar
x.	Cyprus	xi.	Jordan	xii.	Oman
xiii.	India	xiv.	Kuwait	xv.	Pakistan
xvi.	Indonesia	xvii.	Lebanon	xviii.	Philippines
xix.	Qatar	xx.	Singapore	xxi.	Sri Lanka
xxii.	Syrian Arab Rep.	xxiii.	Thailand	xxiv.	United Arab Emirates

By focusing on these 24 nations, the study balances regional diversity against the need for complete, comparable data. Although excluding some Asian countries may limit certain cross-regional comparisons, it ensures that the analyses of stationarity testing, clustering, and subsequent policy implications are derived from comprehensive, reliable datasets, thus enhancing the internal validity of our findings.

3.2 Data Source: IMF Financial Development Index

The IMF Financial Development Index (FD Index) serves as the central variable in this study. It consolidates information on:

- Financial Institutions' Depth: Private credit, pension funds, mutual funds, and insurance penetration.
- Financial Institutions' Access: Bank branches or ATMs per 100,000 adults, account ownership.
- Financial Institutions' Efficiency: Cost of banking, net interest margins.
- Financial Markets' Depth: Stock market capitalization, bond market capitalization.
- Financial Markets' Access: Market concentration, foreign listings, ease of listing.
- Financial Markets' Efficiency: Price impact, transaction costs.

These components are aggregated into a single FD Index score for each country-year, available through the IMF's database (Svirydzenka, 2016). 24 Asian economies are chosen based on data completeness from 1989 to 2021, resulting in a near-balanced panel.

3.3 Stationarity Testing (Augmented Dickey-Fuller)

We conduct ADF tests on each country's FD Index series to detect potential unit roots:

$$\Delta(FDIndex)_t = \alpha + \beta t + \gamma(FDIndex)_{t-1} + \sum_{i=1}^{p} \delta_i \Delta(FDIndex)_{t-i} + \varepsilon_t$$

- Null Hypothesis (H_0): $FDIndex_t$ has a unit root (non-stationary).
- Alternative (H_0): $FDIndex_t$ is stationary.
- Decision Rule: p-value < 0.05 → Reject H_0; otherwise accept non-stationarity.

Most countries display non-stationary FD Index series due to long-term uptrends in financial development. We thus detrend these series (subtracting a linear trend or differencing once if needed) so that cyclical or short-run fluctuations become the focal point in subsequent clustering.

3.4 K-Means Clustering

K-means clustering is an iterative, partition-based method where each cluster is defined by its mean value. It is preferred for its efficiency and simplicity, particularly with spherical cluster structures (Raval & Jani, 2016). The optimal number of clusters was established using the Elbow method and Silhouette analysis (Yadav & Sharma, 2013). We apply k-means in two distinct ways:

3.4.1 Time-Domain Clustering

- Observations: Each year (1989–2021) serves as a single data point.
- Variables: Aggregated measures, e.g., the average (or median) FD Index across all countries for that year, potentially combined with other macro indicators (if desired).
- Choice of k: Using Elbow and Silhouette methods, k=3 is typically selected to capture major crisis epochs plus outlier years.

3.4.2 Cross-Country Clustering

- Observations: Each country (24 total) forms one data point.
- Variables: Aggregated or principal-component-transformed FD Index values over the 1989–2021 period. One approach is to calculate an average FD Index for each country or include multiple transformations (e.g., volatility of FD Index across time).
- Choice of k: Similarly, we rely on Elbow and Silhouette scores, commonly finding two or three stable groupings.

3.4.4 Validation and Robustness

K-means clustering requires the user to specify the number of clusters (k) in advance. Choosing an inappropriate value can lead to misleading groupings, so validating the chosen k is crucial for reliable results. In this study, we employed two main methods to guide our selection: the Elbow Method and the Silhouette Method.

3.4.5 Elbow Method

Within-Cluster Sum of Squares (WSS): K-means attempts to minimize the total within-cluster sum of squares (WSS), i.e., the aggregated squared distance of points from their assigned cluster centroids.

Plotting WSS vs. k: We computed WSS values for k ranging from 1 to 10. We then plotted these values against k to form an "elbow plot."

Identifying the "Elbow": The ideal k is often located where a notable bend or "elbow" appears in the plot. Below that point, adding clusters significantly reduces WSS; beyond that point, further increases in k yield diminishing improvements.

Interpretation: By visually inspecting the elbow plot, we looked for a clear inflection. Where the WSS began to level off, we considered it a possible optimal solution.

Practical Example: If k=3 produced a visible break in the slope of the WSS curve, it suggests that going from 2 to 3 clusters significantly improves cohesion, but going to 4 clusters provides comparatively little gain in reducing WSS.

Silhouette Method

Silhouette Analysis: The silhouette score measures how well-separated each data point is from other clusters, compared to the cohesion within its own cluster. Silhouette values range from -1 (poor fit) to +1 (excellent fit).

Average Silhouette Width: for k ranging from 2 to 10, we performed k-means and calculated the average silhouette width for each run, storing the results in a vector.

Plotting Silhouette Scores: We plotted the average silhouette width against k to identify where the score peaked, as higher silhouettes generally indicate more distinct cluster boundaries.

Optimal k: The peak or local maximum of the silhouette plot typically suggests an optimal k. In some cases, multiple k values may produce similar silhouette scores; we then consider additional factors (e.g., interpretability, domain knowledge).

Cross-Method Comparison

Because both methods rely on different metrics, WSS for within-cluster variance and silhouette for between-cluster separation, we used both to cross-verify results. The elbow plot pointed to a certain k where the WSS curve flattened, while the silhouette analysis indicated another. In practice, these methods can converge on the same k value or yield a small range of suitable k values (e.g., k=2 or k=3).

Final Selection and Interpretation

After reviewing the elbow and silhouette plots (and optionally verifying with the fviz_nbclust function for both "wss" and "silhouette" methods):

We identified a plausible optimal range for k (for example, k=2 or k=3).

We checked the cluster assignment output (e.g., k-means_result$cluster) to ensure the interpretability of the resulting groups. Domain knowledge such as whether the clusters aligned meaningfully with known economic or financial traits was also considered.

We visualized the final clusters using fviz_cluster, confirming that the groupings were well-separated in the scaled feature space.

Sensitivity Checks

Finally, we conducted basic sensitivity checks:

- Different Seeds: We ran the algorithm with multiple random seeds (e.g., set.seed(123), set.seed(999)) to ensure stable results.
- Scaling: Because features can vary widely in scale, standardizing (scaling) the data was crucial. We confirmed that re-running k-means without scaling led to less balanced clusters, indicating that scaling helped avoid issues with disproportionately large variance in certain variables.
- nstart Parameter: We set nstart = 25 to mitigate the risk of converging to local minima in k-means. This step reruns the algorithm 25 times with different initial centroids, retaining the best solution.

By combining the IMF FD Index with standard time-series and machine learning techniques, this methodology offers a comprehensive way to identify how financial development evolves under varying economic conditions and across diverse national contexts.

4. Findings and Discussion

4.1 ADF Test Results for FD Index

Table 1summarizes p-values from the ADF test:

Table 1: P-values from the ADF Test

Source: Authors

Country	p-value	Stationary/ non-stationary
Bahrain, kingdom of	0.54475231	non-stationary
Bangladesh	0.22147469	non-stationary
China, P.R: Hong Kong	0.62828873	non-stationary
Cyprus	0.78983574	non-stationary
India	0.53152983	non-stationary
Indonesia	0.04416818	Stationary
Iran, Islamic Rep. of	0.99000000	non-stationary
Israel	0.03453247	Stationary
Japan	0.03925151	Stationary
Jordan	0.61697114	non-stationary
Kuwait	0.25705502	non-stationary
Lebanon	0.13435225	non-stationary
Malaysia	0.74614532	non-stationary
Maldives	0.12515868	non-stationary
Myanmar	0.62571891	non-stationary
Oman	0.08760745	non-stationary
Pakistan	0.74805144	non-stationary
Philippines	0.33829034	non-stationary
Qatar	0.83876928	non-stationary
Singapore	0.97525813	non-stationary
Sri Lanka	0.33996178	non-stationary
Syrian Arab Rep.	0.04268464	Stationary
Thailand	0.41338213	non-stationary
United Arab Emirates	0.37257407	non-stationary

- Non-Stationary FD Index: Examples include Bahrain, Bangladesh, India, Iran, Kuwait, Lebanon, Maldives, Myanmar, Oman, Pakistan, Philippines, Sri

Lanka, and the United Arab Emirates, all with p-values above 0.05. These countries exhibit rising or volatile FD Index trends over time.

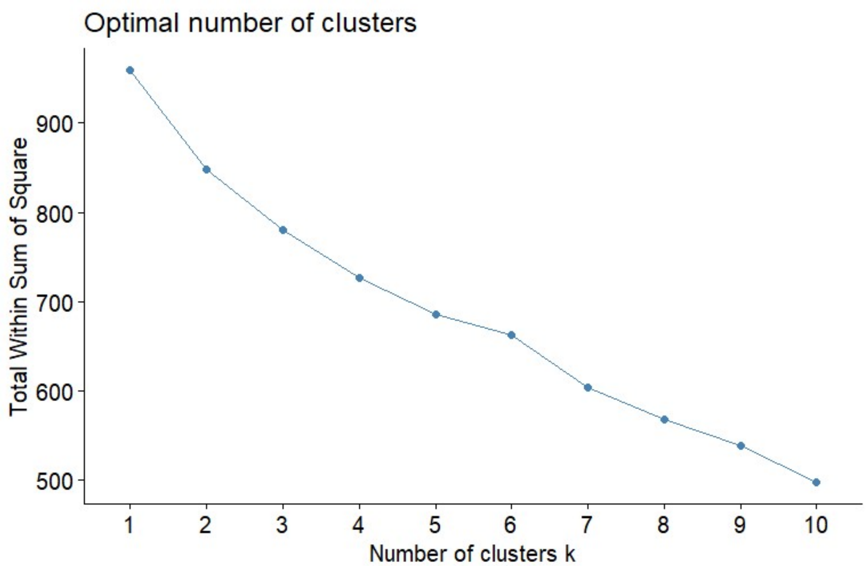
- Stationary or Weakly Stationary FD Index: A small number, like Japan, Israel, or Jordan, with p-values under 0.05, suggesting fewer large-scale trends or more stable progression in financial development.

Such findings reflect structural transformations in emerging markets, where FD Index scores often start at low levels and rise steadily as reforms unfold (Svirydzenka, 2016). We apply detrending to each non-stationary country series, ensuring that subsequent clustering emphasizes cyclical changes or specific deviations from the long-term trajectory.

4.2 Time-Domain Clustering

Figure 1: The results of K-means clustering according to the Elbow method

Source: Authors



After standardizing the year-level aggregates, we applied both the Elbow Method (using WSS) and the Silhouette Method (using average silhouette width) to determine the optimal number of clusters. According to these plots, k=3 offered the best balance between within-cluster variance and separation. We therefore selected k=3 for k-means, which identified distinct epochs in financial development.

Figure 2: The results of K-means clustering according to the Silhouette method

Source: Authors

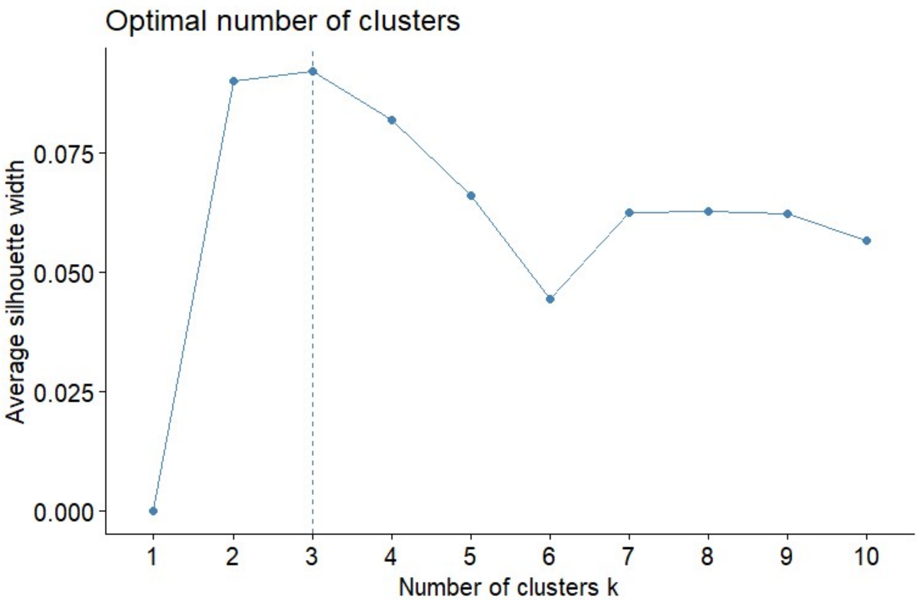


Figure 3: Optimal number of clusters

Source: Authors

4.2.1 Cluster 1: (Late 1980s–Mid-1990s, 1998, 2002–2006, 2017)

- The late 1980s to mid-1990s saw many Asian states liberalizing banking sectors, but financial development (FD Index) remained relatively low overall.
- 1998 continued the aftershocks of the 1997 crisis, with FD Index metrics showing stagnation or dip in several Southeast Asian countries.
- 2002–2006: Renewed growth in banking and capital markets, coinciding with global liquidity expansion.
- 2017: Surge in digital financial services, stable FD Index growth in many countries, and cryptocurrency speculation globally.

4.2.2 Cluster 2: (1999–2001, 2007–2016, 2018–2021)

- 1999–2001: Dot-Com bubble—equity-based funding rose in select markets, but volatility also increased.
- 2007–2016: The Global Financial Crisis and Eurozone issues dampened FD Index improvements in several Asian economies, though some emerged more resilient due to post-1997 reforms.
- 2018–2021: Heightened trade tensions and the COVID-19 shock reconfigured financial markets. Many governments enacted unprecedented stimulus, altering FD Index trajectories (sometimes artificially boosting access or depth in the short run).

4.2.3 Single-Year Cluster (1997)

- The Asian Financial Crisis triggered swift capital outflows, currency collapses, and abrupt declines in FD Index scores for Thailand, Indonesia, Malaysia, and beyond. The uniqueness of 1997 data yields its own cluster, underscoring the crisis's regional severity.

Collectively, these temporal clusters illustrate how global or regional shocks (Dot-Com crash, GFC, COVID-19) shape aggregated financial development patterns across Asia.

4.3 Cross-Country Clustering

When applying k-means to the 24 countries using long-run FD Index metrics, we relied on both the Elbow Method (using WSS) and the Silhouette Method (using average silhouette width) to identify the optimal number of clusters. The results indicated that k=2 struck the best balance between minimizing within-cluster variance and maximizing cluster separation. Consequently, we selected k=2 for k-means clustering, revealing two distinct groupings among the 24 countries in terms of their financial development trajectories.

Figure 4: The results of K-means clustering according to the Elbow method

Source: Authors

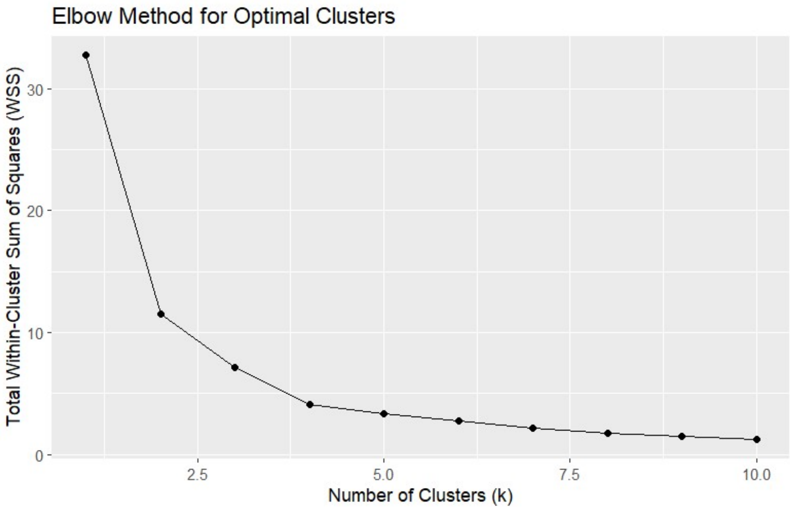


Figure 5: The results of K-means clustering according to the Silhouette method

Source: Authors

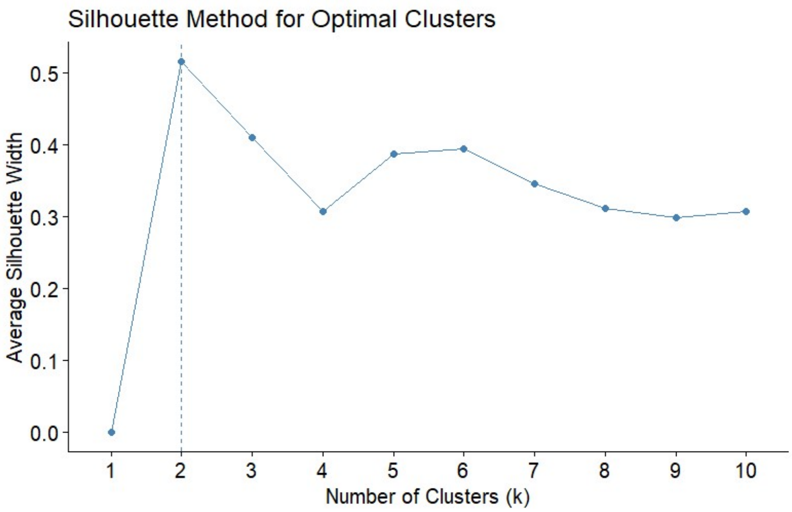
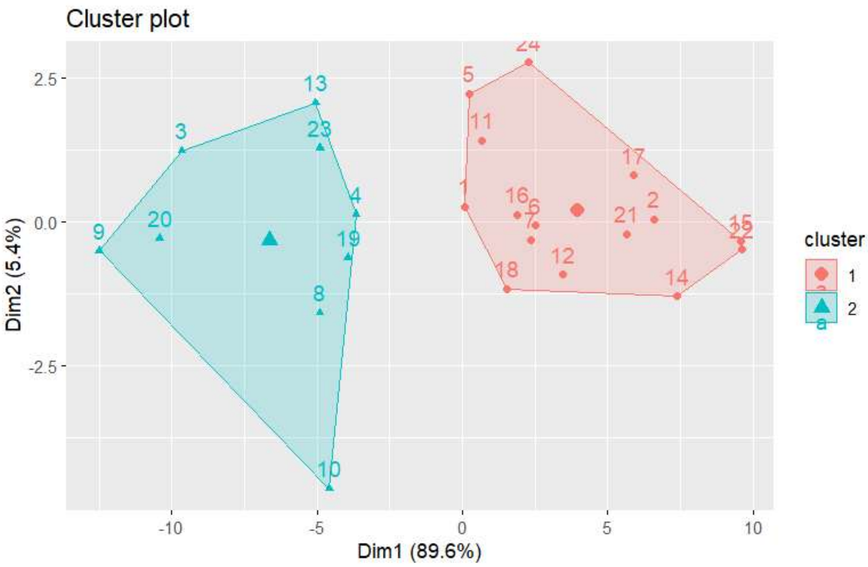


Figure 6: Optimal number of clusters

Source: Authors



4.3.1 Cluster 1: Predominantly emerging or resource-based economies

- Examples: Bangladesh, Iran, Kuwait, Lebanon, Maldives, Myanmar, Oman, Pakistan, Sri Lanka, Syrian Arab Rep., etc.
- Characterized by relatively lower average FD Index, potentially reflecting constraints in financial institutions (limited banking penetration) or markets (small bond/equity markets). Volatility in FD Index may also be higher, suggesting uneven reforms and periodic setbacks due to shocks.

4.3.2 Cluster 2: Generally, more advanced or rapidly maturing markets.

- Examples: Japan, Singapore, Israel, Malaysia, Thailand, Hong Kong (China), Qatar, Cyprus, Jordan.
- Higher FD Index scores, indicating deeper and more accessible financial institutions and markets. Malaysia and Thailand, though sometimes labeled "emerging," have comparatively stronger financial infrastructures than many peers, driving them into a more advanced cluster. Japan, Singapore, and Hong Kong are major financial hubs, with robust banking, equity, and bond markets.

Notably, certain Gulf states (Qatar, UAE) may shift between clusters depending on sub-indicators (e.g., significant capital market investments offset by weaker bank access or efficiency). Similarly, countries like India could trend upward over time, reflecting large-scale financial inclusion initiatives, digital payment systems, and progressive reforms.

4.4 Discussion of Key Insights

- Impact of the FD Index on Crisis Resilience: The year-based clustering strongly associates major shocks with dips or plateaus in aggregated FD Index growth. Countries with higher initial FD Index often manage crises better, consistent with arguments that mature financial systems provide buffers against capital flight (Sahay et al., 2015).
- Structural Convergence vs. Persistent Gaps: While all countries have generally improved their FD Index scores since 1989, cross-country clustering reveals persistent structural gaps. Regulatory frameworks, technological adoption, and institutional quality continue to differentiate advanced financial centers from emerging peers.
- Policy Implications: Policymakers in lower-FD Index cluster countries might focus on improving financial access (e.g., promoting fintech, expanding banking infrastructure), ensuring robust legal protections, and fostering capital market depth to mitigate future crises.
- Future Shocks and Digital Finance: Rapid digitalization since the 2010s suggests that a purely "traditional" FD Index might soon need expansion to incorporate fintech developments. The volatility of 2020–2021 under COVID-19 conditions foreshadows how new forms of finance (mobile banking, e-wallets) can shape cluster transitions.

In sum, the FD Index-based analysis clarifies how Asia's financial development pathways align with global cycles while maintaining critical internal distinctions. Incorporating additional institutional or technological variables could further refine these patterns.

5. Limitations and Recommendations for Future Researchers

Several limitations warrant acknowledgment:

- Annual Data Frequency: Using annual FD Index scores may mask rapid intra-year shifts or crisis responses. Higher-frequency (quarterly, monthly) data could reveal more granular dynamics.
- Exclusion of External Variables: Although the FD Index is comprehensive, other indicators—like public debt levels, capital flow volatility, or political risk—could deepen explanatory power.
- Rigid Partitioning: K-means forces each observation (year or country) into a single cluster. This approach might overlook borderline cases with overlapping features.
- Institutional Nuances: While FD Index includes facets of depth, access, and efficiency, local governance, legal frameworks, and cultural factors also influence financial outcomes.
- Data Coverage: Variations in data availability across countries and time periods mean the panel is not perfectly balanced, potentially introducing minor biases.

5.1 Recommendations

- Incorporate Wider Macroeconomic Indicators: Adding inflation, exchange rate regimes, or external debt data to clustering might uncover deeper interconnections.
- Adopt Dynamic Clustering: Consider algorithms that permit cluster memberships to change year by year, capturing gradual transitions in financial structures.
- Include Institutional Indices: World Bank Governance Indicators or Transparency International scores might explain why countries with similar FD Index levels differ in stability.
- Compare with Non-Asian Regions: A global analysis could confirm whether Asia's FD Index trajectories are unique or mirror patterns in Latin America, Africa, or Eastern Europe.

- Fintech Emphasis: Future FD Index updates or custom sub-indicators (digital payments, mobile banking usage) could track the rapid pace of financial innovation in Asia.

These steps would refine cluster interpretability and enhance policy relevance, offering a richer picture of how economies evolve under both normal and crisis conditions.

6. Conclusion

By applying stationarity assessments (via the Augmented Dickey-Fuller test) and k-means clustering to the IMF Financial Development Index for 24 Asian countries over the 1989–2021 period, this study sheds light on the interplay between financial development trajectories and major regional or global shocks. Time-based clustering pinpoints crucial epochs including the Asian Financial Crisis (1997), the Dot-Com Bubble (1999–2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020–2021), each leaving discernible marks on aggregate FD Index trends. Meanwhile, cross-country clustering reveals a broad bifurcation between economies with deeper, more efficient financial systems and those still working to broaden access and institutional depth.

The evidence suggests that while crises often spur reforms, persistent structural gaps remain. Higher FD Index scores tend to correlate with enhanced resilience, yet the road to deeper financial markets can also introduce new forms of vulnerability if not supported by sound regulation and governance. Policymakers may leverage these findings to focus on targeted improvements such as boosting financial inclusion, digitalization, and prudential oversight to buffer future shocks. Scholars and investors, in turn, can harness FD Index-based clustering to refine risk assessments, develop region-specific strategies, and investigate how emerging fintech transformations might reshape the map of Asia's financial development.

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