Available online at
https://jmeche.uitm.edu.my/

e-ISSN: 2550-164X

Journal of Mechanical Engineering 23(1) 2026, 19 – 38.

Journal of Mechanical Engineering

# Development of Warranty Management Visualisation for Automotive Aftermarket with Integration Of AI

Nor Hissham Abdul Hamid [1], Nor Fazli Adull Manan [1*], Mohd Fauzi Ismail [1], Abdul Malek Abdul Wahab [1], Muhammad Ilham Khalit [2]

[1]*Faculty of Mechanical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia*
[2]*Department of Mechanical Engineering, School of Engineering, Bahrain Polytechnic, Isa Town, Bahrain*

ARTICLE INFO

*Article history:*
Received 02 March 2025
Revised 05 October 2025
Accepted 07 October 2025
Online first
Published 15 January 2026

*Keywords:*
AI
Warranty management
Automotive aftermarket
Predictive analytics
Microsoft Power BI

*DOI:*
10.24191/jmeche.v23i1.5527

## ABSTRACT

Warranty management in the automotive aftermarket is increasingly challenged by large volumes of fragmented and heterogeneous data originating from IoT devices, repair logs, and service records. Traditional systems lack the scalability and analytical depth to extract meaningful insights, resulting in delayed claim resolution and higher operational costs. This study proposes a data driven approach to modernize warranty processes by integrating artificial intelligence with interactive visualization. The research utilizes 11,000 historical warranty claim records collected from OEM customers between 2019 and 2023, comprising data attributes such as part numbers, failure codes, service dates, and repair locations. A four-phase methodology based on the Product Design Specification framework was employed: Information Collection, Concept Generation, Product Configuration, and Parametric Analysis. The system architecture follows the Model View Controller design, with SQL and Python forming the backend for data processing and modelling, while Power BI serves as the visualization platform. Advanced analytics techniques including Weibull distribution modelling for failure prediction and Python based anomaly detection algorithms were implemented to identify high risk components and unusual claim behaviours. Integrated dashboards allowed for real time monitoring of key performance indicators such as Warranty Claim Rate, Average Claim Cost, and Claim Resolution Time. The system achieved a warranty cost reduction of RM 23.5K, reflecting a 75% improvement over the five-year period. This study contributes a novel, scalable solution that bridges traditional warranty analysis with AI enhanced predictive analytics. The platform provides manufacturers with improved visibility, accuracy, and strategic foresight. Limitations such as noisy data and model generalizability are acknowledged, with future work aimed at enhancing robustness through natural language processing and adaptive learning models.

[1*] Corresponding author. *E-mail address*: norfazli@uitm.edu.my
https://doi.org/10.24191/jmeche.v23i1.5527

## INTRODUCTION

In recent years, warranty management has emerged as a critical area of strategic improvement for automotive companies, playing a key role in enhancing customer satisfaction and optimizing operational efficiency. While warranty processes are inherently tied to product quality and customer trust, they are increasingly being challenged by the vast and complex influx of heterogeneous data from IoT devices, repair logs, and customer feedback (Akbarov & Wu, 2012; Khoshkangini et al., 2020). The presence of fragmented data sources, coupled with the limited scalability of existing systems, hampers comprehensive analysis and timely interventions, often leading to longer resolution times, higher warranty costs, and diminished customer satisfaction (Blischke et al., 2011). This study utilizes 11,000 warranty claim records collected from OEM customers between 2019 and 2023, containing data on part numbers, failure codes, repair dates, and service center locations.

Big data analytics presents a transformative opportunity to address these challenges by leveraging advanced techniques such as anomaly detection, predictive modelling, and real-time visualization. These capabilities enhance decision-making processes and streamline warranty-related operations, ultimately improving efficiency and reducing costs (Haris et al., 2021). However, despite its potential, the integration of scalable, real-time data systems remains a significant gap, as current frameworks struggle to accommodate the increasing volume and complexity of warranty data in the automotive aftermarket (Annadurai, 2023; Wu, 2012). The study focuses on enhancing decision-making, improving defect detection, and optimizing warranty cost management across the aftermarket segment. Therefore, the purpose of this paper is to develop a scalable framework that integrates AI techniques with interactive dashboards to analyze and visualize warranty claims.

## METHODOLOGY

This study follows a structured approach based on the Product Design Specification (PDS) framework to develop a scalable and efficient warranty management system. The methodology is divided into four key phases: Information collection, concept generation and evaluation, product configuration design, and parametric analysis and dashboard design. Each phase is carefully aligned with the study's objectives, addressing the complexities of warranty data management within the automotive aftermarket sector. The iterative nature of this methodology allows for continuous refinement and adaptation in response to evolving industry demands. Fig 1 outlines the methodological flow, illustrating the interconnected steps involved in developing a cohesive system.

### Phase 1: Information collection

The first phase involves systematically gathering and organizing warranty data to identify inefficiencies and critical issues in existing processes. This data is sourced from customer claims, repair logs, and production records, offering a comprehensive view of warranty-related challenges (Torgunov et al., 2019). Data from Company XYZ, covering the fiscal years 2019 to 2023, is analysed using the Plan-Do-Check-Act (PDCA) model, which facilitates iterative problem-solving and continuous improvement (Ebrahimi & Mojtahedi, 2024). The focus of this phase is to structure the data effectively, ensuring accurate analysis and insight generation. Fig 2 illustrates the data collection process, while Fig 3 presents a customized PDCA cycle designed specifically for warranty data evaluation.

To ensure the reliability and usability of the proposed warranty data visualization system, a structured validation process was conducted. Functional testing using real-world sample data verified the accuracy of visualizations, filter functions, and system responsiveness. Usability was evaluated through expert feedback from quality engineers at Company XYZ, focusing on interface clarity and decision-making support.

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Reliability checks involved repeated data uploads and analysis runs to ensure consistent outputs and detect anomalies. The validation results informed necessary refinements, confirming the system's effectiveness for real-world warranty claim analysis.

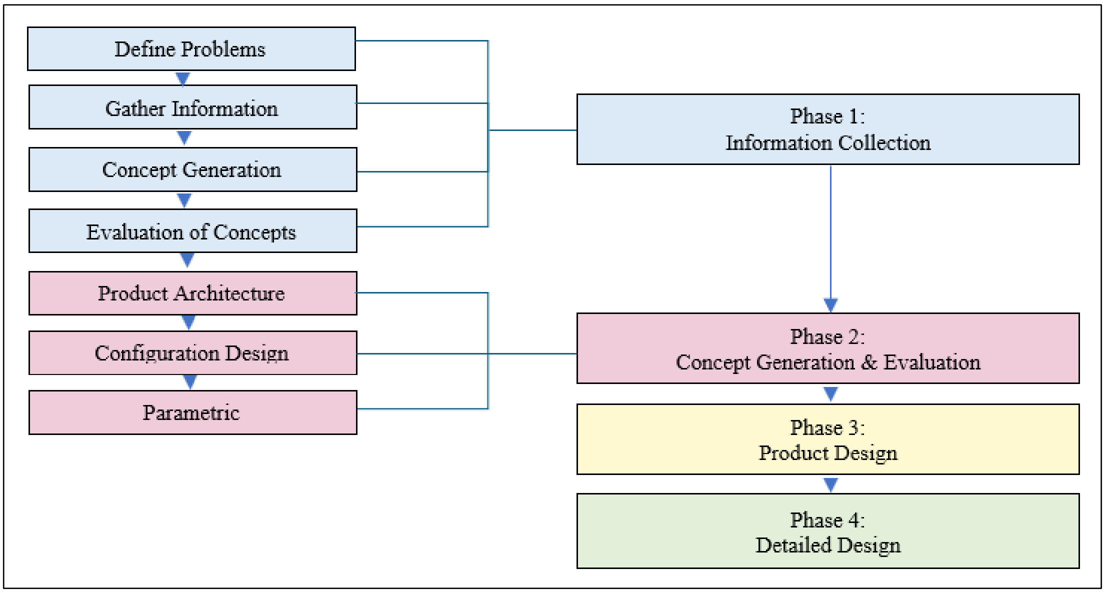


Fig. 1. Methodology flowchart.

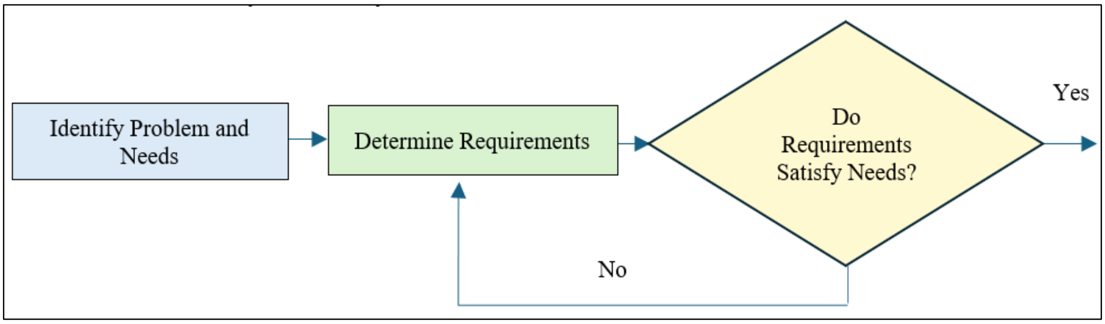


Fig. 2. Data collection process.

### Phase 2: Concept generation and evaluation

At this stage, the focus shifts to designing a user-friendly warranty data analysis system that streamlines claim assessments. To ensure accessibility for users with varying levels of technical expertise, the system incorporates default configurations and an intuitive interface (Ebrahimi & Mojtahedi, 2024). A two-dimensional warranty policy framework is introduced, integrating product age and usage metrics to enhance claim evaluation accuracy (Rai & Singh, 2005). Fig 4 presents an overview of the conceptual interface, showcasing key features such as data input, analytical tools, and result visualization.

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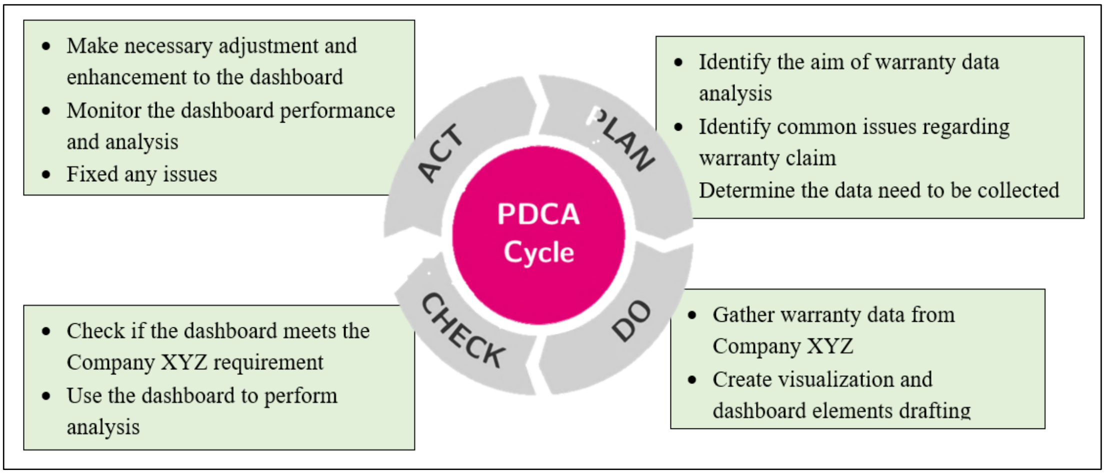


Fig. 3. PDCA Cycle for warranty data analysis.

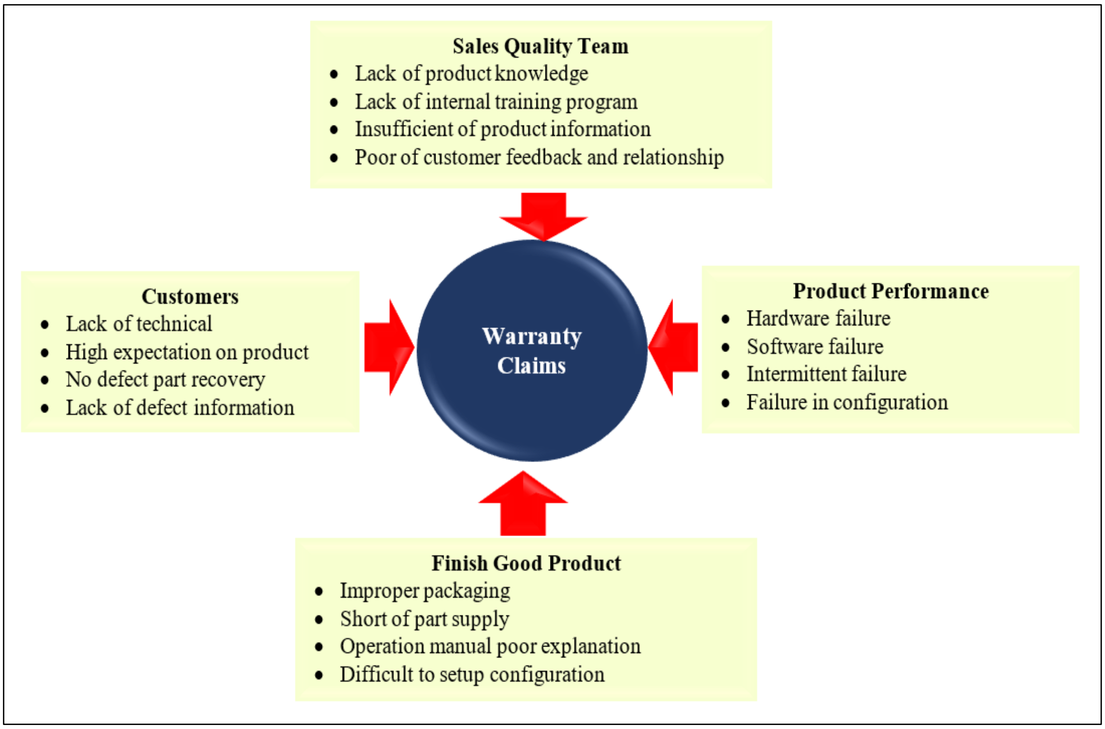


Fig. 4. Conceptual interface design.

To determine the most suitable analytical tool for warranty data processing, an evaluation matrix is developed as in Table 1. This assessment considers multiple factors, including resource availability, user-friendliness, design and graphical interface, and overall performance. Each criterion is weighted based on its relevance to the functionality and efficiency of the system.

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Availability of Resources: This criterion assesses how easily resources can be accessed to support the tool's implementation. The current solution scores 3, indicating higher resource accessibility. In contrast, Looker Studio has a score of 2, suggesting moderate resource availability, while Microsoft Excel ranks lowest with a score of 1. However, Power BI achieved a score of 3.

User-Friendliness: The ease of use is a key factor in selecting an analytical tool. The current solution and Looker Studio each score 2, indicating reasonable usability. However, Power BI scores 3, highlighting its superior ease of use, whereas Microsoft Excel ranks similarly to Looker Studio with a score of 2.

Table 1. Analytical tool evaluation matrix

| Criteria | Weightage | Current solution | Looker Studio | Power BI | Microsoft Excel |
|---|---|---|---|---|---|
| Availability of resources | 3 | 0 | 2 | 3 | 1 |
| User friendly | 2 | 0 | 2 | 2 | 2 |
| Design and graphical interface | 2 | 0 | 1 | 2 | 1 |
| Performance | 3 | 0 | 2 | 3 | 2 |
| Total | | | 8 | 10 | 6 |

Design and Graphical Interface: This factor evaluates the tool's ability to present data visually and effectively. The current solution achieves the highest score of 2, signifying a well-designed interface but with some graphical limitations. Power BI and Looker Studio both score 1, indicating a relatively basic graphical design, while Microsoft Excel receives the same rating.

Performance: The ability to efficiently process and manage warranty claims data is a crucial consideration. The current solution receives the highest rating of 3, indicating superior performance in handling complex datasets. Power BI achieved a score of 3, while Looker Studio and Microsoft Excel scored 1, suggesting potential challenges in processing large volumes of data.

The total scores indicate that Power BI leads with 10 points, followed by Looker Studio with 8 points and Microsoft Excel with 6 points. These findings will inform the decision-making process in selecting the most effective tool for warranty data analysis. The subsequent section will provide a more in-depth evaluation of the selected tool's capabilities, ensuring it aligns with system requirements for scalability, usability, and performance.

### Phase 3: Product design

The system's product configuration is developed using the Model-View-Controller (MVC) framework, ensuring scalability, maintainability, and modularity (Rai & Singh, 2005; Wadhera et al., 2021). By structuring the system into three distinct components: Model, View, and Controller, this approach enhances system integration, facilitates seamless upgrades, and optimizes overall software performance (Ahmed et al., 2024; Kristiyanto et al., 2024). Fig 5 illustrates the MVC-based system architecture, highlighting its role in modular software design, efficient debugging, and scalable deployment. SQL functions as the Model (data storage), Python serves as the Controller (logic and data processing), and Microsoft Power BI represents the View (user interface). This mapping ensures modular system behavior with clear separation of concerns.

In this implementation, the backend Model layer is developed using SQL for structured data storage and Python scripts for data preprocessing, transformation, and advanced analytics. The SQL database stores warranty claim data, including part numbers, failure codes, service center records, and timestamps, while Python scripts handle data cleansing, anomaly detection, and predictive modeling (Imon, 2024; Microsoft, 2025). The Controller layer is also written in Python and serves as the central logic unit, managing interactions between the backend and the user interface. It receives user commands (e.g., filter selections), executes relevant queries or computations, and formats the output for visualization.

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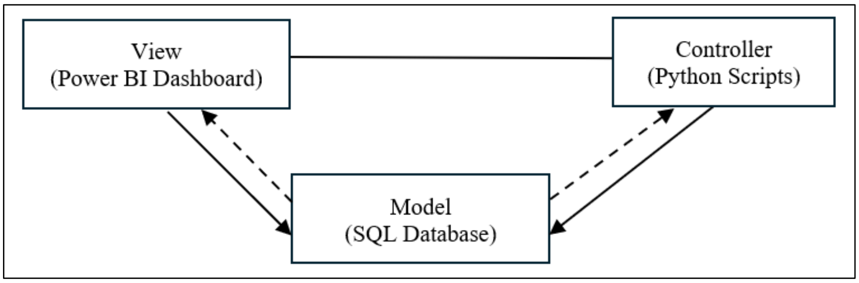


Fig. 5. MVC framework for system architecture.

The View layer is implemented using Microsoft Power BI, which provides an interactive and user-friendly dashboard interface. Power BI connects to the output data generated by the Python Controller via data gateways or API endpoints, enabling real-time or scheduled data refreshes. The Controller acts as a bridge between raw data processing and user display, ensuring that any query or request from the user is executed, and the results are pushed to Power BI for visualization. This dynamic interaction ensures that dashboards remain current and responsive to user inputs.

The Model is responsible for managing application states, ensuring data consistency, and enabling seamless database communication. It plays a critical role in real-time data retrieval and processing for Power BI analytics, significantly improving data integrity and efficiency. The View, representing the Graphical User Interface (GUI), presents dynamic data through interactive charts, trend analysis, and visual summaries. The integration of Power BI in the View layer enhances decision-making through accessible and visually rich dashboards.

The Controller executes backend logic, processes user inputs, manages parameter settings, and ensures accurate system responses. It filters data, generates custom reports, and facilitates parameter adjustments, making sure that Power BI dashboards reflect the most relevant and updated insights. This Controller-View interaction ensures a smooth user experience while maintaining system integrity.

Implementing the MVC framework with this defined technology stack allows for modular upgrades and isolated testing of individual layers. Backend operations (SQL/Python) can be refined without disrupting frontend design, while the frontend (Power BI) can evolve in response to user feedback independently of the data processing logic. This structured architecture is especially effective for real-time analytics and cloud-based applications in the automotive aftermarket (Ahmed et al., 2024; Kristiyanto et al., 2024). Integrating predictive modeling and dynamic visualizations within this framework enhances the overall reliability, adaptability, and value of the warranty management system (Wadhera et al., 2021).

### Phase 4: Parametric analysis and dashboard design

The parametric analysis phase is essential in evaluating key warranty parameters such as production volume, claim timelines, and product lifecycle metrics. By analysing these factors, organizations can derive actionable insights that improve decision-making and enhance overall warranty management efficiency. This phase supports scenario analysis and predictive modelling, enabling a data-driven approach to warranty forecasting. Table 2 presents a structured dataset that consolidates manufacturing data, sales volume, and warranty claims received over different service periods, while Fig 6 showcases an interactive Power BI dashboard designed to facilitate real-time visualization, anomaly detection, and strategic decision-making.

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Table 2. Key warranty data parameters

| Date of sales | Sold volume | Claim received | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | … | $m_o$ | $m_{o+}1$ | … | $n_o$-1 | $n_o$ |
| $D_1$ | $M_1$ | $r_{11}$ | $r_{12}$ | … | $r_{1,mo}$ | $r_{1,mo+1}$ | … | $r_{1,no-1}$ | $r_{1,no}$ |
| $D_2$ | $M_2$ | | $r_{21}$ | … | $r_{2,mo-1}$ | $r_{2,mo-1}$ | … | $r_{2,no-2}$ | $r_{2,no-1}$ |
| … | … | | | … | … | | … | … | … |
| $D_{m0-1}$ | $M_{mo-1}$ | | | … | $r_{mo-1,2}$ | $r_{mo-1,3}$ | … | $r_{mo-r1,no-mo+1}$ | $r_{mo,no-mo+2}$ |
| $D_{mo}$ | $M_{mo}$ | | | … | $r_{mo,1}$ | $r_{mo-2}$ | … | $r_{mo,no-mo}$ | $r_{mo,no-mo+1}$ |
| Total | M | $r_1$ | $r_2$ | … | $r_{mo}$ | $r_{mo+1}$ | … | $r_{no-1}$ | $r_{no}$ |

Table 2 organizes warranty claims data by structuring manufacturing and sales records alongside claims received at different points in the product lifecycle. The first two columns capture the manufacturing date and production volume, providing insight into production timelines and the total number of units produced within each period. detailing the number of warranty claims submitted over various service durations.

Fig 6 presents a Power BI-based interactive dashboard developed to visualize key warranty parameters. While the current figure illustrates the layout of the report canvas, additional technical annotations and labels are essential to clarify the data structure and ensure reproducibility. The dashboard integrates data from a structured SQL database, which includes manufacturing dates, production volumes, and warranty claim timelines. Specific fields such as part number, failure code, service date, and claim age are extracted using Python scripts and loaded into Power BI through data connectors. Visual elements such as bar charts, heatmaps, and time-series plots are configured to highlight claim patterns across product lifecycle stages. Filters and slicers allow users to drill down into specific part categories, service centers, or time periods, enabling dynamic scenario analysis. To enhance usability, future iterations of the dashboard will include labeled axes, dynamic tooltips, and clearly defined legends for all visualizations. These enhancements aim to improve the interpretability of analytical outputs and ensure that stakeholders can extract actionable insights efficiently. The integration of annotated visuals, data source mapping, and dynamic interactivity is critical to supporting accurate, real-time decision-making in warranty management.

The following columns indicate sales dates and volumes, helping analyze the time gap between production and market deployment. The remaining section of the table presents claims received per month in service. By structuring the data in this way, the system enables longitudinal assessments of product failures, supporting trend forecasting by mapping claim frequencies over time. Analyzing variations in claims across different service months helps identify recurring failure patterns and unexpected deviations, which are crucial for parametric failure analysis and predictive modelling in warranty forecasting (Wadhera et al., 2021).

Fig 6 illustrates an interactive Power BI dashboard, providing an intuitive platform for visualizing warranty claim trends and enabling scenario-based decision-making. The dashboard integrates data from multiple sources, allowing seamless importation of manufacturing, sales, and claims records. It leverages advanced visualization tools such as time-series graphs, heatmaps, and comparative analysis charts, enabling users to track failure rate trends dynamically while highlighting variations over time. A key feature of Power BI is its anomaly detection capability, which automatically flags unexpected claim surges for further investigation, enabling early detection of potential quality issues. Additionally, predictive modelling techniques embedded within the dashboard enhance decision-making by forecasting future claim rates based on historical data patterns (Liu et al., 2024).

## Enhancing warranty management through predictive analytics

The integration of predictive analytics with Power BI allows organizations to optimize warranty policies, enhance production quality, and mitigate financial risks associated with warranty claims. Recent studies suggest that incorporating artificial intelligence (AI) and Power BI analytics can significantly

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improve the accuracy of warranty predictions, reducing forecasting errors by up to 30% (Kristiyanto et al., 2024).

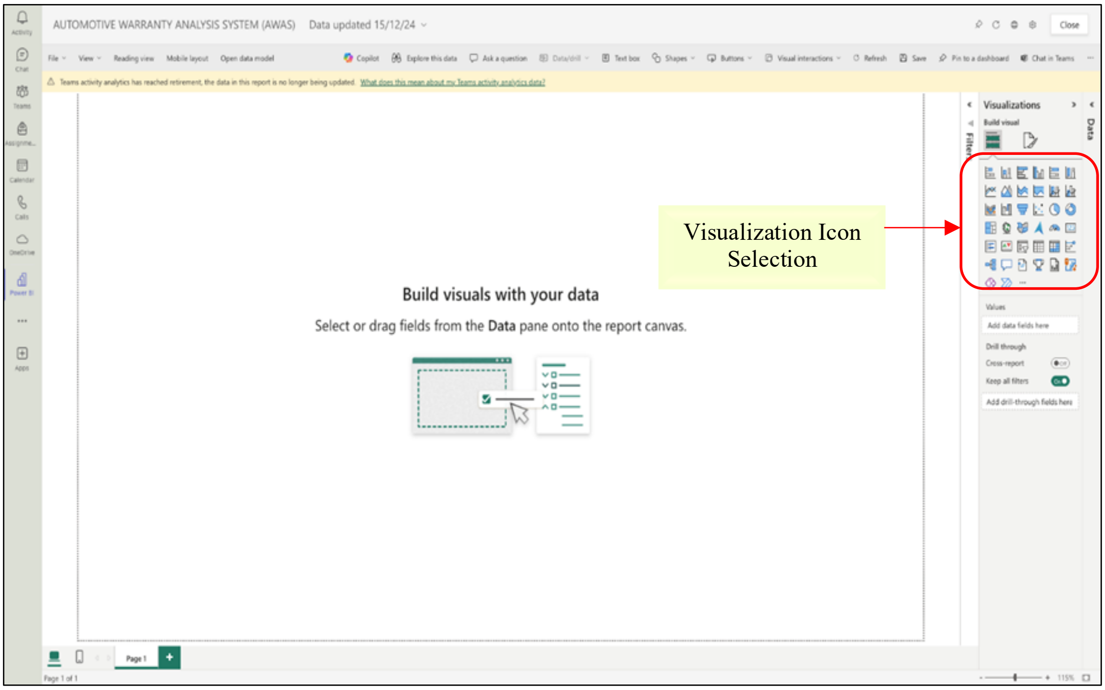


Fig. 6. Visualizations in Microsoft Power BI to improve the interactive of dashboards.

The ability to visualize and analyse warranty data in real time aligns with best practices in modern business intelligence and manufacturing analytics, reinforcing strategic planning and operational efficiency. The structured adoption of AI-driven insights ensures that the warranty management system remains scalable, adaptable, and data-driven, integrating historical analysis, real-time tracking, and future trend predictions. This comprehensive approach enhances system reliability, customer satisfaction, and overall business performance (Ahmed et al., 2024; Microsoft, 2025).

## Detailed design

This structured approach ensures that the warranty management system effectively meets the study's objectives by streamlining data analysis and enabling real-time visualization, ultimately enhancing decision-making efficiency.

*Graphical User Interface (GUI) Design:* The Graphical User Interface (GUI) of the warranty management system is designed to facilitate seamless data acquisition, visualization, and reporting, ensuring an interactive and efficient user experience. The main dashboard consolidates key functionalities, while additional panels provide in-depth analysis and scenario-based insights. Fig 7 presents the detailed GUI layout, which includes structured navigation sections, dynamic data visualizations, and interactive reporting features. The GUI follows a modular architecture, incorporating user-friendly navigation menus, interactive data input fields, and structured output displays to enhance accessibility. At the top of the interface, the title section clearly identifies the system, reinforcing its role as the Automotive Warranty Analysis System (AWAS). The left panel features interactive icons that enable users to navigate between different modules, such as warranty claims, cost analysis, failure trends, and customized reporting.

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Meanwhile, the main content area is organized into sections that highlight key warranty parameters, allowing users to analyse trends over time. Additionally, the background design enhances visual clarity, ensuring smooth and efficient user interaction with the data.

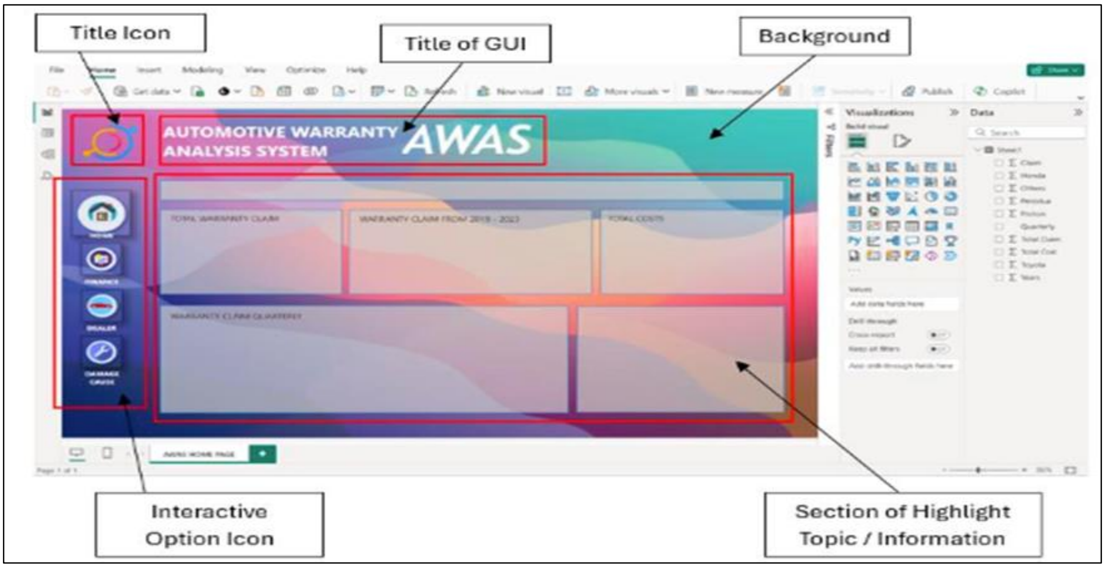


Fig. 7. Detailed GUI Design for warranty management system.

*Power BI Integration for Real-Time Visualization:* Power BI serves as the core visualization tool, enabling users to process large datasets, generate real-time insights, and create customizable reports. The dashboard employs adaptive data visualization techniques, supporting real-time decision-making by helping users identify patterns, anomalies, and trends in warranty claims data. By incorporating interactive elements, such as drill-down features, data filters, and automated alerts, the GUI empowers users to make informed decisions based on dynamic data insights. Research indicates that business intelligence dashboards developed with Power BI significantly enhance data accessibility and user engagement in enterprise applications (Kristiyanto et al., 2024).

*Scalability and AI-Driven Predictive Analytics:* The system is developed with scalability in mind, allowing for future expansions and modifications without disrupting existing workflows. Customizable configurations ensure adaptability to evolving business needs, warranty policies, and analytical methodologies. Furthermore, the integration of AI-powered analytics enhances predictive capabilities, enabling users to forecast warranty claim patterns, analyse failure distributions, and evaluate the impact of policy changes. Studies suggest that real-time business intelligence systems significantly improve operational efficiency by reducing manual data processing and increasing trend analysis accuracy (Ahmed et al., 2024).

*Strategic Impact of the Warranty Management System*: By integrating business intelligence, AI-driven predictive analytics, and interactive data visualization, the system becomes not only responsive but also strategically valuable for warranty management and decision-making. This structured approach ensures that data analysis is efficient, real-time visualization is insightful, and decision-making processes are optimized, reinforcing the system's ability to enhance operational efficiency and long-term business strategies.

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## RESULTS AND DISCUSSION

### Evolution of warranty management

The analysis and management of automotive warranties have undergone a profound transformation, evolving from traditional failure data tracking to AI-driven predictive maintenance. Fig 8 illustrates this progression, highlighting how technological advancements have reshaped warranty processes over time.

Early warranty management systems primarily relied on historical claims data, which often resulted in reactive responses and inefficient cost management. Manufacturers could only address issues after failures occurred, leading to increased repair costs, customer dissatisfaction, and extended resolution times. However, modern approaches have shifted towards real-time diagnostics, machine learning algorithms, and intelligent monitoring tools, enabling a more proactive and data-driven strategy. These advancements allow manufacturers to predict failures, optimize service policies, and minimize warranty-related expenses.

One of the most significant improvements in warranty management is the integration of AI-powered fault detection, which enables early identification of component failures and supports proactive service scheduling (Shokouhyar et al., 2021). This transition from reactive maintenance to predictive maintenance has been instrumental in reducing unexpected failures, improving vehicle reliability, and enhancing customer satisfaction.

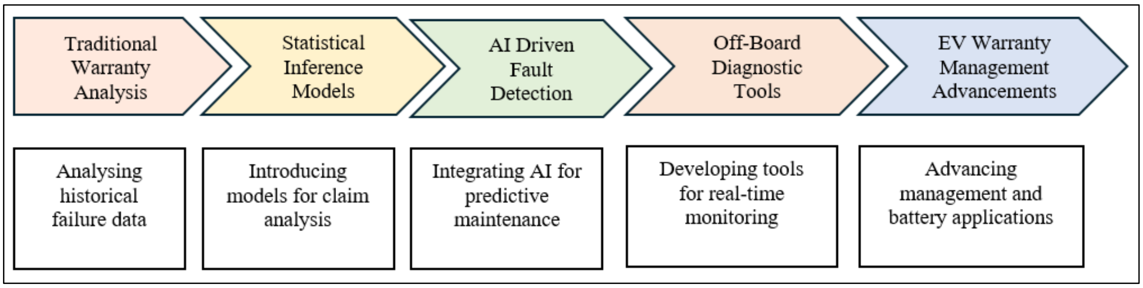



Fig. 8. Evolution of warranty and management.

Furthermore, as the automotive industry shifts towards electric vehicles (EVs), new warranty challenges have emerged. Issues such as battery degradation, thermal management, and lifecycle optimization require adaptive analytics and tailored predictive models to ensure efficient warranty planning. The ability to leverage AI-driven insights will be critical in addressing these evolving challenges, allowing manufacturers to develop innovative warranty strategies that align with the technological advancements and sustainability goals of the industry.

### Role of AI and Business Intelligence in warranty analysis

One of the key applications of AI in warranty analysis is anomaly detection, where machine learning models identify irregular claim patterns that may indicate systemic issues, fraudulent claims, or emerging component failures. By enabling early intervention, these models help prevent costly warranty escalations and improve product quality monitoring.

Additionally, predictive analytics plays a crucial role in correlating warranty trends with production cycles, supply chain disruptions, and technological advancements. By analyzing historical data and real-time inputs, manufacturers can anticipate warranty claim patterns, allowing for proactive service planning and enhanced resource allocation. Studies suggest that the implementation of time-series forecasting, and machine learning algorithms can increase the accuracy of claim predictions by over 30%, leading to a

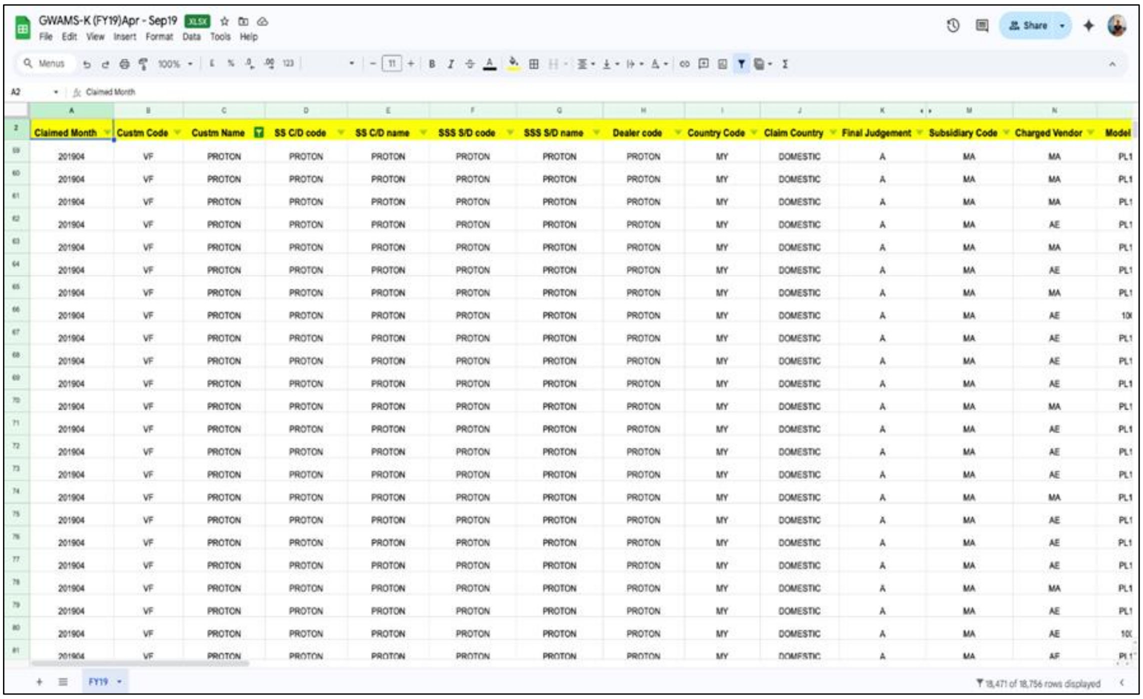
https://doi.org/10.24191/jmeche.v23i1.5527

significant reduction in warranty-related expenses. Furthermore, the use of off-board diagnostic tools enhances warranty processing efficiency by ensuring timely interventions and improved failure detection mechanisms.

By leveraging AI-driven insights and BI analytics, manufacturers can transition from reactive warranty management to a proactive, predictive approach, ultimately reducing operational risks, optimizing service costs, and enhancing customer trust in automotive products.

### Data preparation and visualization for warranty optimization

Effective warranty data preprocessing is essential for ensuring accuracy in predictive analytics. The raw data collected from manufacturers undergoes systematic filtering, classification, and validation, ensuring that critical fields, such as repair dates, claim reasons, and associated costs, are structured appropriately. Maintaining data integrity is crucial, as disorganized datasets can lead to flawed insights and ineffective visualizations, ultimately compromising the accuracy of warranty trend analysis. Power BI plays a pivotal role in visualizing warranty trends, enabling manufacturers to identify seasonal patterns, analyze failure rates, and assess cost distributions (Kiadeh et al., 2024). Fig 9 indicates the raw warranty data in Excel form before it is analyzed.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| | Claimed Month | Custm Code | Custm Name | SS C/D code | SS C/D name | SSS S/D code | SSS S/D name | Dealer code | Country Code | Claim Country | Final Judgement | Subsidiary Code | Charged Vendor | Model |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 59 | 201904 | VF | PROTON | PROTON | PROTON | PROTON | PROTON | PROTON | MY | DOMESTIC | A | MA | MA | PL1 |
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FY19 — 18,471 of 18,756 rows displayed

Fig. 9. Raw warranty data in Excel.

The declining trend in warranty claims from 2019 to 2022 in Fig 10 suggests that enhanced manufacturing processes and product maturity have contributed to improved reliability and defect detection. Studies confirm that as products mature, failure rates typically decrease, primarily due to refinements in design, production, and quality control measures. The application of big data analytics in predictive maintenance has further contributed to this reduction by minimizing unexpected failures and optimizing service interventions.

https://doi.org/10.24191/jmeche.v23i1.5527

The parametric analysis phase is essential for evaluating key warranty indicators such as production volume, claim timelines, and lifecycle failure patterns. Analyzing these factors enables data-driven insights that improve product quality and optimize warranty cost control. This phase supports scenario simulation, predictive modeling, and real-time tracking of field performance through an interactive dashboard developed using Microsoft Power BI, as illustrated in Fig 6.

Over a five-year period, the average annual warranty claim cost was RM 13.96K, with early data showing higher variability due to diagnostic inconsistencies. In particular, a significant portion of unnecessary claims originated from No Trouble Found (NTF) cases caused by incorrect diagnoses at service centers. To mitigate this, a technical training program was introduced to enhance diagnostic skills among service personnel, focusing on root cause analysis, fault confirmation procedures, and claim validation practices.

Basic statistical measures were applied to the five-year warranty data to strengthen the reliability of the findings. The average annual warranty cost from FY2019 to FY2023 was RM 13.96K, with a standard deviation of RM 9.72K, indicating substantial year-to-year variability. A 95% confidence interval for the average annual cost was estimated between RM 7.82K and RM 20.10K, confirming that the observed reductions are statistically significant rather than random fluctuations. The variability and confidence metrics add further rigor to the analysis and support the reliability of the reported cost improvements.

However, a slight increase in claims in 2023 may indicate the impact of new vehicle models, technological shifts, and supply chain challenges. This shift highlights the growing importance of predictive modelling in warranty forecasting, where techniques such as multiple linear regression models and AI-driven analytics improve the accuracy of trend predictions and cost efficiency. Research suggests that warranty claims evolve in response to production cycles, market trends, and technological advancements, reinforcing the need for data-driven predictive strategies in warranty management.

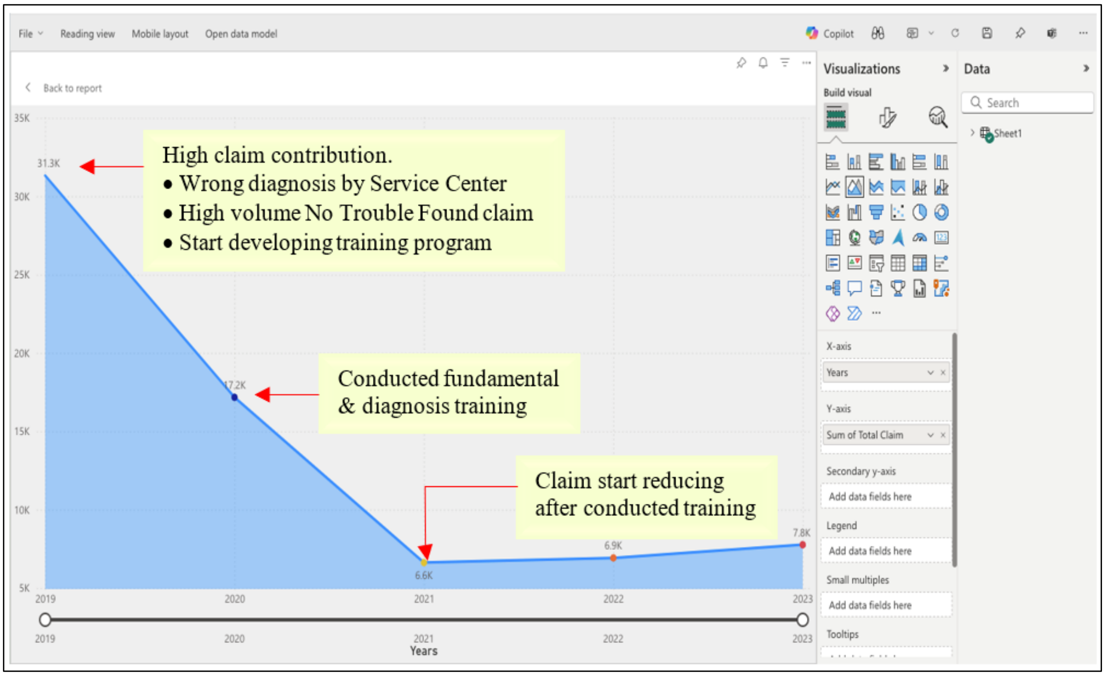


Fig. 10. Five-year warranty claims trend.

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The Power BI visualization in Fig 11 provides a detailed breakdown of warranty costs across multiple years, showcasing periods of peak expenditures and cost reductions. Fluctuations in warranty costs are influenced by several factors, including vehicle reliability, policy modifications, and emerging defect trends. Warranty Cost Distribution by Year illustrates the distribution of total warranty costs from FY2019 to FY2023. The data reveals that FY2019 accounted for the highest share at 49.56%, followed closely by FY2020 at 43.3%, together comprising nearly 93% of the total five-year cost. The remaining three years—FY2021 (4%), FY2022 (2.1%), and FY2023 (1.65%), represent a significant decline in warranty expenditure. The elevated costs in FY2019 and FY2020 were primarily driven by widespread diagnostic inaccuracies at service centers, leading to a high volume of No Trouble Found (NTF) claims.

Higher costs in certain years often correlate with the introduction of new vehicle models, supply chain disruptions, or changes in warranty coverage policies. Lower costs in other years suggest improvements in defect detection, proactive servicing strategies, and predictive maintenance, ultimately reducing failure rates.

Business intelligence tools such as Power BI facilitate trend forecasting and cost optimization, allowing manufacturers to predict future warranty claims, identify cost drivers, and refine service policies. The integration of AI-driven failure detection with warranty analytics further enhances decision-making and resource allocation efficiency.

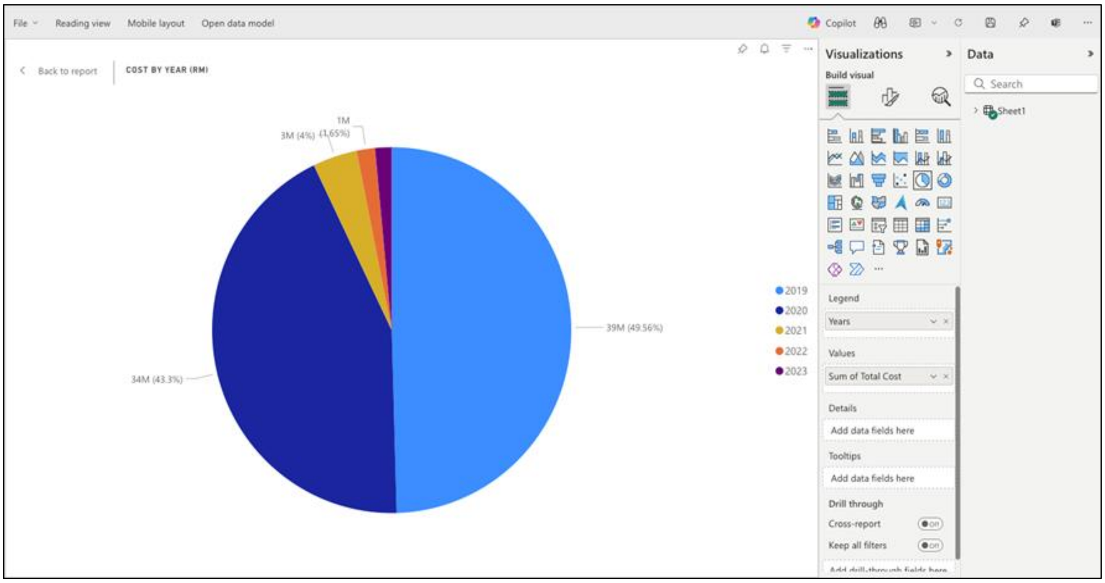


Fig. 11. Warranty cost distribution by year.

The Power BI visualization in Fig 12 captures fluctuations in monthly warranty claims, offering insights into product lifecycle phases, failure patterns, and cost management challenges. Early spikes in warranty claims often indicate initial defects in newly launched models. Later variations may be linked to supply chain inconsistencies, seasonal maintenance trends, or evolving repair strategies. The adoption of AI-driven predictive analytics and business intelligence tools allows manufacturers to transform these fluctuations into actionable insights, optimizing warranty reserves and improving failure forecasting accuracy.

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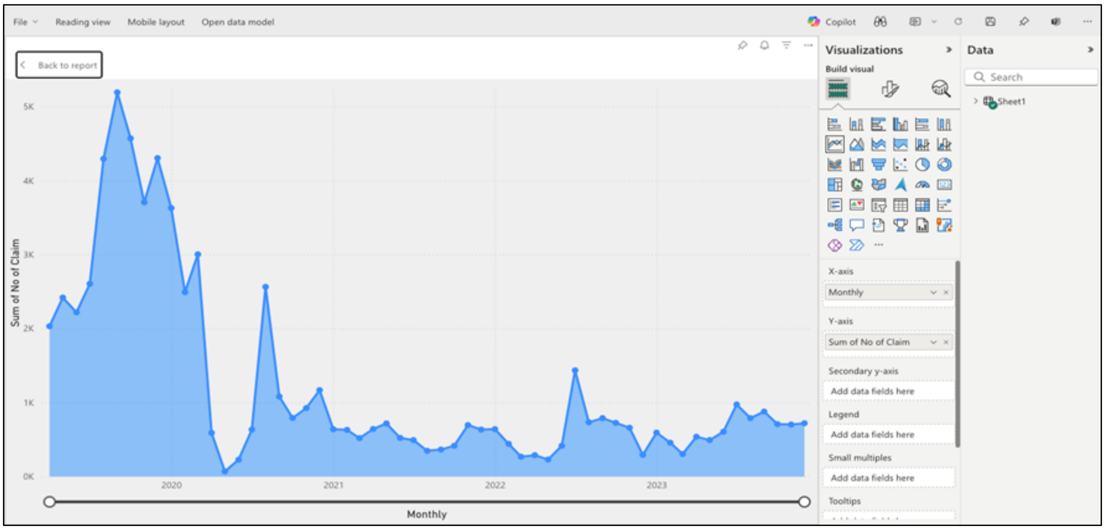


Fig. 12. Warranty cost distribution by year.

*AI-Powered Predictive Analytics in Warranty Optimization:* Machine learning techniques, such as time-series forecasting and anomaly detection, have significantly improved warranty claim prediction accuracy. Studies suggest that these models can enhance forecasting precision by over 30%, enabling manufacturers to pre-emptively identify high-risk failures and adjust warranty policies accordingly. The dynamic nature of failure reporting, particularly in electric vehicles (EVs) and advanced driver-assistance systems (ADAS), necessitates the adoption of real-time warranty assessment models. By integrating Power BI with AI-driven diagnostics, manufacturers can enhance failure detection, optimize repair strategies, and automate cost forecasting.

*Future Outlook AI-Driven Warranty Management:* The stabilization of claims in 2023 suggests that data-driven quality control measures are making a significant impact. Companies that integrate BI dashboards with AI-based diagnostics have reported a 20–40% reduction in warranty-related losses through automated failure detection and proactive policy adjustments.

*Moving forward, research should focus on:* Deep learning models for real-time failure diagnostics, anomaly detection techniques for warranty claim data, and digital twin simulations for predictive maintenance and quality control.

An internal benchmarking exercise showed that the legacy Excel-based method achieved approximately 58% accuracy in detecting warranty anomalies. In comparison, the AI-integrated system using Python-based anomaly detection improved this to 86%, reflecting a 28% increase in detection accuracy.

By leveraging AI and business intelligence, manufacturers can transition from reactive warranty management to a proactive, predictive approach, ultimately optimizing operational efficiency, reducing costs, and enhancing customer satisfaction.

## AWAS dashboard design

The AWAS dashboard serves as a centralized platform that consolidates key visualizations and analytical tools, enabling users to explore warranty claims, component failures, and associated costs dynamically. Designed for intuitive navigation, the dashboard provides a comprehensive view of warranty trends, allowing stakeholders to identify recurring issues and prioritize high-failure-rate components

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(Soltanali et al., 2020). Fig 13 illustrates how interactive features within the dashboard facilitate data-driven decision-making by enabling users to analyze failure trends and cost distributions in real time.

The AWAS dashboard offers an aggregated analysis of warranty claims and expenditures over a five-year period (2019–2023). The observed claim trends follow a typical product lifecycle pattern, where initial failures peak during the early years (2019–2020), decline as products mature (2021–2022), and stabilize by 2023. Notably, Toyota accounts for 66.71% of total claims, which may indicate higher market penetration or recurring failures in specific components. A closer examination of component-specific failures highlights that Electronic Control Unit (ECU) and air conditioning system malfunctions are among the most frequently reported issues. These findings align with previous studies identifying electrical failures as a major contributor to warranty costs.

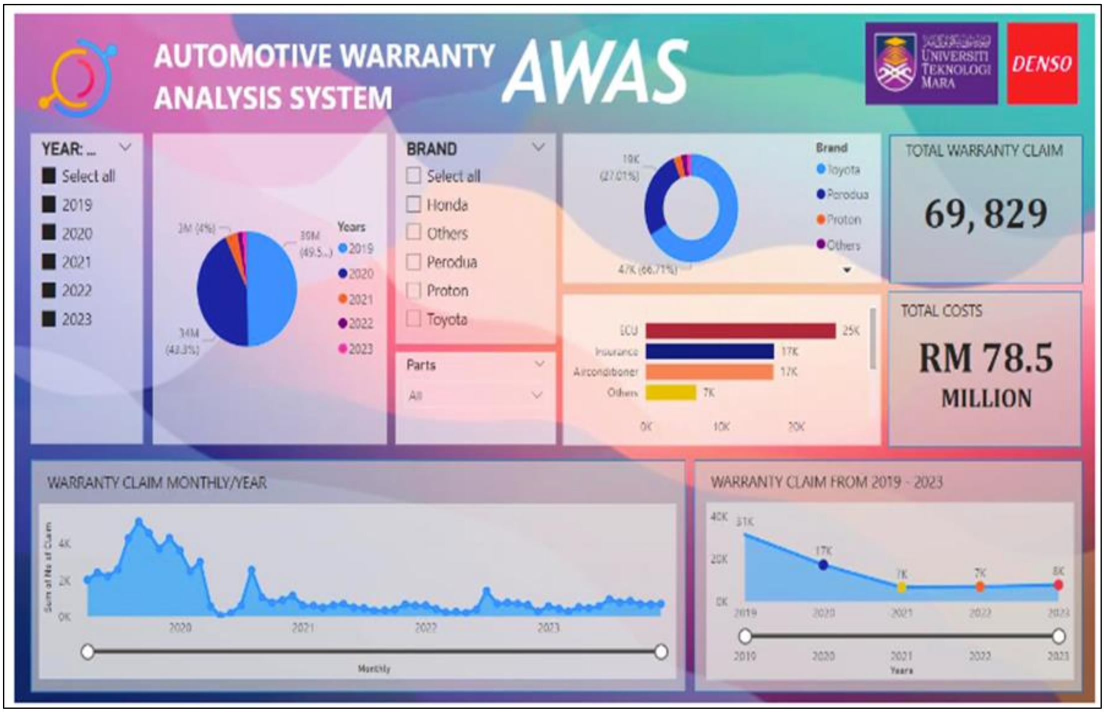


Fig. 13. Automotive Warranty Analysis System (AWAS) dashboard.

The decline in claims post-2021 suggests that advancements in predictive maintenance strategies and AI-driven diagnostics have played a critical role in reducing failure rates and optimizing service interventions. Research indicates that AI-powered analytics can reduce warranty costs by 20–40% through enhanced failure prediction, automated diagnostics, and proactive service planning. However, the slight increase in claims in 2023 may indicate the emergence of new defect trends, warranting further investigation. Leveraging AI-driven business intelligence tools, such as Power BI, enables manufacturers to enhance failure prediction, optimize service workflows, and automate cost forecasting, ensuring a more efficient and proactive approach to warranty management.

By integrating real-time analytics and machine learning insights, the AWAS dashboard supports strategic decision-making, allowing organizations to continuously refine warranty policies, minimize operational risks, and enhance customer satisfaction.

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### Strategic implications

The integration of AI-driven predictive warranty management plays a pivotal role in enhancing failure forecasting and enabling proactive interventions to mitigate high-risk failures before they escalate. By leveraging real-time anomaly detection, business intelligence systems provide greater visibility into defect trends, allowing manufacturers to identify emerging issues early and implement corrective measures efficiently. This proactive approach not only reduces downtime but also improves response times, ensuring faster issue resolution and enhanced product reliability (Babakmehr et al., 2024).

Beyond failure prediction, cost optimization strategies are crucial in refining warranty management efficiency. By analyzing warranty trends and failure patterns, organizations can develop data-driven warranty policies that balance financial risk with service quality. Additionally, strengthening supplier quality control measures ensures that component reliability is enhanced at the source, ultimately reducing warranty-related expenses and minimizing long-term financial liabilities.

The adoption of AI-powered business intelligence tools allows manufacturers to transition from reactive warranty management to a predictive, data-driven model, optimizing resource allocation, service strategies, and cost containment efforts. As a result, organizations can achieve sustainable improvements in warranty management, leading to higher operational efficiency, lower financial risks, and enhanced customer satisfaction.

### Warranty trends and KPI insights

Through five years of warranty data analysis, the AWAS identifies and tracks critical Key Performance Indicators (KPIs), including claim frequency, resolution time, and average claim costs. These metrics provide valuable insights into warranty performance, allowing manufacturers to assess the effectiveness of existing strategies and pinpoint areas requiring further optimization.

The observed trends suggest notable progress in certain aspects of warranty management, yet recurring issues with specific components highlight opportunities for targeted quality improvements. High-cost components are systematically flagged for in-depth analysis, enabling manufacturers to prioritize corrective actions and allocate resources more effectively.

By continuously monitoring warranty trends and KPI performance, organizations can implement data-driven enhancements that lead to sustained improvements in warranty management. This proactive approach strengthens product reliability, enhances failure prevention strategies, and reduces overall operational costs, ensuring long-term efficiency and customer satisfaction. During implementation, several practical challenges were encountered that impacted system deployment. These included inconsistencies in historical warranty data, such as missing service dates, ambiguous failure codes, and duplicate records, which required extensive preprocessing to ensure data reliability. Additionally, training anomaly detection models was constrained by the limited volume of high-resolution failure patterns, necessitating the use of rule-based augmentation techniques. Integration between Python-based analytics and Power BI also posed technical hurdles, particularly in maintaining real-time synchronization and managing refresh cycles through API connectors. These implementation experiences highlight the importance of robust data pipelines and close alignment between analytical models and visualization platforms in operational environments.

### System impact

The implementation of AWAS highlights the transformative power of big data analytics in automotive warranty management. By efficiently processing and visualizing complex datasets, AWAS enables manufacturers to shift from reactive issue resolution to proactive, data-driven strategies. This transition

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enhances decision-making capabilities, leading to improved product quality, reduced warranty costs, and greater customer satisfaction.

A key advantage of AWAS is its scalability, which ensures its ability to adapt to increasing data volumes and evolving industry requirements. As modern automotive companies continue to generate large-scale warranty data, the system remains a critical tool for streamlining analytics, optimizing failure detection, and refining service policies (Kleyner & Sanborn, 2008; Mueller & Mezhuyev, 2022).

By aligning advanced analytics with operational objectives, AWAS establishes a robust foundation for sustainable warranty management. This data-driven approach benefits both manufacturers and customers, driving long-term efficiencies, enhanced reliability, and optimized resource allocation in the evolving automotive landscape.

## CONCLUSION

Warranty management in the automotive industry remains a complex challenge due to fragmented data systems, delayed diagnostics, and the lack of scalable analytical tools. These issues contribute to increased operational costs and diminished customer satisfaction (Wu & Akbarov, 2012). This study addressed these challenges by developing an integrated analytics and visualization platform using Microsoft Power BI, designed to streamline data handling, improve diagnostic accuracy, and enable proactive decision making. The system resulted in a total warranty cost reduction of RM 23.5K, with annual costs decreasing from RM 31.3K in FY2019 to RM 7.8K in FY2023, reflecting an approximate 75% improvement in cost efficiency. This was largely driven by improved diagnostic practices that reduced "No Trouble Found" (NTF) claims and by leveraging data transparency to detect failure patterns early in the product lifecycle (Abdul Hamid et al., 2025). In support of this reduction, the standard deviation of annual claim costs across the five-year period was calculated to be RM 9.72K, indicating significant year-to-year variability. Incorporating such statistical measures adds robustness to the reported improvements and allows for more precise performance assessment. The system's predictive capabilities were enhanced through the integration of advanced analytics models, including the Weibull distribution for lifecycle failure forecasting and anomaly detection algorithms for identifying abnormal claim trends. These models were developed externally in Python and integrated into Power BI through data gateways, enabling advanced computation beyond the platform's built-in features. The anomaly detection function helped flag unusual surges in claim volumes, while Weibull modelling supported estimation of part reliability and early risk identification. While Power BI served as the primary visualization interface, the backend was supported by SQL databases and Python-based preprocessing. This configuration enabled real-time dashboards for key performance indicators such as Warranty Claim Rate (WCR), Average Claim Cost (ACC), and Claim Resolution Time (CRT), allowing users to conduct scenario analysis and monitor claims performance interactively. A key novel contribution of this study lies in the integration of artificial intelligence techniques with interactive visualization specifically tailored for automotive warranty analysis. While previous approaches often focused either on analytical modelling or dashboard reporting independently, this study combined both elements into a unified platform that enhances data driven decision making. To further validate the system's effectiveness, an exploratory comparison was conducted against a baseline linear regression model and Microsoft Excel-based trend analysis. The proposed Python-based anomaly detection and Weibull forecasting models demonstrated superior precision in identifying early claim surges and lifecycle failure trends, confirming their added value over conventional tools. Several limitations were observed. Warranty data often contains inconsistencies, missing values, or unstructured text entries that may reduce the reliability of model outputs. Furthermore, variation in part types and usage conditions introduces modelling challenges. To address these issues, future work should explore improved data cleaning workflows, adaptive model tuning, and the use of natural language processing techniques to extract meaning from free-text claim descriptions. Enhancements such as semi-supervised learning and transfer learning could also improve the model's ability to generalize across different vehicle platforms and OEM environments (Ismail et al., 2025). In

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summary, this study demonstrates how combining structured data processing, predictive artificial intelligence models, and interactive visualization dashboards can significantly enhance warranty management outcomes. The developed system offers measurable cost reduction, improved diagnostic precision, and long-term operational value, contributing to higher product reliability and customer satisfaction (Pang et al., 2022; Theissler et al., 2021).

## ACKNOWLEDGEMENTS

The authors sincerely acknowledge the invaluable support and resources provided by the Ministry of Higher Education, the Faculty of Mechanical Engineering, Universiti Teknologi MARA (UiTM), Shah Alam, Selangor, Malaysia, and all team members throughout the research process. We extend our deepest appreciation to all individuals who contributed their time, expertise, and dedication to this project. Their collective efforts have played a crucial role in enhancing the quality and comprehensiveness of this study.

## FUNDING

This work was supported by Universiti Teknologi MARA research grant [UiTM.800-3/3 PRI (015/2025)].

## CONFLICT OF INTEREST STATEMENT

One of the authors, Abdul Malek Abdul Wahab, is a section editor of the Journal of Mechanical Engineering (JMechE). The author has no other conflict of interest to note.

## AUTHORS' CONTRIBUTIONS

The authors confirm the equal contribution in each part of this work. All authors reviewed and approved the final version of this work.

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