Thyroid Insight: Navigating Disease Data Through Interactive Visualization with Prediction

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ABSTRACT

The thyroid gland, located in the neck, plays a crucial role in regulating metabolism, growth, and energy through hormones such as thyroxine (T4) and triiodothyronine (T3). Disorders such as hypothyroidism, hyperthyroidism, and thyroid cancers are often linked to iodine deficiency and genetics. However, limited public awareness and delayed diagnosis can lead to severe health complications. Analysing thyroid disease data is challenging due to its complexity and unstructured nature, making advanced analytical techniques essential. This paper addresses these challenges by developing an interactive dashboard with predictive capabilities. The system integrates Big Data analytics and predictive modelling to improve understanding and support proactive management of thyroid health. It follows a structured methodology, including planning, analysis, design, development, and testing, using data from Kaggle and the UCI Machine Learning Repository. The dashboard employs Microsoft Power BI for visualizations and the Random Forest algorithm for predictive modelling. Evaluation using the Technology Acceptance Model (TAM) with 35 respondents produced encouraging results across dimensions such as Perceived Ease of Use (4.28), Perceived Usefulness (4.61), Attitude (4.54), and Intention to Use (4.50). User feedback highlighted the dashboard's intuitive design, clarity in presenting complex information, and potential to raise awareness about thyroid health. While the findings are based on a limited evaluation, results indicate that the system may contribute to improving public awareness, supporting early detection, and empowering users to make informed health decisions. With future improvements, such as real-time data integration and expanded datasets, the system could further enhance healthcare practices and public education regarding thyroid diseases, promoting proactive health management.

1. INTRODUCTION

Technology has rapidly transformed many aspects of daily life, particularly in the healthcare sector, where advances in data analytics and visualization are revolutionizing how medical information is interpreted and applied (Wang et al., 2024). One such advancement is the use of Big Data in managing health conditions such as thyroid disorders. These disorders, including hypothyroidism, hyperthyroidism, and thyroid cancer, affect millions of individuals worldwide, creating a growing need for effective diagnosis and management strategies (Keestra et al., 2021). However, despite their prevalence, early detection and awareness remain limited due to the complexity of thyroid health data and a lack of accessible tools for the general public (Zhao et al., 2024).

Many thyroid patients face challenges in understanding their condition and accessing appropriate resources. According to Fariduddin et al. (2024), integrating predictive technologies with healthcare

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systems can improve early detection and patient awareness. While previous studies have investigated medical data management systems, few have successfully combined Big Data analytics with real-time health monitoring for thyroid disorders. Some initiatives have developed interactive dashboards that provide users with access to their health data, symptoms tracking, and potential treatment options. However, these systems often lack advanced predictive models and real-time monitoring capabilities, which are crucial for proactive thyroid health management.

This study builds on prior work by integrating Big Data analytics, predictive modelling, and interactive visualization to develop the "Thyroid Insight" dashboard. The system aims to raise public awareness of thyroid diseases, support early detection, and enable users to take a more proactive role in managing their health. Utilizing data from reputable sources such as Kaggle and the UCI Machine Learning Repository, and applying predictive algorithms such as Random Forest, the dashboard forecasts potential health risks and offers actionable insights (Muniswamaiah et al., 2023). By combining predictive analytics with real-time data collection tools, the system offers a more comprehensive solution that bridges the gap between healthcare providers and individuals.

The purpose of this study was to evaluate the effectiveness of the dashboard in supporting early detection and delivering actionable insights into thyroid health. By assessing user satisfaction, system usability, and overall functionality, the project aims to provide a practical tool for improving thyroid disease management and fostering a more informed, health-conscious society. The "Thyroid Insight" system was developed using Microsoft Power BI for visualization and the Random Forest algorithm for predictive analytics, resulting in an intuitive platform designed to enhance the understanding and management of thyroid health.

2. RELATED WORK

In the field of thyroid disease management, the application of big data analytics and machine learning has shown great promise for improving diagnosis, treatment, and public awareness. Thyroid disorders such as hypothyroidism, hyperthyroidism, and thyroid cancers affect millions worldwide. Besides, the thyroid gland is essential for regulating metabolism through the production of hormones such as T4 and T3, and disruptions in this system can lead to various health complications. Managing these conditions involves interpreting complex datasets, including hormone levels, patient records, and medical histories, which makes traditional diagnostic methods less effective (Zhao et al., 2024). Advanced analytical tools and visualization platforms are therefore essential for addressing this complexity.

Numerous studies have explored predictive modelling and data visualization for thyroid health, but most focus on either predictive accuracy or data presentation, rather than integrating both into a user-accessible, real-time platform. Several relevant works have made strides in these areas, providing a foundation for advancing visualization and predictive systems in thyroid disease management.

2.1 CancerMAS dashboard

The CancerMAS Dashboard, developed by the by the Advanced Analytics Engineering Centre at Universiti Teknologi MARA, is a web-based platform for visualizing cancer incidence data in Malaysia (Hamidi et al., 2020). It presents data on cancer types, gender, ethnicity, and geographical distribution using bar charts, scatter plots, and heat maps. While it demonstrates strong visualization capabilities for public health analysis, it lacks predictive modelling, personalized risk assessment, and application to thyroid disease. Our work adapts these visualization strengths while integrating machine learning-based prediction tailored to thyroid disorders.

2.2 Thyroid disease prediction using selective features and machine learning techniques

Chaganti et al. (2022) applied selective feature selection, to improve thyroid disease prediction accuracy. Using Random Forest, they achieved 0.99 accuracy, demonstrating the value of targeted feature selection. However, their system remains model-centric, without translating results into visuals, interactive tools for non-specialist users. In contrast, our approach embeds predictive models within a user-friendly dashboard, enabling both technical accuracy and public accessibility.

2.3 Detecting thyroid disease using optimized machine learning model based on differential evolution

Gupta et al. (2024) developed an optimized AdaBoost model enhanced with Differential Evolution (DE) and CTGAN for data augmentation, achieving 0.998 accuracy. While this approach addresses data imbalance and achieves high performance, it does not include a visualization interface for communicating predictions to patients or healthcare providers. Our system builds on such predictive strength by combining it with interactive visualization and a focus on user engagement.

2.4 International agency for research on cancer

The International Agency for Research on Cancer (IARC) platform provides global cancer statistics, including thyroid cancer data, via interactive heatmaps (Terrasse, 2025) . Users can filter by demographic variables and explore trends over time. While highly customizable for epidemiological analysis, it does not offer predictive capabilities or personalized health insights. Our dashboard addresses this gap by merging population-level visualization with individual-level predictions for thyroid health.

To position this research within the existing literature, Table 1 presents a comparative overview of the related works discussed. The table evaluates each system based on key attributes, including visualization capabilities, predictive modelling, real-time data integration, and focus area, while also noting their primary limitations. This structured comparison reveals a recurring gap: existing works often excel in either visualization or prediction but rarely combine both within a single, user-accessible platform tailored for thyroid disease management. Moreover, none of the reviewed studies fully integrate real-time monitoring, despite its growing importance for proactive health management. The proposed “Thyroid Insight” dashboard addresses these shortcomings by unifying predictive analytics, interactive visualization, and the potential for real-time data integration, thereby offering a more comprehensive solution to enhance public awareness and support early detection.

Table 1. Comparison table of related work

Study/System	Visualization	Prediction	Real-Time Data	Focus Area	Gap Filled by This Study
CancerMAS Dashboard (Hamidi et al. (2020)	✓ Strong charts, maps	✗ None	✗ No	No prediction or thyroid-specific data	Combines similar visualization with thyroid-specific predictions
Chaganti et al. (2022))	✗ None	✓ RF (0.99 accuracy)	✗ No	No interactive/public-friendly visualization	Embeds prediction into user-friendly dashboard
Gupta et al. (2024)	✗ None	✓ AdaBoost+DE (0.998)	✗ No	No visualization or public engagement	Combines high-accuracy prediction with visualization
IARC (Terrasse, 2025)	✓ Interactive heatmaps	✗ None	✗ No	No predictive or personalized insights	Adds predictive analytics to population-level visualizations

3. METHODOLOGY

This research adopted a structured System Development Life Cycle (SDLC) approach to guide the development of the proposed system. The SDLC methodology provides a systematic framework that ensures progress through clearly defined stages, emphasizing comprehensive analysis, thoughtful design, efficient development, and rigorous testing. The phases encompassed in this methodology are Planning, Analysis, Design, Development, and Testing, which collectively contributed to the creation of an interactive dashboard for thyroid disease management with predictive capabilities. A breakdown of each phase is presented below.

3.1 Planning phase

The Planning phase is the foundation of the project, where the problem statement is defined and the research objectives, scope, and significance are established. This phase is critical for setting the direction for the entire study. To achieve this, a comprehensive literature review was conducted to identify current challenges in thyroid disease prediction and management. The primary objective was to integrate Big Data analytics with predictive modelling to enhance public awareness, support early detection, and improve understanding of thyroid diseases. The project's scope was defined as the development of an interactive dashboard using appropriate datasets. The datasets used in this study were obtained from the UCI Machine Learning Repository (Quinlan, 1987) and Kaggle's Thyroid Disease dataset (Kaggle, 2021). These sources were selected for their public availability, structured format, and widespread use in peer-reviewed studies, making them reliable benchmarks for machine learning research (Fernández-Delgado et al., 2014). The UCI dataset contains patient records with hormone measurements, demographic details, and diagnostic labels derived from clinical examinations, while the Kaggle dataset includes more recent and diverse cases contributed by the medical data science community.

3.2 Analysis phase

The Analysis phase focuses on identifying and examining the system requirements, relevant literature, and technologies that align with the project's objectives. Key components analysed in this phase include Big Data sources, such as patient records and hormone level measurements, data visualization tools, such as Microsoft Power BI, and Machine Learning Models, particularly the Random Forest algorithm. A comprehensive review of existing research was also conducted to evaluate current solutions in thyroid disease prediction and related healthcare applications. In addition, this phase involved assessing the hardware and software requirements necessary for effective system implementation. The selected technologies include Microsoft Power BI for visualization, Python and Jupyter Notebook for machine learning model development, and the Random Forest algorithm for predictive analysis. The primary goal of the analysis phase was to ensure that the proposed system would meet performance and user expectations while maintaining compatibility with the chosen tools and resources.

3.3 Design phase

The Design phase defines the system architecture, user interface, and data structure. This phase involved creating visual representations, such as Entity Relationship Diagrams (ERD), to conceptualize data flow and system interactions. A sitemap was developed to illustrate user navigation within the interactive dashboard. The interface incorporated key features, including data visualization elements such as graphs, pie charts, and prediction input forms. The dashboard was designed to be intuitive and user-friendly, enabling users to easily interpret complex thyroid health data. Wireframes were created for the main section of the dashboard, including the homepage, disease statistics, thyroid disorder types, and the prediction result page. These design activities were essential to ensuring a coherent layout, efficient navigation, and an optimal user experience.

3.4 Development phase

The Development phase involved building the system based on the designs established in the previous phase. Two primary activities were carried out during this phase:

i. Developing the Web Application: The system was implemented as a web-based application using Python and Microsoft Power BI as the primary development tools. Python was employed for backend scripting, particularly to handle machine learning models, data processing, and prediction tasks. Microsoft Power BI was used to create interactive data visualizations for displaying thyroid disease statistics. The application was designed to retrieve data from various sources, perform data cleaning and preprocessing, and present the processed information in an accessible format through the dashboard interface.

ii. Integration of Predictive Models: After the core web application was built, the next step was to integrate the predictive models. The Random Forest algorithm was applied to develop predictive models for thyroid disease classification and prediction based on patient data, including hormone levels and medical history. Data preprocessing, feature selection, and handling of missing values were essential steps before training the models. The Random Forest algorithm (Breiman, 2001) was employed for thyroid disease classification and risk prediction. Hyperparameter tuning was conducted using Grid Search with 5-fold cross-validation to determine the optimal number of trees (n_estimators), maximum tree depth (max_depth), and the number of features considered at each split (max_features). To mitigate overfitting, the minimum samples required to split a node (min_samples_split) was adjusted, and tree depth was constrained. Model evaluation was performed using accuracy, precision, recall, and F1-score metrics (Sokolova & Lapalme, 2009), with the dataset split into 80% training and 20% testing subsets. The final tuned model achieved an accuracy of 98.5% and an F1-score of 0.984, outperforming baseline models such as Logistic Regression and Decision Tree. Once validated, the model was serialized using the joblib library and integrated into the application, enabling real-time predictions from user-provided inputs, including hormone levels (T3, T4, TSH), patient age, and medical history.

3.5 Testing phase

The Testing phase was carried out to evaluate the system's functionality, usability, and reliability. Usability testing was conducted with a group of 35 participants from diverse backgrounds to ensure accessibility and inclusivity. A Technology Acceptance Model (TAM) survey was administered to measure user acceptance focusing on key dimensions such as Perceived Ease of Use, Perceived Usefulness, Attitude, and Intention to Use. Participant Feedback played a crucial role in refining the system, enhancing the user interface, and ensuring that the final product effectively addressed the needs of the target audience.

4. RESULTS AND DISCUSSIONS

4.1 Interfaces of the Thyroid Insight system

This section presents the interfaces and functionality of the proposed system. Designed with user accessibility as a priority, the system features an intuitive interface suitable for both healthcare professionals and the general public. The main page includes several key sections that provide access to core features, such as interactive data visualizations, disease prediction results, and detailed information on thyroid health. Fig. 1 illustrates the system's main interface.

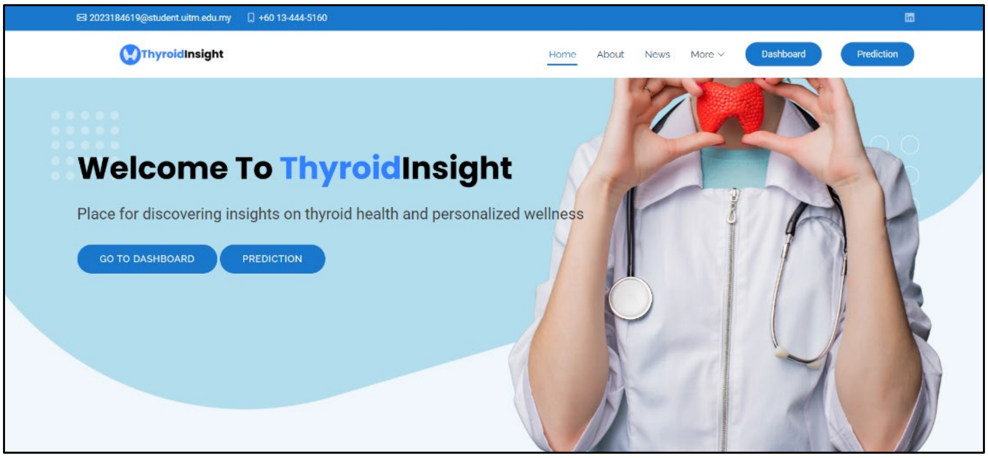


Fig. 1. Main interface of Thyroid Insight system

The main interface of the system is the dashboard, which provides an overview of thyroid disease data. It features interactive visualizations, including graphs, pie charts, and trend lines developed using Microsoft Power BI. These visualization enables users to explore thyroid disease data through various filters and viewing options. The dashboard presents key insights such as diseases prevalence, age distributions, and variations in hormone levels, thereby supporting informed health decision-making. Fig.2 – Fig. 7 present the interfaces of visualization dashboards.

The interface also features a prediction results section, where users can input their health data, such as age, hormone levels, and medical history, to receive personalized risk assessments for thyroid diseases. These predictions are generated using machine learning models, specifically the Random Forest algorithm, trained on dataset from the UCI Machine Learning Repository. Integrating these models into the system enables the delivery of real-time, personalized health insights, thereby supporting proactive thyroid disease management.

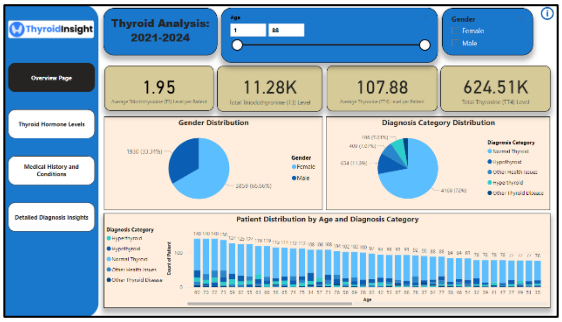


Fig. 2. Overview page

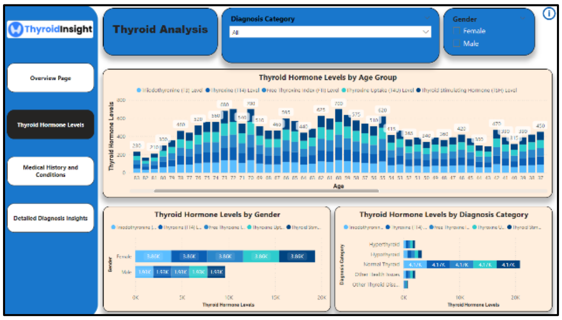
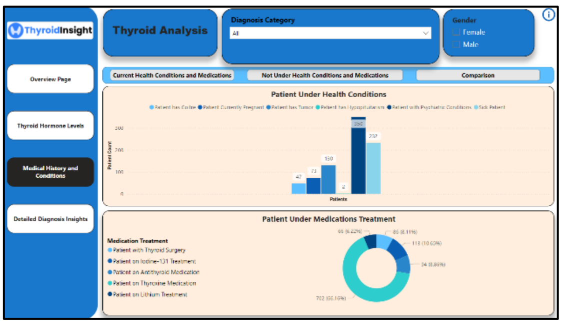


Fig. 3. Thyroid hormone levels page



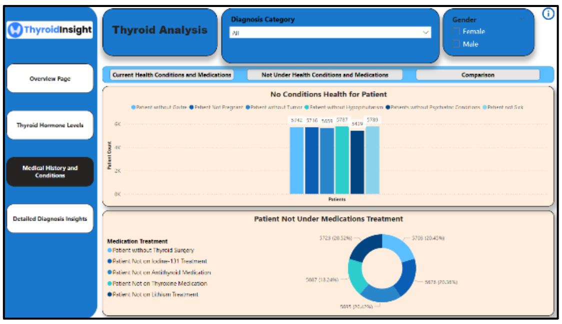


Fig. 4. Medical history page

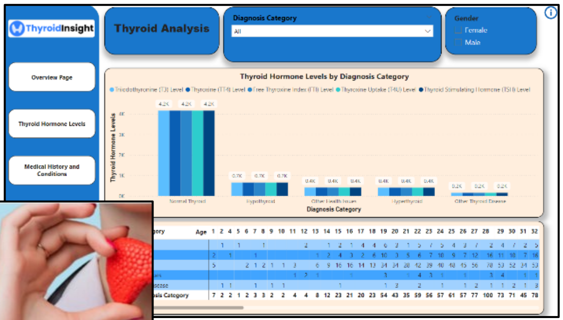
Fig. 5. Medical history page

Fig. 6. Comparison page

Fig. 7. Detailed diagnosis page

The prediction module is a key feature of the Thyroid Insight system. Upon entering their health data, users receive predictive results regarding their thyroid health status. This feature leverages the Random Forest algorithm, which analyses multiple data points and generates predictions based on established patterns within the dataset. Fig. 8 illustrates the interfaces for the prediction form.

The prediction results are displayed on a dedicated page, as shown in Fig. 9, presenting users with their estimated likelihood of developing a thyroid disorder. For instance, the system may indicate a user's risk of hypothyroidism based on their hormone levels, age, and medical history. These predictions are designed to empower individuals to take proactive measures in maintaining their thyroid health. In addition, the results include tailored recommendations for managing health, informed by the specific risk factors identified by the model.



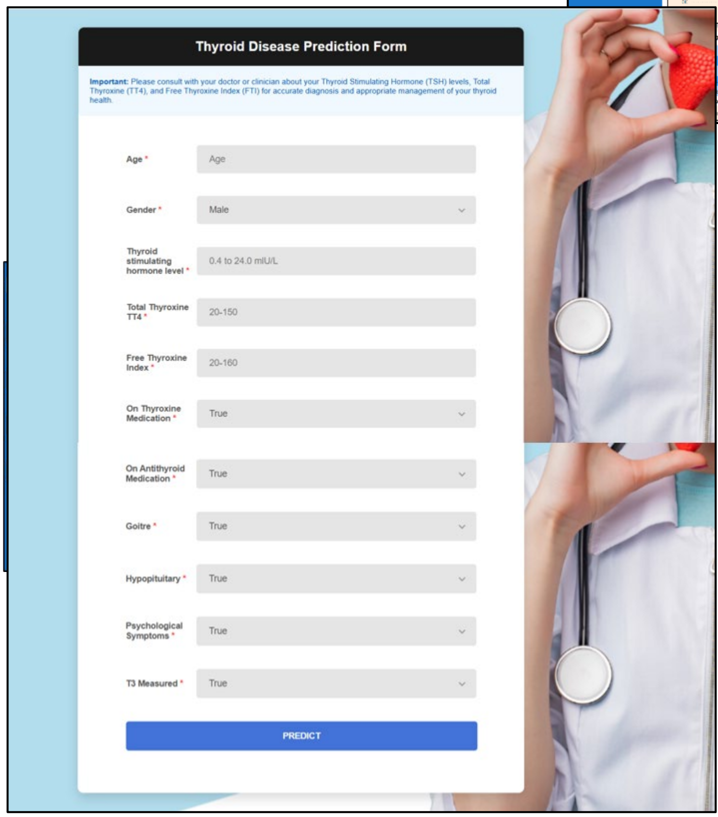


Fig. 8. Prediction form

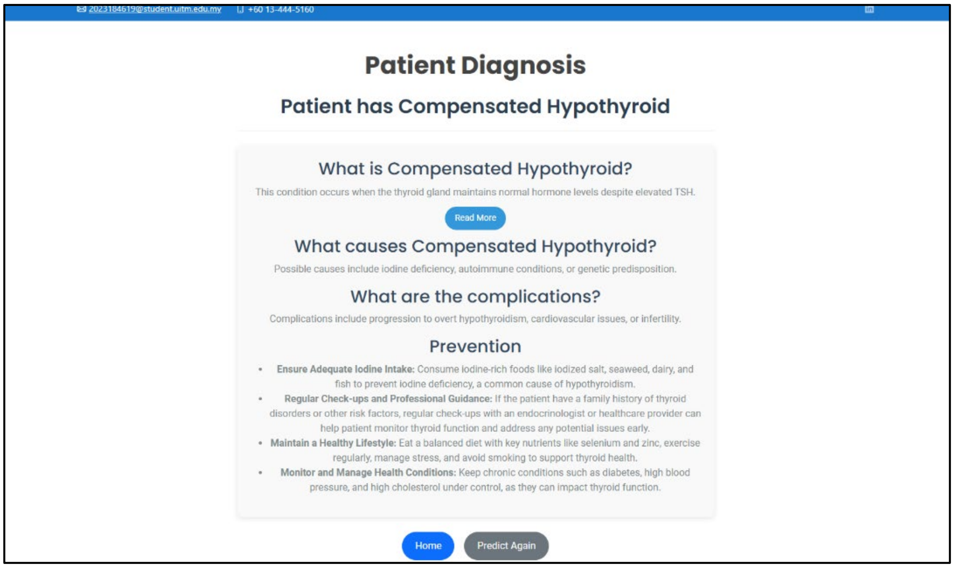


Fig. 9.

Prediction result page

4.2 The Findings of The Study

This section presents the dimensions assessed during the user acceptance testing of the Thyroid Insight system. The evaluation employed the Technology Acceptance Model (TAM), which measures four key dimensions which are Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude (ATT), and Intention to Use (BI). Each dimension reflects a distinct aspect of user experience and offers valuable insights into how the system was received by participants. The results from the user testing were compared across these dimensions to highlight areas of strength and identify opportunities for improvement. Fig. 10 presents a comparison of the average scores for PEU, PU, ATT, and BI.

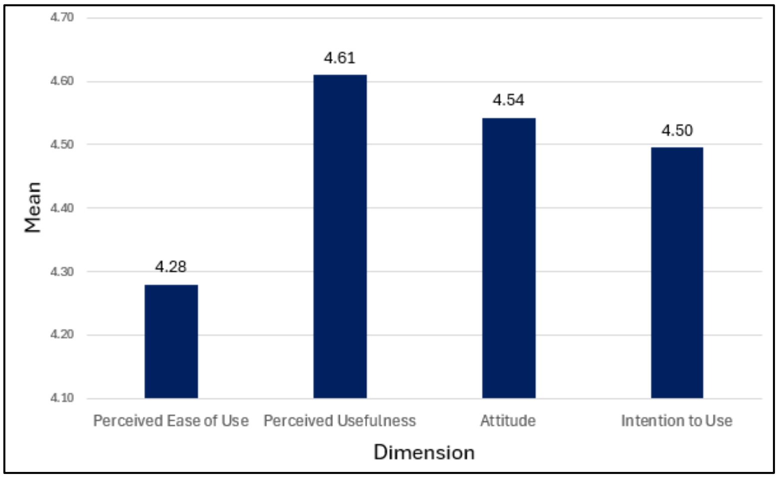


Fig. 10. Comparison of each dimension

As shown in Fig. 10, the highest-rated dimension is Perceived Usefulness (PU), with an average score of 4.61. This suggests that respondents view the "Thyroid Insight" dashboard as highly beneficial and effective in enhancing their understanding of thyroid diseases. The Attitude (ATT) dimension follows closely, with an average score of 4.54, reflecting a strong positive attitude among users and indicating their satisfaction, enjoyment, and appreciation of the dashboard's features and functionality. Intention to Use

(BI) ranks next, with an average score of 4.50, demonstrating that most respondents intend to continue using the dashboard and recommend it to others, further underscoring its perceived value and impact.

Perceived Ease of Use (PEU) has the lowest average score among the dimensions, at 4.28. While still positive, this slightly lower score suggests that some users encountered minor challenges with the dashboard's usability. Feedback from the usability testing revealed that certain participants, particularly those less familiar with technology, found the data input process and navigation between dashboard sections less intuitive. Contributing factors may include the number of required input fields, the presence of technical terminology in the prediction forms, and the absence of step-by-step prompts or contextual help. The implication for future development is that simplifying the navigation structure, reducing cognitive load, and integrating supportive features such as tooltips, guided workflows, or onboarding tutorials could further improve PEU. Enhancing ease of use is not only expected to increase satisfaction but may also positively influence both attitude and intention to use, as perceived simplicity plays a critical role in TAM-based adoption models.

Overall, the Thyroid Insight system received positive feedback across all four TAM dimensions, particularly in terms of Perceived Usefulness and Intention to Use. The system was recognized for its ability to enhance understanding and awareness of thyroid diseases, offering users a valuable tool for early detection and health management. While the system scored well on Perceived Ease of Use, there is room for improvement in simplifying the user input process and providing more guidance for less tech-savvy users. Attitude results suggest that while users are generally satisfied, there is potential for further customization and features to increase engagement and usefulness. By addressing these areas of improvement, future iterations of the system can enhance both user experience and its overall impact on thyroid disease management.

5. CONCLUSION

The development of the Thyroid Insight system represents a significant contribution to the field of thyroid disease management through the integration of Big Data analytics, machine learning models, and advanced data visualization tools. This research addressed the need for a user-friendly, interactive platform that promotes public awareness, supports early detection, and enhances understanding of thyroid health. By analysing large datasets from reliable sources, the system delivers insightful predictions and visualizations that enable users to manage their thyroid health more effectively.

The integration of predictive models, such as the Random Forest algorithm, enabled the system to provide personalized risk assessments based on individual health data, making it a valuable tool for early intervention and proactive health management. The system's intuitive dashboard, developed using Microsoft Power BI, delivers an engaging and informative user experience, presenting complex medical data in clear and accessible format for both healthcare professionals and the general public.

Furthermore, this research contributed to the advancement of usability testing methodologies by engaging a diverse group of 35 participants in a comprehensive evaluation of the system. The positive feedback and high satisfaction levels validated the system's effectiveness, confirming that it met its objectives of improving understanding and raising awareness about thyroid diseases. The usability testing also identified areas for enhancement, including simplifying the prediction input process and introducing additional customization features, which will inform future system improvements.

The integration of Big Data and machine learning to predict thyroid disease risk represents an innovative approach to healthcare management. The system's ability to deliver personalized insights empowers individuals to take a more active role in managing their health, while also supporting healthcare providers in delivering targeted interventions. By addressing the complexity of thyroid disease data, the system fosters a more informed and proactive approach to thyroid health management.

Overall, the Thyroid Insight system provides a practical and effective solution for understanding and managing thyroid diseases. Its success demonstrates the potential of integrating advanced technologies to improve healthcare outcomes, offering a valuable tool for individuals seeking to monitor and manage their thyroid health. The contributions of this research pave the way for future advancements in healthcare technology, particularly through the incorporation of more personalized dataset and real-time health monitoring, which could further enhance the system's accuracy, usability, and overall impact.

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interest.

8. AUTHORS' CONTRIBUTIONS

Mohd Nizam Osman and **Azim Md Nasib** conceived of the original and presented idea and developed the theory as well as the system development process. **Khairul Anwar Sedek**, **Mushahadah Maghribi** and **Nor Arzami Othman** verified the analytical methods. Mohd Nizam Osman encouraged Azim Md Nasib to explore a specific aspect, supervised the findings, and conducted the experiments. Mushahadah Maghribi contributed to the interpretation of the results. All authors discussed the results and contributed to the final version of the manuscript.

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