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A GPT-Based Applied Computing System for Interpretable OBD-II Vehicle Diagnostics and Safe Driving Support

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ABSTRACT

Modern vehicles are equipped with On-Board Diagnostics (OBD-II) systems that continuously generate data on engine performance, emissions, and driving behaviour. However, most OBD-II applications present diagnostic information in technical formats intended for automotive professionals, limiting interpretability for non-technical drivers. As a result, fault codes and warning alerts are often misunderstood or ignored, leading to delayed maintenance, unsafe driving practices, and increased vehicle ownership costs. This study proposes SmartCarMate, a GPT-based cross-platform applied computing system designed to enhance the accessibility and interpretability of OBD-II diagnostics while promoting safer driving behaviour. The system integrates real-time OBD-II data acquisition via a Bluetooth adapter with an AI-assisted interpretation layer that translates fault codes and sensor readings into human-readable explanations accompanied by prioritised action guidance. Additional features include driving behaviour analysis, trip tracking, maintenance reminders, and safety-oriented feedback to support preventive vehicle care. SmartCarMate was implemented as a cross-platform mobile application using the Flutter framework and evaluated through User Acceptance Testing involving drivers with varying automotive knowledge. Evaluation methods included task-based testing and a five-point Likert-scale questionnaire assessing usability, clarity, trust, and intention to continue use. Results indicate consistently high user acceptance ($\mu > 3.9$), improved understanding of diagnostic alerts, and increased confidence in maintenance decisions, demonstrating that AI-assisted interpretation enhances usability and decision support in vehicle health monitoring systems.

1. Introduction

Recent advances in vehicle sensing and connectivity have accelerated the adoption of On-Board Diagnostics (OBD-II) systems, enabling continuous monitoring of engine performance, emissions, and driving behaviour. Concurrently, artificial intelligence (AI) and machine learning (ML) models have been widely integrated with OBD-II data for applications such as predictive maintenance, eco-driving

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optimisation, behavioural classification, and risk detection [1-5]. These studies demonstrate substantial technical progress, particularly in algorithmic accuracy, anomaly detection, and predictive modelling, confirming OBD-II telemetry as a robust data foundation for intelligent vehicle systems.

However, the dominant orientation of these systems remains analytical rather than interpretive. Prior work primarily evaluates improvements in classification performance, prediction accuracy, or optimisation metrics [1-5], with limited attention to how diagnostic outputs are understood and acted upon by non-technical drivers. In practice, many OBD-II applications expose raw fault codes, parameter dashboards, or numerical risk scores that presuppose automotive literacy. While such outputs may satisfy technical evaluation criteria, they do not necessarily support informed decision-making among everyday vehicle users. The result is a persistent gap between data availability and actionable understanding, where drivers receive alerts without sufficient contextual explanation of severity, urgency, or recommended next steps.

Recent surveys explicitly recognise this limitation. Studies have called for explainable AI (XAI) mechanisms that can translate predictive outputs into interpretable guidance [6], while others advocate integrating generative AI techniques to contextualise vehicle diagnostics in natural language [7]. Although some mobile OBD platforms incorporate reminder systems or simplified descriptions [8,9], these implementations typically remain rule-based or notification-driven and do not provide adaptive, prioritised reasoning about risk and maintenance decisions. Moreover, emerging work on large language models (LLMs) highlights their capacity to synthesise structured data into conversational explanations [6,7]. Yet, empirical implementations of such models within real-time OBD-II systems remain scarce.

This imbalance between predictive intelligence and interpretive usability represents a critical research gap. While significant effort has been devoted to improving algorithmic detection and scoring mechanisms, comparatively little work has operationalised generative AI as a real-time interpretive interface that bridges technical diagnostics and everyday driver comprehension. Addressing this gap is particularly important in contexts where unsafe driving behaviour and delayed maintenance contribute to accident risks and public safety concerns [2,5,10].

Accordingly, this study aims to design and evaluate SmartCarMate, a GPT-based applied computing system that integrates real-time OBD-II sensing with natural-language diagnostic interpretation and driving behaviour feedback. Unlike prior systems that emphasise analytics alone, the proposed system prioritises interpretability and decision support for non-expert users. The significance of this work lies in demonstrating that user-centred, generative-AI-driven diagnostic interfaces can enhance usability, trust, and decision confidence, thereby advancing intelligent vehicle systems from data-reporting tools toward actionable decision-support companions.

This study contributes to the literature in three ways. First, it operationalises GPT-based generative AI as an interpretive layer for OBD-II diagnostics within a functional mobile system. Second, it proposes a unified architecture integrating sensing, behavioural analysis, and contextual explanation in a cross-platform application. Third, it provides empirical evidence through structured User Acceptance Testing that interpretability-oriented design significantly improves perceived usefulness and user acceptance in early-stage deployment.

The remainder of this paper is organised as follows: Section 2 reviews related work; Section 3 presents the system architecture and methodology; Section 4 reports evaluation results; Section 5 discusses theoretical and practical implications; and Section 6 concludes with future research directions.

2. Related Work

Research on OBD-II-based vehicle systems has expanded rapidly due to advances in embedded sensing, mobile platforms, and machine learning. Although these studies differ in technical focus, they can be analytically organised into three streams: (i) fault and vehicle health monitoring, (ii) driving behaviour and eco-driving analytics, and (iii) remote or IoT-based diagnostic platforms. While each stream advances analytical capability, comparatively less attention has been given to interpretability and decision support for non-technical drivers.

2.1 Fault and Vehicle Health Monitoring Systems

Rimpas *et al.,* [3] developed a real-time vehicle monitoring framework that collects engine parameters and diagnostic trouble codes (DTCs) for fault classification using machine learning. Their contribution lies in improving detection accuracy and demonstrating the feasibility of cloud-assisted vehicle diagnostics. Similarly, Malekian *et al.,* [11] proposed a smartphone-based vehicle monitoring architecture that integrates OBD-II data transmission with cloud storage, emphasising data accessibility and remote analytics. Sawant and Mane [12] focused on low-cost embedded OBD-II monitoring systems for continuous vehicle health assessment, while N S *et al.,* [13] designed a mobile application capable of displaying real-time sensor values and DTC outputs.

Although these studies strengthen system connectivity and detection performance, they primarily display raw parameters, fault codes, or brief textual alerts. Iskandar *et al.,* [9] incorporated reminder mechanisms into a mobile OBD platform to support maintenance scheduling, yet the system relies on rule-based notifications without contextual explanation of fault severity. Nguyen *et al.,* [8] extended this approach by integrating recommendation modules. However, the recommendations remain predefined and do not provide adaptive reasoning about urgency or risk trade-offs.

A comparison across these systems reveals a consistent emphasis on fault detection, data streaming, and alert generation. Interpretive explanation, specifically the translation of DTCs into prioritised, context-aware guidance, remains limited. As a result, technical completeness does not necessarily translate into user comprehension.

2.2 Driving Behaviour and Eco-Driving Systems

Driving behaviour analytics represents another major research stream. Michailidis *et al.,* [1] applied machine learning to classify driving styles and assess sustainability-related indicators, demonstrating high classification accuracy. Kumar and Jain [2] focused on predictive maintenance modelling using behavioural signals extracted from OBD-II data, showing improved early detection of abnormal vehicle conditions. Yen *et al.,* [4] examined eco-driving optimisation through behavioural data analysis, while Peppes *et al.,* [5] investigated risk detection mechanisms based on vehicular telemetry. Malik and Nandal [10] further linked behavioural patterns with accident risk prediction.

These studies collectively advance predictive intelligence by refining behavioural classification models and optimisation techniques. However, user interaction is typically restricted to dashboards, performance scores, or efficiency metrics. For example, while Kumar and Jain [2] demonstrate predictive precision, the study does not address how predicted risks are explained to drivers. Similarly, Yen *et al.,* [4] provide behavioural efficiency insights but offer limited discussion of interpretive feedback mechanisms.

Thus, although driving analytics research significantly improves model performance, it does not systematically address how drivers interpret and act upon these analytical outputs. The cognitive gap between behavioural scoring and actionable guidance remains underexplored.

2.3 Remote and IoT-Based Diagnostic Platforms

IoT-based vehicle diagnostics extend OBD-II capabilities through cloud integration and remote access. Malekian *et al.,* [11] introduced an IoT architecture for continuous vehicle monitoring, supporting fleet-level diagnostics. Jeong *et al.,* [14] implemented a remote vehicle monitoring system for maintenance professionals, focusing on system reliability and data transmission efficiency. Hadraoui *et al.,* [15] proposed a cloud-assisted vehicle diagnostic framework designed for large-scale fleet management.

These systems demonstrate strong scalability and connectivity. However, their interfaces are tailored primarily for technicians or fleet managers rather than private drivers. Reports generated by such platforms typically assume technical expertise, limiting usability for everyday vehicle owners. Consequently, while IoT integration enhances system reach, it does not inherently improve interpretability for lay users.

Table 1 summarises how current OBD-II systems map to user needs across these three focus areas, highlighting a consistent emphasis on data collection, connectivity, and machine-learning accuracy rather than interpretability or everyday decision support.

Table 1
Comparison of existing OBD-II systems capabilities and user experience

Focus Area	Typical Capabilities	User Experience	Key Limitations	Representative Studies
Fault and vehicle health monitoring	Real-time OBD-II data acquisition; DTC reading; cloud upload; smartphone display	Raw values and fault codes; basic alerts or reminders	Requires technical knowledge; limited explanation of severity or urgency	[3],[8], [9], [11], [12], [13]
Driving behaviour and eco-driving	Classification of driving style; harsh event detection; fuel and emission optimisation using ML/DL	Dashboards, scores, or generic tips	Limited explanation of why behaviours are risky or how to improve	[1],[2],[3],[4],[5], [10]
Remote and IoT-based diagnostics	IoT gateways; cloud analytics; remote access for fleets or technicians	Interfaces designed for experts or fleet managers	Not suitable for lay drivers; lacks decision support	[8],[11],[13],[14], [15]

Across these three research streams, existing work consistently prioritises data acquisition, predictive modelling, and connectivity infrastructure. Fault monitoring studies optimise detection mechanisms [3], behavioural analytics research improves classification accuracy [1], and IoT systems strengthen remote diagnostics [11]. However, few studies operationalise generative or explainable AI mechanisms capable of translating technical diagnostics into prioritised, human-readable decision guidance.

Recent surveys explicitly call for this transition. More *et al.,* [6] argue that explainable AI should be integrated into vehicle diagnostics to improve user trust. Shirole *et al.,* [7] propose generative AI approaches to contextualise technical outputs in natural language. Yet, empirical implementations within real-time OBD-II mobile systems remain limited.

Therefore, the literature reveals a clear imbalance: predictive intelligence in OBD-II systems is well developed, but interpretive decision support for non-technical drivers is insufficiently addressed. The system proposed in this study differs from prior work by positioning generative AI as an interpretive layer rather than as a predictive engine. By integrating real-time sensing with natural-language explanation and prioritised action guidance, SmartCarMate directly addresses the documented gap between technical analytics and everyday driver decision-making.

3. Methodology

This study adopted the Waterfall Software Development Life Cycle (SDLC) as a structured and sequential methodology for the development of SmartCarMate. The Waterfall model is widely recognised as a linear SDLC that progresses through clearly defined phases, including requirements analysis, design, implementation, testing, and deployment, with each phase completed before the next begins [16,17]. Prior studies indicate that Waterfall is particularly suitable for systems with well-defined and stable requirements, and for applications where documentation, validation, and traceability are critical to ensure reliability and reproducibility [16-18].

In applied computing domains involving sensor-based and data-driven systems, such as vehicle diagnostics and monitoring applications, the structured nature of Waterfall supports precise data handling, controlled system integration, and systematic verification [16,18,19]. Automotive and OBD-II diagnostic systems have previously employed iterative or structured Waterfall-style lifecycles to manage requirement definition, sensor integration, and validation in a disciplined manner [20]. These characteristics align with SmartCarMate’s objectives, where core functionalities, such as OBD-II data acquisition, AI-assisted diagnostic interpretation, and driving behaviour feedback are identifiable at an early stage and require rigorous validation due to their safety-relevant context.

3.1 Methodology Phases

The Waterfall SDLC adopted in this study consists of sequential phases of requirements analysis, planning and design, implementation, testing, and deployment. Each phase was executed with explicit deliverables that informed subsequent stages, ensuring systematic progression from problem analysis to system validation [17,19].

3.1.1 Requirements analysis

The requirements analysis phase examined common vehicle maintenance routines and identified limitations of existing OBD-II mobile applications. This involved analysing routine practices such as engine oil maintenance, coolant temperature monitoring, battery health assessment, and driving behaviour analysis to understand safety and maintenance concerns typically overlooked by non-technical drivers. In parallel, widely used OBD-II applications, including Torque Pro, Car Scanner, and OBD Fusion, were reviewed to assess their functionality, usability, and explanatory limitations. This process enabled the identification of functional gaps, particularly in interpretable diagnostics, AI-assisted driving behaviour feedback, and predictive maintenance support. Consistent with structured SDLC practices, the findings were consolidated into a validated set of functional and non-functional requirements to guide subsequent development stages [16,17,19].

3.1.2 Planning and design

During the planning and design phases, the validated requirements were translated into system architecture specifications, interface layouts, and operational workflows. The design focused on supporting users with varying levels of automotive knowledge by combining simplified visual indicators for casual drivers with access to more detailed diagnostic information for experienced users. Interface mock-ups and technical diagrams, including use case, activity, sequence, and data flow diagrams, were developed to model system interactions, data exchange, and module responsibilities. Structured design artefacts are commonly recommended for data-driven and AI-assisted systems to support verification and controlled integration [16,18].

3.1.3 Implementation

The implementation phase developed SmartCarMate as a cross-platform mobile application integrated with an ELM327 OBD-II Bluetooth adapter. Core system modules included real-time OBD-II data acquisition, vehicle parameter visualisation, AI-assisted diagnostic interpretation, driving behaviour analysis, maintenance reminders, and safety-oriented feedback. Modules were implemented incrementally based on approved design artefacts and integrated into a unified system to ensure consistency and real-time performance.

3.1.4 Testing and deployment

Finally, the testing and deployment phases focused on validating system functionality and operational reliability. The system underwent staged verification, beginning with controlled testing using OBD-II simulation tools, followed by real-world validation using ELM327 adapters connected to production vehicles. The application was subsequently deployed to a limited group of users for practical evaluation, enabling feedback-driven refinement prior to broader use. This phased validation approach reflects established practices in sensor-based and vehicle diagnostic systems, where controlled testing is essential to ensure dependable operation [18].

3.2 Evaluation Procedure

The SmartCarMate system was evaluated using UAT conducted through an online questionnaire, a method commonly employed to assess operational readiness, usability, and user satisfaction in mobile and web-based systems [21-22]. Online survey-based UAT is widely used in transport and vehicle-related technology studies to capture acceptance and usage intention across heterogeneous driver populations, particularly in early validation stages [23-25].

The evaluation instrument employed a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) to measure user perceptions of the system. Likert-scale questionnaires are a standard approach for assessing usability, perceived usefulness, and ease of use in mobile, vehicular, and human–machine interaction studies, including those grounded in the Technology Acceptance Model (TAM), and usability evaluation frameworks [23,24,26,27]. Early-stage system evaluations frequently rely on structured electronic surveys with modest sample sizes to assess feasibility and perceived value prior to large-scale deployment [26-28].

Evaluation items were organised into five dimensions, specifically interface design, information quality and feedback clarity, ease of use and navigation, driving safety and readability, and overall satisfaction and intention to continue use. These dimensions closely correspond to widely adopted constructs such as usability, usefulness, satisfaction, and acceptance in mobile application [26,27, 29]. In the context of driver–vehicle interaction and automotive applications, perceived usefulness, interface usability, and user satisfaction are consistently identified as key determinants of acceptance and continued use [23-25,30].

In addition to quantitative Likert-scale items, the questionnaire included open-ended questions to capture qualitative user feedback. The inclusion of qualitative responses is recommended in usability and acceptance studies to triangulate quantitative results and provide contextual insights, particularly for safety-related and context-dependent applications such as in-vehicle systems [26,28, 29,30].

Collected data were analysed using descriptive statistics, with results presented as response distributions and summary measures. Descriptive analysis is commonly adopted in formative and early-stage validation of mobile and transport technologies, where the objective is to assess feasibility, usability, and perceived usefulness rather than to conduct hypothesis-driven statistical testing [26,29,30].

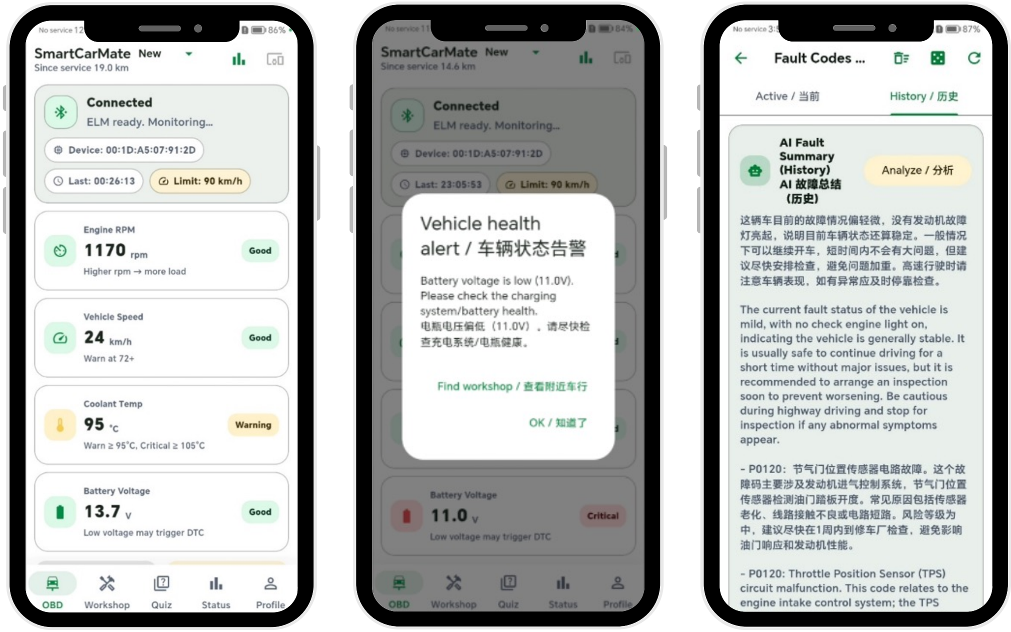
The structured SDLC artefacts and evaluation protocol described in this section are intended to support reproducibility and adaptation in similar applied computing systems involving sensor-based diagnostics and AI-assisted interpretation.

4. Results and Discussion

4.1 The Proposed System Interface

This section presents SmartCarMate's user interface, which was designed to support real-time vehicle monitoring while minimising cognitive load, particularly during driving scenarios. Key design principles include simplified visual indicators, clear textual labels, and AI-assisted explanatory panels to translate technical diagnostics into human-readable guidance.

Figure 1 illustrates the main SmartCarMate user interface, illustrating three key interaction components designed to support real-time vehicle monitoring and decision support. The real-time vehicle health dashboard displays essential OBD-II parameters such as speed, RPM, coolant temperature, and battery voltage using simplified visual layouts. The vehicle health alert interface highlights abnormal readings and warning conditions to draw immediate user attention. The diagnostic explanation interface provides natural-language interpretation of detected issues together with prioritised action guidance. Together, these interfaces support the system's objective of improving interpretability while minimising cognitive load during driving scenarios.



(a) (b) (c)

Fig. 1. SmartCarMate user interface: (a) Real-time vehicle health dashboard with OBD-II key parameters; (b) Vehicle health alert highlighting abnormal readings; (c) AI-assisted diagnostic explanation interface

4.2 Participant Profile

UAT was conducted with 20 respondents, selected to reflect the intended user population of everyday drivers with varying levels of driving experience and vehicle familiarity. The demographic characteristics of the respondents are summarised in Table 2. The sample was evenly distributed by gender (50% male, 50% female), reducing gender-related response bias. Most respondents were aged 21–30 years (60%), with representation from older age groups, providing reasonable age diversity. Importantly, 75% of participants reported that they regularly drive or own a car, indicating that the evaluation feedback is grounded in real-world driving experience rather than hypothetical use. Driving experience ranged from less than one year to more than six years, with both novice (40%) and experienced drivers (30% with more than six years) represented.

Table 2
Demographic data

Category		Number of Respondents	Percentage (%)
Gender	Male	10	50
	Female	10	50
Age	Below 20	0	0
	21 – 30	12	60
	31 – 35	3	15
	36 – 40	3	15
	Above 40	3	10
Driving Status	Regularly drives a car	15	75
	Does not regularly drive a car	5	25
Years of Driving Experience	Less than a year	8	40
	1 – 5 years	6	30
	More than 6 years	6	30

4.3 Usability, Information Quality and User Acceptance

Overall user perceptions of SmartCarMate were evaluated across five dimensions, such as usefulness, ease of use, information quality, driving safety, and satisfaction. Mean Likert scores (μ) were calculated for each dimension to provide a concise and interpretable summary of user acceptance. Higher μ values indicate stronger agreement and more positive user perception.

Table 3 summarises the mean scores and their interpretations. All evaluated dimensions achieved mean scores above μ = 3.9, indicating consistently positive user perception across functional and experiential aspects of the system. Satisfaction (μ = 4.12) and usefulness (μ = 4.09) emerged as the strongest dimensions, while ease of use (μ = 3.92), although still positive, showed comparatively greater scope for improvement.

Table 3
Mean user acceptance scores by category

Category	Mean Score (μ)	Interpretation
Usefulness	4.09	High perceived usefulness in understanding vehicle condition and actions
Ease of Use	3.92	Generally easy to use, with minor onboarding, or navigation friction
Information Quality	4.04	Clear and understandable diagnostic explanations
Driving Safety	4.00	Acceptable readability and low perceived distraction
Satisfaction	4.12	Strong overall satisfaction and acceptance

To facilitate cross-dimensional comparison, Figure 2 presents a visual summary of the mean scores. The figure highlights that satisfaction, usefulness, and information quality form the strongest acceptance cluster, while ease of use remains slightly lower yet still within a positive range.

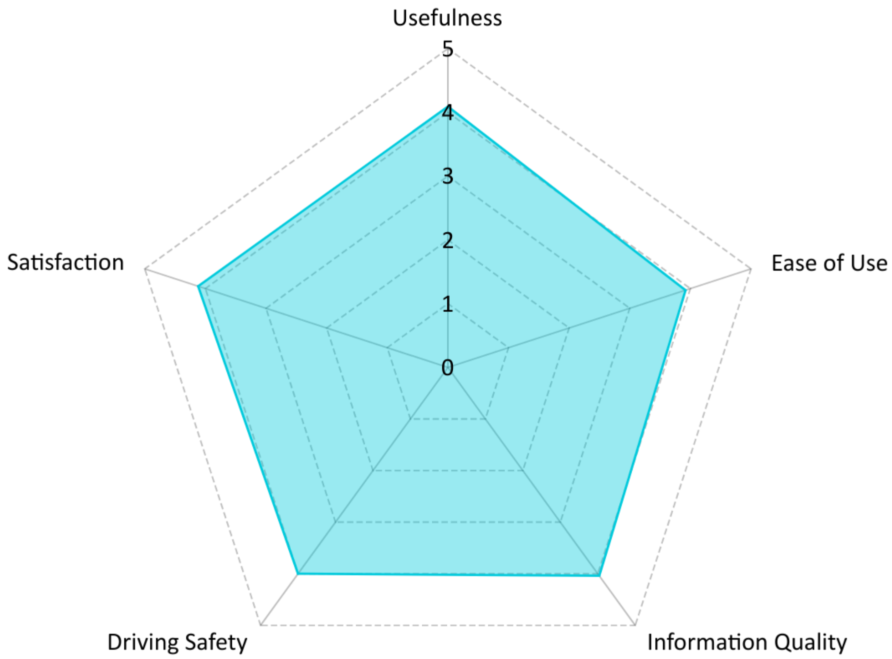


Fig. 2. Mean user acceptance scores across usability, information quality, driving safety, and satisfaction dimension

4.3.1 Interface design and ease of use

Interface-related evaluation items indicate strong positive perceptions of SmartCarMate's visual design and interaction flow. Respondents largely agreed that the app's purpose is clear, the layout is clean and visually consistent, and icons and labels are intuitive. These findings align with the high overall ease-of-use score ($\mu = 3.92$) reported in Table 3.

However, the presence of neutral responses across several ease-of-use items suggests that first-time users may experience minor initial learning friction. While most respondents were able to locate key features such as trip history, diagnostic records, and settings, the results indicate that additional onboarding mechanisms, such as guided walkthroughs or contextual prompts, could further reduce early cognitive load without altering core functionality. The positive ease-of-use and information quality scores ($\mu = 3.92$ and $\mu = 4.04$) are consistent with the interface design illustrated in Figure 1, which emphasises simplified visual presentation and contextual diagnostic explanation.

4.3.2 Information quality and diagnostic feedback

Information quality achieved a strong mean score ($\mu = 4.04$), reflecting positive user perception of both dashboard clarity and diagnostic explanation effectiveness. Respondents indicated that core vehicle parameters, including speed, RPM, coolant temperature, and battery voltage, are presented in an understandable format.

Notably, the diagnostic explanations received high agreement ratings, demonstrating the system's ability to translate technical OBD-II fault codes into meaningful, human-readable guidance. Users also reported that suggested actions accompanying warnings or fault codes were clear and helpful, indicating that SmartCarMate supports informed decision-making rather than merely presenting alerts or raw data. Trust in the accuracy of displayed readings was similarly high, reinforcing confidence in the system's monitoring capabilities and supporting its suitability for real-world use.

4.3.3 Maintenance Support and Connectivity

Perceptions of maintenance reminders were positive but more mixed compared to other dimensions. While users recognised the value of preventive maintenance support, the relatively lower agreement levels suggest that improvements in reminder timing, wording, or personalisation could enhance perceived usefulness.

Connectivity-related feedback further reflects the practical challenges of sensor-based mobile systems. Initial OBD-II connection was generally rated positively. However, reconnection experiences showed greater variability. This variability is likely attributable to differences in Bluetooth conditions, device compatibility, or vehicle states, highlighting the importance of robust reconnection logic and clearer connection-status feedback in real-world deployments.

4.3.4 Driving safety, satisfaction, and intention to use

Driving safety achieved a mean score of $\mu = 4.00$, indicating that users generally perceive the app as readable and non-distracting during driving. This outcome is particularly significant for in-vehicle applications, where excessive cognitive load or visual complexity can compromise safety.

Overall satisfaction recorded the highest mean score ($\mu = 4.12$), and intention to continue using the app was similarly high. These results suggest that SmartCarMate is perceived as a practical and valuable tool rather than a one-time novelty. High satisfaction and continued-use intention indicate strong potential for real-world adoption, provided that identified usability refinements are addressed.

4.4 Discussion

The evaluation results provide empirical evidence that SmartCarMate effectively addresses a key limitation identified in prior OBD-II–based vehicle diagnostic systems, which is the disconnect between technically rich diagnostic data and everyday driver understanding. Unlike conventional OBD-II applications that primarily expose raw values, fault codes, or numerical scores, SmartCarMate demonstrates that AI-assisted interpretive explanations can significantly enhance user trust, comprehension, and acceptance, even at an early deployment stage.

The strongest performance was observed in satisfaction ($\mu = 4.12$) and usefulness ($\mu = 4.09$), indicating that users recognise tangible benefits in understanding vehicle condition and responding appropriately to warnings. This finding is particularly important given that many existing OBD-II applications fail to provide sufficient contextual guidance for non-technical drivers.

Similarly, the high information quality score ($\mu = 4.04$) reinforces the effectiveness of the AI interpretive layer in translating complex OBD-II data into understandable insights. These results support emerging applied computing perspectives that emphasise explainable and human-centred AI, particularly in safety-relevant domains such as vehicle diagnostics.

Although ease of use remained positive ($\mu = 3.92$), its comparatively lower score highlights a common design trade-off in multifunctional mobile systems. The findings suggest that while the system is generally learnable, additional onboarding support could further enhance early user experience without compromising system capability.

Connectivity-related variability further illustrates the challenges inherent in real-time, sensor-based applications that depend on external hardware and wireless communication. This underscores the importance of resilient error handling and transparent system feedback in applied computing systems deployed in heterogeneous environments.

Overall, the findings demonstrate that SmartCarMate's contribution lies not in data acquisition alone, but in the integration of interpretive mechanisms with real-time OBD-II monitoring to support user understanding, trust, and sustained use. The results confirm that interpretability, clarity, and actionable feedback are critical determinants of acceptance in vehicle diagnostic applications and that systems designed with these principles can achieve high user satisfaction even in early-stage evaluations.

From a broader applied computing perspective, these findings suggest that interpretability-oriented AI design may be as critical as analytical accuracy in achieving user trust and sustained adoption in safety-critical, data-intensive systems.

5. Conclusion and Future Work

This study presents SmartCarMate, a GPT-based applied computing system that integrates real-time OBD-II diagnostics with natural language interpretation, shifting vehicle monitoring from data-centric reporting toward user-centric decision support. Unlike conventional OBD-II applications that prioritise raw data presentation or technician-oriented fault codes, SmartCarMate focuses on interpretability and actionable guidance for everyday drivers. The evaluation results demonstrate that this design philosophy is both technically feasible and well-received by users.

User Acceptance Testing results indicate consistently positive perceptions across all evaluated dimensions, with mean scores exceeding $\mu = 3.9$ in every category. Overall satisfaction achieved the highest score (μ = 4.12), reflecting strong acceptance and validating the system's practical relevance. This outcome suggests that users perceive SmartCarMate as a meaningful aid rather than a novelty tool, supporting its potential for sustained real-world use. Future work corresponding to this dimension will focus on longitudinal field studies to assess continued engagement, habit formation, and behavioural impact over extended usage periods.

The usefulness dimension (μ = 4.09) confirms that users value SmartCarMate's ability to support understanding of vehicle condition and appropriate responses to warnings. This result directly validates the core contribution of the system, which is AI-driven interpretability. Future enhancements will aim to expand this capability by incorporating context-aware explanations, such as tailoring diagnostic advice based on driving history, vehicle age, or environmental conditions, thereby increasing perceived relevance and personalisation.

The strong performance in information quality (μ = 4.04) demonstrates that AI-assisted diagnostic explanations effectively bridge the gap between technical OBD-II data and layperson understanding. Building on this strength, future work will explore adaptive explanation levels, allowing users to switch between simplified and advanced diagnostic narratives, as well as integrating visual explanation aids to further enhance comprehension.

Although ease of use achieved a positive score (μ = 3.92), it was the lowest among the evaluated dimensions, highlighting a clear opportunity for refinement. Future improvements will therefore prioritise first-time user onboarding, including guided walkthroughs, contextual tooltips, and progressive feature disclosure. These enhancements are expected to reduce initial cognitive load and improve early-stage usability without altering the system's core functionality.

The driving safety dimension (μ = 4.00) indicates that SmartCarMate is generally perceived as readable and non-distracting during driving. This finding is critical for in-vehicle applications and supports the suitability of the system for real-time monitoring scenarios. Future work will focus on driving-mode optimisation, such as adaptive alert timing, simplified interfaces during motion, and optional voice-based feedback, to further minimise distraction while maintaining situational awareness.

Finally, variability observed in maintenance reminders and OBD-II reconnection experiences highlights technical challenges inherent to sensor-based mobile systems. Future development will address these issues through improved Bluetooth reconnection logic, clearer connection-state feedback, and customisable maintenance reminder schedules aligned with user preferences and vehicle usage patterns.

In summary, SmartCarMate demonstrates a novel applied computing contribution by combining GPT-based interpretive intelligence with real-time vehicle diagnostics to enhance accessibility, safety, and user trust. The strong empirical results, together with clearly identified improvement pathways mapped to evaluation outcomes, position SmartCarMate as a scalable and impactful solution with significant potential for further research, deployment, and commercialisation. Beyond the specific implementation, this work contributes a transferable design principle for applied computing systems in safety-critical domains, specifically, interpretability and explanatory support are primary determinants of user trust, acceptance and sustained use.

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References

[1] Michailidis, Emmanouel T., Antigoni Panagiotopoulou, and Andreas Papadakis. "A review of OBD-II-based machine learning applications for sustainable, efficient, secure, and safe vehicle driving." *Sensors* 25, no. 13 (2025): 4057. https://doi.org/10.3390/s25134057

[2] Kumar, Raman, and Anuj Jain. "Driving behavior analysis and classification by vehicle OBD data using machine learning: R. Kumar et al." *The Journal of Supercomputing* 79, no. 16 (2023): 18800-18819. https://doi.org/10.1007/s11227-023-05364-3

[3] Rimpas, Dimitrios, Andreas Papadakis, and Maria Samarakou. "OBD-II sensor diagnostics for monitoring vehicle operation and consumption." *Energy Reports* 6 (2020): 55-63. https://doi.org/10.1016/j.egyr.2019.10.018

[4] Yen, Meng-Hua, Shang-Lin Tian, Yan-Ting Lin, Cheng-Wei Yang, and Chi-Chun Chen. "Combining a universal OBD-II module with deep learning to develop an eco-driving analysis system." *Applied Sciences* 11, no. 10 (2021): 4481. https://doi.org/10.3390/app11104481

[5] Peppes, Nikolaos, Theodoros Alexakis, Evgenia Adamopoulou, and Konstantinos Demestichas. "Driving behaviour analysis using machine and deep learning methods for continuous streams of vehicular data." *Sensors* 21, no. 14 (2021): 4704. https://doi.org/10.3390/s21144704

[6] More, Abhijeet, Sahil Khane, Darshan Jadhav, Himansu Sahoo, and Yogesh Kisan Mali. "Auto-shield: Iot based OBD application for car health monitoring." In *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pp. 1-10. IEEE, 2024. https://doi.org/10.1109/ICCCNT61001.2024.10726186

[7] Shirole, Vaibhav, Aniket K. Shahade, and Priyanka V. Deshmukh. "A comprehensive review on data-driven driver behaviour scoring in vehicles: technologies, challenges and future directions." *Discover Artificial Intelligence* 5, no. 1 (2025): 26. https://doi.org/10.1007/s44163-025-00244-6

[8] Le Nguyen, Ngoc, Minh Khoi Nguyen, Duy Thong Nguyen, Thanh Phat Le, and Thanh Tuyen Nguyen. "Research and Development of a Remote Vehicle Diagnostic Device via Mobile Application." *Journal of Technical Education Science* 20, no. 04SI (2025): 149-160. https://doi.org/10.54644/jte.2025.1906

[9] Iskandar, Karto, Alfred Tambayong, Muhammad Rafif Fawwaz Mulya, Steven Cendra Elfanlie, and Maria Grace Herlina. "Mobile-based car diagnostic application using onboard diagnostic-II scanner." *ComTech: Computer, Mathematics and Engineering Applications* 14, no. 2 (2023): 129-141. https://doi.org/10.21512/comtech.v14i2.9138

[10] Malik, Meenakshi, and Rainu Nandal. "A framework on driving behavior and pattern using On-Board diagnostics (OBD-II) tool." *Materials Today: Proceedings* 80 (2023): 3762-3768. https://doi.org/10.1016/j.matpr.2021.07.376

[11] Malekian, Reza, Ntefeng Ruth Moloisane, Lakshmi Nair, Bodhaswar T. Maharaj, and Uche AK Chude-Okonkwo. "Design and implementation of a wireless OBD II fleet management system." *IEEE Sensors Journal* 17, no. 4 (2016): 1154-1164.https://doi.org/10.1109/JSEN.2016.2631542

[12] Sawant, Pooja Rajendra, and Yashwant B. Mane. "Design and development of on-board diagnostic (OBD) device for cars." In *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*, pp. 1-4. IEEE, 2018. https://doi.org/10.1109/ICCUBEA.2018.8697833

[13] N S, A., H. C. Reddy, and K. Gaurav. 2021. "Design of Onboard Vehicle Diagnosis Fault Monitoring System Using IoT and Machine Learning." *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering* 9 (8). https://doi.org/10.17148/IJIREEICE.2021.9802

[14] Jeong, YiNa, SuRak Son, EunHee Jeong, and ByungKwan Lee. "An integrated self-diagnosis system for an autonomous vehicle based on an IoT gateway and deep learning." *Applied Sciences* 8, no. 7 (2018): 1164. https://doi.org/10.3390/app8071164

[15] El Hadraoui, Hicham, Nada Ouahabi, Nabil El Bazi, Oussama Laayati, Mourad Zegrari, and Ahmed Chebak. "Toward an intelligent diagnosis and prognostic health management system for autonomous electric vehicle powertrains: A novel distributed intelligent digital twin-based architecture." *IEEE Access* 12 (2024): 110729-110761. https://doi.org/10.1109/ACCESS.2024.3441517

[16] Sawarkar, Gurudev, and Dipesh Rajput. "Comparative analysis of various software development life cycle." *International Journal of Computer Science and Mobile Computing* 11, no. 8 (2022): 1-8. https://doi.org/10.47760/ijcsmc.2022.v11i08.001

[17] Hossain, Mohammad Ikbal. "Software development life cycle (SDLC) methodologies for information systems project management." *International Journal For Multidisciplinary Research* 5, no. 5 (2023): 1-36.https://doi.org/10.36948/ijfmr.2023.v05i05.6223

[18] Olorunshola, Oluwaseyi Ezekiel, and Francisca Nonyelum Ogwueleka. "Review of system development life cycle (SDLC) models for effective application delivery." In *Information and Communication Technology for Competitive Strategies (ICTCS 2020) ICT: Applications and Social Interfaces*, pp. 281-289. Singapore: Springer Singapore, 2021. https://doi.org/10.1007/978-981-16-0739-4_28

[19] Ghumatkar, R. S., and A. Date. 2023. “Software Development Life Cycle (SDLC).” *International Journal for Research in Applied Science and Engineering Technology* 11 (11): 1162–1165. https://doi.org/10.22214/ijraset.2023.56554

[20] Juwono, Jeremy Nathanael, Nicolas Don Bosco Julienne, Anthonie Samuel Yogatama, and Mochammad Haldi Widianto. "Motorized Vehicle Diagnosis Design Using the Internet of Things Concept with the Help of Tsukamoto's Fuzzy Logic Algorithm." *Journal of Robotics and Control (JRC)* 4, no. 2 (2023): 202-216. https://doi.org/10.18196/jrc.v4i2.17256

[21] Otaduy, Itziar, and Oscar Diaz. "User acceptance testing for Agile-developed web-based applications: Empowering customers through wikis and mind maps." *Journal of Systems and Software* 133 (2017): 212-229. https://doi.org/10.1016/j.jss.2017.01.002

[22] Leung, Hareton KN, and Peter WL Wong. "A study of user acceptance tests." *Software quality journal* 6, no. 2 (1997): 137-149. https://doi.org/10.1023/A:1018503800709

[23] Mourya, S. K. 2025. “Comparative Analysis of Testing Tools for In-House Application UAT: Assessing Tricentis, Qyrus, and TestSigma.” *World Journal of Advanced Research and Reviews* 26 (2): 1607–1614. https://doi.org/10.30574/wjarr.2025.26.2.1814

[24] Peemanee, Jindarat, Wisaruta Kongtong, Kittiyanee Salangam, Sutana Boonlua, and Ranitha Weerarathna. "Innovation acceptance and usage behavior of smart electric vehicle applications." *International Journal of Analysis and Applications* 23 (2025): 116-116. https://doi.org/10.28924/2291-8639-23-2025-116

[25] Oviedo-Trespalacios, Oscar, Oliver Briant, Sherrie-Anne Kaye, and Mark King. "Assessing driver acceptance of technology that reduces mobile phone use while driving: The case of mobile phone applications." *Accident Analysis & Prevention* 135 (2020): 105348. https://doi.org/10.1016/j.aap.2019.105348

[26] Hajesmaeel-Gohari, Sadrieh, Firoozeh Khordastan, Farhad Fatehi, Hamidreza Samzadeh, and Kambiz Bahaadinbeigy. "The most used questionnaires for evaluating satisfaction, usability, acceptance, and quality outcomes of mobile health." *BMC Medical Informatics and Decision Making* 22, no. 1 (2022): 22. https://doi.org/10.1186/s12911-022-01764-2

[27] Cheah, Wai-Hun, Norhasiza Mat Jusoh, Myat Moe Thwe Aung, Azizah Ab Ghani, and Husbani Mohd Amin Rebuan. "Mobile technology in medicine: development and validation of an adapted system usability scale (SUS) questionnaire and modified technology acceptance model (TAM) to evaluate user experience and acceptability of a mobile application in MRI safety screening." *Indian Journal of Radiology and Imaging* 33, no. 01 (2023): 036-045. https://doi.org/10.1055/s-0042-1758198

[28] Othman, Nor Arzami, Mohd Nizam Osman, Khairul Anwar Sedek, and Muhammad Farid Mohd Bohari. "Development of mobile application with geolocation technology for car service workshop." *Journal of Computing Research and Innovation (JCRINN)* 7, no. 2 (2022): 338-348.https://doi.org/10.24191/jcrinn.v7i2.327

[29] Weichbroth, Paweł. "Usability of mobile applications: a systematic literature study." *Ieee Access* 8 (2020): 55563-55577. https://doi.org/10.1109/ACCESS.2020.2981892

[30] Chen, Shih-Chieh, and Chong De Tee. "A Research on the Usability Evaluation of Telecommunication and Navigation Applications in In-Vehicle Infotainment Systems." In *2024 21st International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pp. 53-60. IEEE, 2024. https://doi.org/10.1109/JCSSE61278.2024.10613713

Appendix

Table A1
Detailed user acceptance testing results

Category	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Usefulness	Q1: The app helps me understand my vehicle's current condition.	0 (0%)	0 (0%)	4 (20%)	6 (30%)	10 (50%)
	Q2: I understand what actions to take when a fault or warning appears.	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
	Q3: The app helps me interpret diagnostic fault codes (DTCs).	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
	Q4: The app improves my awareness of vehicle maintenance needs.	0 (0%)	0 (0%)	7 (35%)	7 (35%)	6 (30%)
	Q5: The trip summaries help me understand my driving behaviour.	0 (0%)	0 (0%)	7 (35%)	6 (30%)	7 (35%)
Ease-of-Use	Q1: The app was easy to learn to use.	0 (0%)	0 (0%)	8 (40%)	6 (30%)	6 (30%)
	Q2: I could easily find the features I needed.	0 (0%)	0 (0%)	10 (50%)	5 (25%)	5 (25%)
	Q3: The app navigation is clear and logical.	0 (0%)	0 (0%)	6 (30%)	7 (35%)	7 (35%)
	Q4: Connecting the app to the OBD device was easy.	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
	Q5: Reconnecting to the OBD device was smooth.	0 (0%)	0 (0%)	9 (45%)	6 (30%)	5 (25%)
Information Quality	Q1: The main dashboard information is easy to understand.	0 (0%)	0 (0%)	5 (25%)	7 (35%)	8 (40%)
	Q2: The DTC explanations are clear and understandable.	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
	Q3: The suggested actions provided by the app are helpful.	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
	Q4: Maintenance reminders are useful for service planning.	0 (0%)	0 (0%)	9 (45%)	6 (30%)	5 (25%)
	Q5: I trust the accuracy of the readings shown by the app.	0 (0%)	0 (0%)	6 (30%)	7 (35%)	7 (35%)
Driving Safety	Q1: The app screen is readable while driving.	0 (0%)	0 (0%)	8 (40%)	6 (30%)	6 (30%)
	Q2: Using the app does not distract me while driving.	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
Satisfaction	Q1: Overall, I am satisfied with the SmartCarMate app.	0 (0%)	0 (0%)	6 (30%)	6 (30%)	8 (40%)
	Q2: I intend to continue using this app in the future.	0 (0%)	0 (0%)	6 (30%)	5 (25%)	9 (45%)