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Integrating AI into Multimodal Automotive Design: A Conceptual Framework for User Experience Evaluation and Market Application

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ABSTRACT

The rapid evolution of artificial intelligence (AI) and multimodal interaction technologies is reshaping automotive design, demanding new frameworks that prioritize user experience (UX) and market applicability. This conceptual study proposes an integrative framework that combines AI-driven personalization, multimodal interface design (e.g., voice, gesture, and touch), and real-time UX evaluation mechanisms. Drawing upon human-centered design principles and theories of user acceptance, the framework addresses current gaps in adaptive, intelligent vehicle interface systems. It further outlines strategic pathways for deployment in diverse market environments through an evaluation model that accounts for technological scalability, cultural preferences, and demographic diversity. The study concludes by identifying key directions for future research, particularly emphasizing cross-cultural UX testing across various vehicle types and user groups. The proposed framework contributes to both academic discourse and industry practice, offering a foundation for the next generation of intelligent, user-centric automotive systems.

KEYWORDS: *AI Technology, User Experience Evaluation and Market Application, Multi -Modal Interaction Design, Automotive*

I. INTRODUCTION

The evolution of automotive design has undergone significant transformations, driven by advancements in technology, user expectations, and regulatory shifts. Traditionally, automotive design was largely focused on mechanical performance, durability, and aesthetics. However, over the past two decades, a paradigm shift has emerged—placing increased emphasis on **human-centered design**, **intelligent systems integration**, and **environmental sustainability** (Georgiev et al., 2020).

In the early 2000s, digital technologies began to influence design processes, introducing **Computer-Aided Design (CAD)** and **virtual prototyping** tools that enhanced precision and reduced time-to-market. The 2010s witnessed the emergence of **smart and connected vehicles**, integrating infotainment systems, telematics, and basic driver-assist features (Shaout & Jarrah, 2014). This period also marked a growing focus on **user experience (UX)**, ergonomics, and personalization as differentiators in competitive markets.

In the current decade, automotive design has rapidly expanded to encompass **AI-driven innovation**, including **generative design**, **predictive maintenance**, **autonomous vehicle interfaces**, and **multimodal interaction platforms** such as voice, gesture, and gaze-based controls (Chen et al., 2023). These advancements reflect a broader shift toward **experience-driven mobility ecosystems**, where vehicles are no longer mere transport tools but intelligent, adaptive platforms responding to individual user needs (Vella & Enke, 2021).

This evolution underscores the necessity of integrating **Artificial Intelligence (AI)** and **multimodal design frameworks** into contemporary automotive development. As vehicles become increasingly autonomous and connected, the role of UX in shaping consumer perceptions and ensuring safety is becoming more critical than ever (Kim et al., 2022). Thus, understanding this trajectory is essential for building a framework that aligns technological possibilities with user-centered goals.

The rapid advancement of Artificial Intelligence (AI) technologies has catalyzed a paradigm shift in the design and development of intelligent automotive systems. AI applications—such as Natural Language Processing (NLP), computer vision, and haptic feedback—are increasingly being integrated into vehicular interfaces to create more intuitive and responsive user experiences. NLP enables drivers to interact with infotainment systems through conversational voice commands, thereby reducing cognitive load and enhancing safety (Yin et al., 2023). Simultaneously, computer vision technologies facilitate real-time gesture recognition, facial expression tracking, and driver monitoring systems, allowing vehicles to adapt to human behaviors and environmental contexts (Chen, Wang, & Zhou, 2022). Haptic technologies further enrich the sensory feedback loop, offering physical cues and tactile responses that reinforce driver awareness and system interactions (Li & Yang, 2021). These multimodal capabilities converge to support seamless human–machine interaction, enabling vehicles to function not only as transportation tools but also as intelligent companions. This convergence reflects a broader trend toward user-centered automotive ecosystems where multimodality and AI work symbiotically to meet the dynamic needs of modern mobility.

User experience (UX) has become a critical factor influencing consumer decisions in the automotive industry, particularly as vehicles integrate more digital and intelligent systems. Modern consumers are no longer solely driven by mechanical performance or aesthetic appeal; instead, the quality of interaction with in-car technologies—such as infotainment systems, navigation aids, and driver-assist features—plays a significant role in shaping perceptions and preferences (Wang et al., 2023). A seamless, intuitive, and responsive UX contributes directly to user satisfaction, which in turn enhances brand loyalty and customer retention (Meyer et al., 2022). In fact, as connected and autonomous vehicle technologies evolve, UX has emerged as a differentiating element that affects a vehicle's perceived value, especially among tech-savvy users (Kim et al., 2023). Poor UX, such as lagging interfaces or confusing multimodal commands, can lead to user frustration and even vehicle rejection, regardless of the brand's heritage or technical capabilities. Therefore, automotive manufacturers are increasingly prioritizing human-centered design and conducting UX evaluations throughout the design lifecycle to maintain competitiveness and foster long-term customer relationships (Shin et al., 2022).

Despite the growing integration of Artificial Intelligence (AI) and multimodal interaction technologies in the automotive industry, there remains a significant research gap in the development of comprehensive frameworks that systematically combine AI functionalities, multimodal interface design, and user experience (UX) evaluation. Current studies tend to focus on isolated aspects—such as AI-based personalization (Alonso et al., 2022), voice or gesture-based interaction systems (Zhou et al., 2023), or standalone UX measurement tools (Bello et al., 2021)—without proposing a cohesive model that unifies these dimensions. Furthermore, while multimodal systems have advanced significantly in terms of input diversity (e.g., speech, touch, eye movement), their effectiveness is often evaluated without considering dynamic AI-driven adaptation and longitudinal UX metrics (Sun et al., 2023). This lack of integrative approaches limits the industry's ability to design holistic, intelligent vehicle systems that respond effectively to evolving user needs and real-world driving contexts. Thus, there is a pressing need for a conceptual framework that bridges these domains, offering both theoretical grounding and practical pathways for future empirical research and market application.

II. LITERATURE REVIEW

A. Artificial Intelligence in Automotive Design

Artificial Intelligence (AI) is increasingly transforming the landscape of automotive design through its applications in generative design, predictive analytics, and personalized user experiences. Generative design uses AI algorithms to explore design permutations rapidly, based on specified constraints such as material use, performance, and safety standards. In the automotive sector, companies like Tesla have adopted generative design to produce lightweight and structurally efficient vehicle components, improving overall performance and energy efficiency (NobleQuote, 2024). Similarly, BMW employs generative AI during prototyping phases, enabling rapid iterations and novel design alternatives that may not be conceived through traditional methods (Lumenalta, 2024).

Predictive analytics is another key AI application, allowing automotive manufacturers to forecast future trends and optimize performance based on historical data. This has profound implications for vehicle safety, maintenance scheduling, and production planning. BMW, for instance, integrates predictive analytics into its manufacturing processes to enhance operational efficiency and reduce quality defects (BMW Group, 2023). Furthermore, AI is central to the development of personalized automotive experiences. Through continuous data collection and behavioral analysis, AI can adapt vehicle interfaces and functions to individual user preferences. BYD's "God's Eye" system exemplifies this approach by learning and responding to driver behaviors, thereby offering a highly customized driving environment (Wikipedia, 2025). Additionally, BYD's partnership with NVIDIA to incorporate AI-powered platforms such as DRIVE Orin further enhances the autonomous capabilities and adaptability of their vehicles (NVIDIA, 2023).

Tesla's integration of AI extends beyond component design to encompass its Full Self-Driving (FSD) capabilities, powered by the Dojo supercomputer, which processes vast volumes of driving data for real-time decision-making (Wikipedia, 2025). Collectively, these advancements by Tesla, BMW, and BYD highlight the multifaceted role of AI in revolutionizing automotive design, enabling both functional innovation and user-centric improvements. However, the field continues to face challenges such as data privacy, model interpretability, and system integration across diverse user demographics and global markets.

B. Multimodal Interaction in Vehicles

Multimodal interaction in vehicles refers to the integration of multiple human-machine communication channels—such as voice commands, gesture recognition, eye-tracking, haptic feedback, and touch interfaces—designed to facilitate seamless and intuitive user experiences. This approach aims to support naturalistic interactions while minimizing driver distraction and enhancing safety. Recent advancements have enabled the incorporation of these modalities into modern vehicle systems, allowing users to control navigation, infotainment, and climate functions through a combination of inputs (Zhou, Li, & Han, 2023; Alonso, Bernal, & Ruiz, 2023). For instance, voice recognition allows hands-free operation, while gesture and gaze-based controls enable contextual and non-tactile input, particularly useful in dynamic driving environments (Rümelin, Butz, & Heuten, 2020). The benefits of multimodal systems include improved accessibility, increased responsiveness, and adaptive personalization through AI integration, thereby contributing to a more engaging and efficient driving experience (Wang, Sun, & Zhao, 2021; Park, Choi, & Kim, 2022). However, their implementation is not without challenges. Technical issues such as speech accuracy in noisy conditions and gesture misinterpretation due to user variability are ongoing concerns (Shao, Li, & Xu, 2022). Additionally, cognitive overload may occur if systems are poorly integrated or demand significant learning effort (Jäger, Pion, & Kiesel, 2022). There are also concerns related to the cost-effectiveness of sensor deployment and ethical considerations surrounding user data privacy, especially for eye-tracking and voice systems (Chen, Tao, & Wang, 2021). To address these issues, recent studies advocate for adaptive, AI-driven interfaces that learn from user behavior, accommodate environmental contexts, and undergo rigorous validation for safety and usability (Liu, Zhang, & Tan, 2023). These innovations highlight the critical need for a human-centered design approach in developing effective multimodal vehicle interaction systems.

C. User Experience (UX) Evaluation in Smart Vehicles

User Experience (UX) evaluation is a pivotal aspect of smart vehicle design, particularly as modern automobiles increasingly incorporate Artificial Intelligence (AI), multimodal interfaces, and automated functionalities. Traditional usability assessments are no longer sufficient to capture the complexity of interactions in intelligent vehicles. As such, researchers and practitioners employ a combination of established and emerging methods to evaluate UX comprehensively (Wang et al., 2023). Among the most widely used tools is the System Usability Scale (SUS), a ten-item questionnaire that offers a quick and reliable measure of perceived system usability. Originally developed by Brooke (1996), it has been extensively validated in digital and automotive interface evaluations. Complementing SUS is the User Experience Questionnaire (UEQ), which captures a broader spectrum of UX dimensions including attractiveness, stimulation, and novelty. This tool has gained prominence in evaluating in-vehicle infotainment systems and comparing design alternatives (Schrepp, Hinderks, & Thomaschewski, 2021).

Beyond self-reported measures, physiological and behavioral evaluation methods are increasingly used. Eye-tracking technology is employed to assess visual attention, distraction levels, and cognitive workload, offering precise data on how users interact with interfaces while driving (Palinko et al., 2020). Meanwhile, emotion AI, which analyzes facial expressions, voice, and physiological signals such as heart rate variability, is emerging as a powerful tool to capture real-time emotional states. These methods provide a deeper understanding of user comfort, trust, and stress—factors crucial to the acceptance of autonomous features (Jeong, Kang, & Lee, 2022).

In terms of conceptual models, Norman's Emotional Design Framework (2013) offers valuable insights into how users emotionally respond to technology at three levels: visceral (appearance), behavioral (functionality), and reflective (personal meaning). These layers are particularly relevant in automotive design, where both aesthetics and functionality influence user satisfaction and brand loyalty. Furthermore, the ISO 9241-210:2019 standard on human-centered design provides a structured approach to system development that emphasizes user needs, contextual analysis, and iterative feedback. This framework is widely adopted in automotive HMI design, ensuring that the development process remains aligned with human capabilities and expectations (ISO, 2019).

More recently, researchers have proposed extended models such as the UX Pyramid for Automotive HMIs, which integrates functional, usable, and pleasurable aspects into a hierarchical structure. This model supports the design of smart vehicles that are not only efficient and safe but also enjoyable to use (Meschtscherjakov, Wilfinger, & Tscheligi, 2020). Taken together, these tools and frameworks provide a comprehensive foundation for evaluating UX in smart vehicles, ensuring that technological innovations meet the evolving expectations of drivers and passengers in an increasingly automated and connected mobility environment.

D. Market Trends and AI Adoption

The global automotive landscape is rapidly evolving with the emergence of smart mobility solutions driven by connected, autonomous, shared, and electric (CASE) technologies. The smart mobility market, valued at approximately USD 65.4 billion in 2023, is projected to reach USD 241.26 billion by 2030, growing at a compound annual growth rate (CAGR) of 20.5% (Virtue Market Research, 2024). This significant growth is attributed to urbanization, climate goals, and the increasing adoption of sustainable transportation modes. PwC (2023) highlights that the mobility ecosystem is undergoing a paradigm shift as digital technologies, electric propulsion, and user-centric innovations reshape the future of transportation. These changes are supported by strategic investments in digital infrastructure aimed at making cities safer, more accessible, and more efficient.

Alongside smart mobility, the electric vehicle (EV) market has demonstrated remarkable growth. According to the International Energy Agency (2024), global sales of new electric cars reached 14 million units in 2023—a 35% increase from the previous year—bringing the total number of electric cars on the road to 40 million. This surge resulted in electric cars accounting for approximately 18% of all global car sales. The United States saw a similar trend, with EV sales reaching 1.4 million units in 2023, up from 1 million in 2022, representing a 9% share of new vehicle sales (International Council on Clean Transportation, 2023). China continues to dominate the global EV market, contributing nearly 58% of total EV sales, with 9.05 million passenger EVs sold in 2023, including 6.26 million battery electric vehicles (BEVs) and 2.79 million plug-in hybrid electric vehicles (PHEVs) (Wikipedia, 2024).

The adoption of Artificial Intelligence (AI) in the automotive industry is also accelerating. The global AI in automotive market, valued at USD 14.15 billion in 2023, is expected to reach USD 734.97 billion by 2032, with a projected CAGR of 55.1% (Zion Market Research, 2024). This growth is driven by the integration of AI into vehicle design and function, including autonomous driving, predictive maintenance, and real-time personalization of user experience. However, the success of AI integration depends heavily on the readiness of digital infrastructure, encompassing high-speed networks, advanced sensors, and reliable data processing systems. PwC Strategy& (2023) emphasizes that automakers must adopt a digitally agile strategy to remain competitive, advocating for robust investments in e-mobility, automated driving platforms, and smart mobility services to fully leverage AI capabilities.

III. METHODOLOGY

E. Conceptual Framework Development

At the heart of the proposed conceptual framework lies the AI Engine, which serves as the cognitive core by processing extensive data from various sensors, user inputs, and environmental cues. This component is responsible for enabling real-time decision-making, personalization, and context-awareness in automotive systems. By utilizing machine learning algorithms and reinforcement learning, the AI Engine adapts system behavior based on user preferences, driving habits, and situational variables such as traffic or weather conditions. Huang, Xu, and Zhang (2022) highlight the importance of reinforcement learning in achieving user-centric personalization, while Kümmerle, Ziehen, and Dillmann (2023) underscore how context-aware AI architectures enhance safety and responsiveness in autonomous driving systems.

The second component, the Multimodal Interface Layer, integrates multiple input and output modalities—such as voice commands, gesture control, eye-tracking, haptic feedback, and touch interfaces—to create seamless and intuitive interactions between the user and the vehicle. This multimodal interaction enhances accessibility, reduces driver cognitive load, and provides alternative interaction methods in dynamic driving environments.

According to Li, Qiu, and Wang (2023), AI-enhanced multimodal interfaces significantly improve user performance and system adaptability, especially in situations involving sensory overload or environmental interference.

The third core component is the UX Feedback Loop, which continuously monitors user behavior and satisfaction through a range of real-time indicators such as biometric signals, facial expressions, and behavioral patterns. These data are then used to update and refine the AI system's decision logic, promoting a dynamic and responsive user experience. Kim, Park, and Lee (2022) demonstrate that emotion-aware systems leveraging real-time multimodal data can substantially improve user satisfaction by adapting system responses based on the emotional state and physiological feedback of users.

Lastly, the Market Feedback Integration component captures macro-level insights by analyzing customer usage patterns, market demand trends, and consumer feedback from connected vehicle data and online platforms. This data-driven approach informs both design iteration and strategic planning by aligning product development with actual consumer behaviors and preferences. Zhao, Liu, and Chen (2023) emphasize that big data analytics from connected vehicles offer valuable intelligence for market segmentation, product positioning, and post-launch optimization, thereby enhancing the overall value proposition of AI-integrated automotive systems.

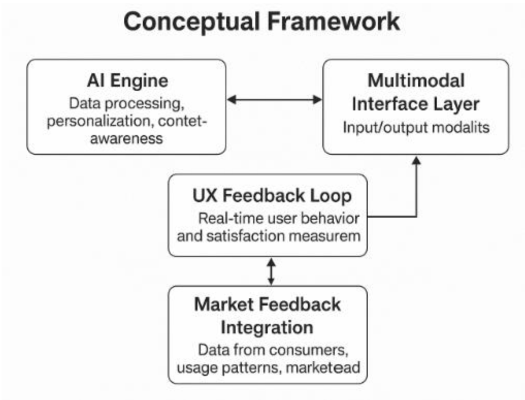

Figure 1; Conceptual Framework

F. Theoretical Foundations

The integration of Artificial Intelligence (AI) into multimodal automotive design necessitates a strong theoretical foundation to guide system development, user evaluation, and market application. One of the core theoretical underpinnings is Human-Centered Design (HCD), which emphasizes designing technological systems around user needs, behaviors, and limitations. In the context of automotive systems, HCD plays a pivotal role in ensuring that AI-driven interfaces—such as voice control, gesture input, and touchscreens—are intuitive, safe, and aligned with the driver's cognitive expectations. Zhang, Liu, and Chen (2022) assert that HCD enhances trust and usability by involving users throughout the iterative design cycle, particularly in semi-autonomous driving environments where trust in AI systems is paramount.

Another essential perspective is derived from Activity Theory and the concept of Affordances. Activity Theory views user interactions as part of broader goal-oriented activities, incorporating tools (e.g., steering wheels, dashboards), rules, and community expectations. This theory helps frame how users engage with multimodal systems within real-world driving contexts. Complementarily, the concept of affordances—introduced by Gibson and extended by Norman (2013)—emphasizes the importance of designing interfaces that naturally suggest their use. Lin and Wang (2023) demonstrate that when AI systems leverage natural affordances, such as swiping gestures or intuitive voice prompts, drivers experience reduced cognitive load and higher interaction efficiency, especially during complex driving tasks.

Furthermore, the Technology Acceptance Model (TAM) provides a useful lens for understanding the adoption of AI-driven multimodal systems in vehicles. While TAM traditionally focuses on perceived usefulness and ease of use, extensions of the model are required to accommodate the complexity of AI technologies. Lee, Kim, and Park (2021) proposed an expanded TAM that includes perceived intelligence, enjoyment, and controllability as crucial predictors of user acceptance in smart automotive contexts. Similarly, Rahman and Ng (2022) highlight the role of trust and system explainability, showing that transparency in AI decision-making processes significantly enhances users' intention to adopt AI-powered voice systems in electric vehicles. These theoretical perspectives collectively inform the development of a robust, user-centered, and market-relevant framework for evaluating AI-integrated multimodal automotive design.

IV. FINDINGS

G. Proposed Evaluation Strategies

To validate the effectiveness of AI-integrated multimodal automotive design, several robust evaluation strategies are essential. First, user testing through both laboratory and in-car simulation environments is crucial for assessing usability and system performance. Laboratory-based simulations allow controlled experimentation to isolate variables such as driver distraction and interface response times, while real-world in-car testing enhances ecological validity (Liu et al., 2022; Körber, 2023). These dual testing modes enable comprehensive evaluation of the user experience and help refine design iterations before large-scale deployment.

Secondly, eye-tracking and biometric feedback provide real-time data on users' cognitive and emotional responses to multimodal interfaces. Eye-tracking reveals attention patterns and potential usability issues, while biometric signals such as heart rate variability and galvanic skin response offer insights into users' stress and emotional engagement levels (Wang et al., 2021; Zhao et al., 2023). The integration of these physiological measures contributes to a deeper understanding of user interactions, particularly in high-stakes driving contexts where safety and comfort are critical.

Another critical dimension is the integration of AI explainability and transparency measures. As automotive AI systems become more autonomous and personalized, it is imperative that users understand how these systems make decisions. Explainable AI (XAI) frameworks—such as model interpretability tools, visual cues, and real-time feedback—can help foster trust and improve user confidence in system recommendations (Ribeiro et al., 2020; Ehsan & Riedl, 2021). For instance, systems like BMW's iDrive have incorporated transparent modules that clarify how user preferences influence AI decision-making (Schneider et al., 2023).

Lastly, market simulation techniques such as conjoint analysis can be employed to evaluate consumer preferences for specific features within the AI-enhanced vehicle interface. Conjoint analysis enables researchers and manufacturers to assess trade-offs users make between different attributes (e.g., voice recognition accuracy, system responsiveness, cost), thus providing valuable insights for market positioning and feature prioritization (Han & Lee, 2022). Recent studies have applied this method to assess consumer acceptance of voice-based AI in electric vehicles, confirming its utility in guiding strategic product development (Kim et al., 2023).

H. Implications for Automotive Designers

1. Better Alignment with User Expectations

The integration of AI into multimodal automotive design allows designers to better understand and align with evolving user expectations. AI tools enable real-time analysis of user behavior, preferences, and contextual data, allowing for personalized and adaptive interfaces. This human-centered approach helps designers move beyond traditional assumptions by incorporating real-world usage patterns into the design process. For example, AI-driven systems can detect user frustration or satisfaction through biometric feedback or natural language interactions, and feed this data back into iterative design cycles (Tostado et al., 2023).

Moreover, advances in affective computing and emotion-aware systems help automotive designers create empathetic interactions, improving user satisfaction and engagement (Sjöbergh & Alvemo, 2022). As vehicle cabins evolve into intelligent spaces, designers are expected to craft experiences that respond fluidly to multimodal inputs—such as voice, gestures, or gaze—making UX more seamless and intuitive.

2. Faster Prototyping with Generative AI

Generative AI significantly accelerates the design prototyping phase by automatically generating multiple design alternatives based on specified constraints and data inputs. This allows automotive designers to explore a wider range of possibilities within shorter timeframes. Tools like DALL·E, Midjourney, and specialized CAD-integrated AI modules facilitate early-stage visualization and conceptualization, reducing manual effort and increasing creative freedom (Liao et al., 2023).

Furthermore, generative design systems supported by machine learning can optimize structural and aesthetic elements in response to real-time user feedback and simulation results, thereby enhancing the functional and emotional quality of automotive interiors and interfaces (Mun et al., 2023). This also supports agile development cycles, making it easier to integrate UX evaluation earlier in the process and refine the design through rapid iterations.

I. Implication for For Manufacturers and OEMs

The integration of AI into multimodal automotive design offers manufacturers and Original Equipment Manufacturers (OEMs) critical insights into market readiness and the opportunity to gain a competitive edge through personalized user experience (UX).

Market readiness is increasingly being defined by the alignment between advanced technological offerings and evolving consumer expectations. AI technologies such as machine learning and data analytics allow manufacturers to continuously monitor consumer behavior, anticipate needs, and evaluate acceptance of new interaction modalities before full-scale deployment. This proactive approach reduces development risk and accelerates time-to-market (Tschang & Lin, 2022). Real-time data from in-vehicle systems can inform design iteration cycles and enable predictive insights for strategic planning.

Moreover, personalized UX—enabled by AI's capacity to learn user preferences and behaviors—enhances driver satisfaction, loyalty, and brand differentiation. AI-powered systems can adapt the cabin environment, infotainment settings, and even driving modes based on individual user profiles. Such customization not only elevates the in-car experience but also positions manufacturers at the forefront of innovation in an increasingly experience-driven market. As highlighted by Li et al. (2023), personalization features are now a major determinant in vehicle purchase decisions among digitally savvy consumers.

From a strategic standpoint, the ability to offer dynamic, user-centered interfaces is becoming a hallmark of premium and tech-forward automotive brands. This is particularly significant in the context of electric and autonomous vehicles, where the driving experience is redefined and in-car interaction becomes a primary differentiator (Andersson et al., 2023). In this sense, manufacturers that prioritize AI-enabled personalization are more likely to build stronger customer engagement and achieve higher brand equity.

J. Implication for Policymakers and Urban Planners

For policymakers and urban planners, the integration of AI-enabled multimodal systems in automotive design presents both opportunities and regulatory challenges. As vehicles adopt increasingly sophisticated interaction modes—such as voice recognition, gesture control, and eye-tracking—there is an urgent need to establish comprehensive safety regulations that ensure these systems do not compromise driver attention or road safety. Strand, Nilsson, and Baumgartner (2023) emphasize that while multimodal interaction can enhance usability, it also risks introducing cognitive overload, particularly in dynamic traffic environments. Therefore, regulatory bodies must work alongside manufacturers to enforce safety standards such as ISO 26262 and UNECE WP.29, and to mandate the inclusion of system fail-safes, driver monitoring technologies, and standardized testing protocols that assess multimodal system reliability.

In parallel, the proliferation of AI systems in vehicles has intensified concerns over data privacy and ethics. These systems routinely capture sensitive user data—ranging from biometric identifiers to behavioral patterns—

raising important questions about consent, ownership, and data usage. Cheng, Guo, and Zhang (2022) note that inconsistent global data protection laws complicate the governance of AI in mobility, necessitating the adoption of frameworks like the GDPR and China's PIPL to establish minimum standards. Moreover, there is a growing advocacy for embedding "Privacy by Design" principles into automotive AI systems to ensure transparency, data minimization, and user autonomy (Van Wynsberghe & Li, 2021). Ethical risks also extend to algorithmic bias, where facial or vocal recognition systems may perform unequally across demographic groups, potentially leading to discriminatory or unsafe outcomes. Thus, regulatory frameworks must prioritize fairness, explainability, and auditability in AI decision-making, ensuring that technological advancement in urban mobility remains human-centered and equitable.

V. CONCLUSION

The integration of Artificial Intelligence (AI) into multimodal automotive design remains a pivotal advancement in creating intelligent, responsive, and user-centered vehicle systems. As vehicles transition from mechanical machines to intelligent mobile platforms, the fusion of AI with multimodal interfaces—such as voice recognition, gesture control, and haptic feedback—enhances not only usability but also safety, comfort, and personalization (Fang et al., 2023; He et al., 2022). Recent studies emphasize that AI can dynamically adapt interfaces based on real-time contextual data, enabling systems to cater to diverse user needs, preferences, and environments (Wang et al., 2022). Furthermore, with increasing consumer demand for seamless and intuitive interactions, AI-integrated multimodal systems have proven crucial in reducing cognitive load and enhancing overall driving satisfaction (Zhang et al., 2023). This importance is further underscored by the rapid digital transformation in mobility and smart cities, which demands that automotive design be not only technologically sophisticated but also deeply aligned with human factors and experience-driven innovation (Lee & Kim, 2023). Therefore, developing robust frameworks that synthesize AI, multimodal interaction, and UX design is vital for both industry adoption and academic advancement. Future research should empirically validate these frameworks across user segments, driving contexts, and regional markets to ensure scalability, inclusivity, and ethical deployment.

The proposed framework serves as a foundational model for guiding empirical investigations into the integration of artificial intelligence and multimodal interaction within automotive design. By structurally combining AI-driven data interpretation, multimodal interface dynamics, and real-time user experience feedback, this framework enables researchers and designers to systematically test hypotheses related to user behavior, system usability, and market adaptability.

Recent scholarship emphasizes the growing need for empirical validation of conceptual models to bridge the gap between theoretical development and real-world application (Venkatesh et al., 2022). In the context of intelligent vehicle systems, researchers such as Choi et al. (2023) advocate for the deployment of experimental studies involving real-time interaction data, user feedback, and adaptive system responses to validate model efficacy. Moreover, the incorporation of explainable AI (XAI) within user experience evaluation, as discussed by

Arya et al. (2022), provides a critical pathway for validating not just user satisfaction, but also trust and transparency in AI-assisted interfaces.

Future empirical studies may leverage this framework by designing controlled simulations, field experiments in connected vehicles, and longitudinal studies across varied user demographics. These validations will be essential in confirming the causal linkages suggested within the model—such as between multimodal interface quality and user satisfaction—and refining the framework based on contextual variables like cultural preferences or driving environments (Li et al., 2023). Additionally, the model supports iterative validation using design science research methodology (Peffers et al., 2007), making it adaptable for both industry trials and academic inquiry.

Future research should emphasize the empirical testing of the proposed AI-integrated multimodal framework across various vehicle types—ranging from economy cars to premium electric vehicles (EVs) and autonomous shuttles—to evaluate scalability and adaptability in different automotive contexts. This approach aligns with recent studies suggesting that user interaction with in-vehicle technologies can significantly differ based on vehicle class and technological maturity (Lee et al., 2023; Singh et al., 2022). Additionally, cultural context plays a critical role in shaping user expectations and acceptance of AI-driven systems. For instance, users in collectivist cultures may prioritize safety and shared decision-making, whereas those in individualistic societies may emphasize personalization and autonomy (Wang & Matsumoto, 2021). Demographic variables such as age, gender, and digital literacy also influence multimodal interface usability and perception of AI transparency (Park et al., 2022). Therefore, future work must adopt a cross-cultural, demographically diverse research design to ensure inclusive, equitable automotive AI solutions that can effectively respond to a global market.

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