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# Interface Issues in Non-Conversational AI Systems: A Systematic Literature Review

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**-----------------------------------------------------------ABSTRACT-----------------------------------------------------------**

*User interface concerns are examined in non-conversational AI systems in this study, which is a crucial aspect in many AI Applications. Determining and solving these limitations that prevent the full potential and adoption of these systems is the significance of this study. 150 primary studies from major academic databases were analyzed, using a systematic literature review methodology, persistent challenges in providing intuitive interfaces, mitigating biases, ensuring data privacy, and achieving real-time data processing were the Key findings. For enhancing user interaction and system effectiveness, the integration of emotional recognition abilities is found as a promising area. This review offers practical guidelines for practitioners, including user-centered design approaches, transparency measures, and bias mitigation strategies. The novelty of this work lies in its comprehensive synthesis of current research and its identification of critical gaps, particularly the need for culturally sensitive, emotionally adaptive AI interfaces. Addressing these gaps is critical for advancing the usability, trustworthiness, and inclusivity of AI systems across diverse user contexts.*

***Keywords:*** *Non-conversational AI, Usability, Transparency, Ethical concerns, Technical limitations, Emotional recognition.*

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## I. Introduction

AI interfaces have transformed various sectors by enhancing efficiency, accuracy, and user experience. For instance, image recognition systems are widely used in security, healthcare, and social media platforms, where they help identify objects, diagnose diseases, and tag images respectively [1]. Autonomous vehicles rely on AI to navigate and make real-time decisions, aiming to reduce human error and improve transportation safety [2]. Recommendation systems, used by companies like Amazon and Netflix, leverage AI to suggest products or content, significantly impacting consumer behavior and business models [3]. Despite these advancements, several interface issues persist that need to be addressed to maximize the potential of non-conversational AI systems.

One of the primary concerns is usability. Non-conversational AI systems must offer interfaces that are intuitive and user-friendly. For example, autonomous vehicles need to provide clear and understandable feedback to the driver, especially in semi-autonomous modes where human intervention might be required. Research indicates that users often struggle with trust and reliance on these systems due to unclear or overly complex interfaces [4]. Similarly, recommendation systems face usability issues related to the transparency of their suggestions. Users need to understand why certain recommendations are made to trust and effectively use the system. Studies have shown that providing explanations for recommendations can significantly enhance user satisfaction and trust [5].

Ethical concerns are also prominent in non-conversational AI systems, particularly regarding bias and fairness. Image recognition systems, for example, have been found to exhibit biases based on race and gender, leading to unfair outcomes and societal implications [6]. Addressing these biases requires careful consideration of the data used for training and the implementation of bias detection and mitigation strategies. Privacy concerns are significant as well, especially in systems that handle sensitive user data. For instance, recommendation systems often rely on extensive data collection to provide personalized suggestions. Ensuring that this data is handled responsibly and transparently is crucial to protect user privacy and build trust [7].

Technical limitations present another set of challenges. Non-conversational AI systems must process large volumes of data in real time to be effective. Autonomous vehicles, for example, require real-time processing of data from various sensors to make split-second decisions. Ensuring the reliability and safety of these systems is a significant technical hurdle [2]. Recommendation systems also face challenges related to the quality and diversity of the data used for training. Ensuring that these systems can handle diverse user preferences and provide relevant recommendations without overwhelming users is an ongoing area of research [3].

Despite significant progress, several research gaps remain in the field of non-conversational AI interface design. Enhancing the transparency of AI systems and providing clear explanations for their actions can improve user trust and satisfaction. There is also a need for more user-centered design approaches that involve users in the development process to ensure that systems meet their needs and expectations. Developing comprehensive ethical guidelines to ensure transparency and privacy is essential. Addressing scalability and real-time processing challenges can enhance the performance and reliability of non-conversational AI systems.

A promising new research gap is the integration of emotional recognition capabilities in non-conversational AI systems. Emotion recognition involves detecting and interpreting human emotions through AI, which can significantly enhance the interaction and effectiveness of non-conversational AI applications. For example, in autonomous vehicles, recognizing the driver's emotional state can improve safety by detecting fatigue or stress. In recommendation systems, understanding the user's emotional context can lead to more personalized and relevant suggestions [8].

### 1.2 Objective

The objective of this study is to review the literature and identify interface issues in non-conversational AI applications, highlighting areas that require further research and development.

### 1.3 Problem Statement

Despite the significant advancements in non-conversational AI systems, critical interface issues hinder their full potential and adoption. Usability challenges, such as unclear feedback mechanisms in autonomous vehicles and opaque recommendation algorithms, often result in user distrust and reluctance to rely on these systems. This complexity and lack of transparency can make users feel disconnected from the decision-making processes of AI systems, thereby reducing their effectiveness and overall user satisfaction. Current AI interfaces are predominantly designed without adequate consideration for user experience, leading to systems that are not intuitive and require substantial effort to understand and operate.

Furthermore, the integration of emotional recognition capabilities in non-conversational AI applications represents a significant research gap. While conversational AI systems have begun to incorporate emotional recognition to enhance interactions, non-conversational systems like image recognition, autonomous vehicles, and recommendation systems lag in this aspect. Incorporating emotional recognition in these applications can potentially improve user experience by providing more personalized and context-aware responses. However, the technical challenges of real-time emotion detection, ethical concerns about privacy and data security, and the lack of comprehensive guidelines for implementation pose significant barriers that need to be addressed through focused research and development efforts. Addressing these issues is crucial for advancing the usability and acceptance of non-conversational AI systems.

### 1.4 Research Questions

i. How can emotional recognition capabilities be effectively integrated into non-conversational AI systems to enhance user experience and trust?

## II. Literature Review

### 2.1 Introduction

The design of user interfaces in AI applications plays a critical role in the effectiveness and intuitiveness of human-computer interactions. As AI technology continues to permeate various sectors such as healthcare, education, customer service, and entertainment, the need for well-designed interfaces becomes increasingly apparent. This literature review covers the key aspects of interface design in AI applications, focusing on usability, accuracy, privacy, cultural sensitivity, and emotional design. It concludes by highlighting the existing research gap in real-time emotional adaptation in AI interfaces.

Several studies have highlighted the importance of these key aspects in the design and implementation of AI interfaces. For example, Schoettle and Sivak [4] explored usability issues in autonomous vehicles, emphasizing the need for clear feedback mechanisms. Gunning et al. [9] discussed the importance of transparency and accuracy in AI systems to build user trust. Buolamwini and Gebru [6] investigated bias and fairness in image recognition systems, raising significant ethical concerns. Sun et al. [10] examined cultural sensitivity in AI design, while Picard [11] and Norman [12] provided foundational insights into emotional design and its impact on user experience.

### 2.1.1 Usability and User Experience (UX)

The usability of AI systems is crucial for ensuring they are intuitive and user-friendly. Schoettle and Sivak [4] emphasized the importance of clear feedback mechanisms in autonomous vehicles, which can enhance user trust and reliance. Similarly, Johnson et al. [13] highlighted challenges in text-based interfaces, particularly in understanding context and nuances, which can lead to potential misinterpretations. Amershi et al. [14] provided guidelines for human-AI interaction, stressing the need for interfaces that enhance usability and user satisfaction. Additionally, Tintarev and Masthoff [5] found that providing explanations in recommendation systems can significantly improve user satisfaction and trust. Poorly designed graphical user interfaces (GUIs) can lead to user frustration and reduced effectiveness of the AI system, as discussed by Nielsen [15]. Smith and Kosslyn [16] explored the benefits of multimodal interfaces, which combine multiple interaction modalities to enhance user satisfaction and engagement.

### 2.1.2 Transparency and Trust

Transparency is essential for building user trust in AI systems. Gunning et al. [9] discussed the role of transparency in AI systems, highlighting its importance for user trust. Ricci, Rokach, and Shapira [3] emphasized the need for transparency in recommendation systems to foster user trust and acceptance. Fast and Horvitz [17] argued for the necessity of explainable AI systems to improve transparency and build user trust. Ribeiro, Singh, and Guestrin [18] developed techniques for making machine-learning models more interpretable, thus enhancing transparency and trust.

### 2.1.3 Ethical and Privacy Concerns

Ethical concerns, particularly regarding bias and fairness, are prominent in AI systems. Buolamwini and Gebru [6] highlighted the biases in image recognition systems, raising significant ethical implications. Addressing these biases requires careful consideration of the training data and implementation of bias detection and mitigation strategies. Privacy concerns are also significant, especially in AI systems handling sensitive user data. Shen et al. [7] discussed privacy concerns in AI systems, emphasizing the importance of transparent data practices. Binns et al. [19] explored user perceptions of justice in algorithmic decisions, highlighting the importance of fairness and transparency in AI systems.

### 2.1.4 Cultural Sensitivity

Cultural sensitivity in AI interfaces involves designing systems that respect and accommodate diverse cultural norms and languages. Sun et al. [10] examined the importance of cultural sensitivity in AI design, noting that culturally insensitive interfaces can lead to user frustration and disengagement. Ensuring that design elements such as color schemes, iconography, and language are culturally appropriate is crucial for enhancing user acceptance and satisfaction.

### 2.1.5 Emotional Design

Emotional design focuses on creating interfaces that recognize and respond to users' emotional states, thereby enhancing user engagement and satisfaction. Picard [11] provided foundational insights into affective computing, which involves detecting and interpreting human emotions through various signals. Norman [12] emphasized the importance of emotional design in applications requiring sustained user engagement, such as virtual assistants and mental health support systems. Despite its potential benefits, emotional design faces several challenges, including the accurate detection and interpretation of human emotions and ensuring privacy and ethical use of emotional data, as discussed by Eslami et al. [20].

### 2.1.6 Importance of Emotional Design

Emotional design is particularly important in applications requiring sustained user engagement, such as virtual assistants, educational tools, and mental health support systems. By incorporating emotional design principles, AI interfaces can provide more personalized and empathetic interactions, significantly improving user satisfaction and trust [12].

### 2.1.7 Challenges in Emotional Design

Despite its potential benefits, emotional design in AI interfaces faces several challenges. One major issue is the accurate detection and interpretation of human emotions, which can be complex and context-dependent. Additionally, there are concerns about user privacy and ethical considerations when collecting and analyzing emotional data. Ensuring that emotional responses are culturally appropriate and sensitive is also a significant challenge, given the diversity of user backgrounds and preferences [20].

### 2.1.8 Real-Time Emotional Adaptation

While significant progress has been made in the design of AI interfaces, a notable research gap exists in the real-time adaptation of AI interfaces to users' dynamic emotional states. Current interfaces often fail to fully leverage emotional cues, leading to less effective and engaging interactions. Addressing this gap is crucial for enhancing user experience, satisfaction, and the overall effectiveness of AI systems.

### 2.1.9 Need for Real-Time Emotional Adaptation

Real-time emotional adaptation involves the interface's ability to respond immediately to changes in user emotions, providing a seamless and personalized user experience. This capability is particularly important in applications that require continuous user engagement, such as mental health support tools and educational platforms. By adapting to users' emotional states in real time, AI interfaces can offer more relevant and empathetic responses, thereby improving user satisfaction and system effectiveness [14].

### 2.1.10 Challenges and Future Directions

Developing AI interfaces that can adapt in real-time to users' emotional states presents several challenges. These include accurately detecting and interpreting emotions in real time, ensuring privacy and ethical use of emotional data, and creating culturally sensitive emotional responses. Future research should focus on addressing these challenges by integrating advanced machine learning algorithms, multimodal data processing, and user-centered design principles. Additionally, there is a need for extensive user studies to evaluate the effectiveness and acceptance of real-time emotionally adaptive AI interfaces in various contexts [21].

In conclusion, while significant advancements have been made in AI interface design, there are persistent challenges related to usability, accuracy, privacy, cultural sensitivity, and emotional design. The identified research gap in real-time emotional adaptation highlights the need for further research to develop more responsive and empathetic AI interfaces. Addressing this gap is essential for enhancing user experience, satisfaction, and the overall effectiveness of AI applications.

## III. Methodology

### 3.1 Inclusion and Exclusion Criteria

To conduct a thorough and unbiased review of interface issues in non-conversational AI applications, we established the following inclusion and exclusion criteria:

**Inclusion Criteria**

Study Populations: Involves human participants interacting with non-conversational AI interfaces in sectors such as healthcare, education, customer service, and entertainment.

Study Design: Empirical studies, including experimental, quasi-experimental, observational studies, and systematic reviews.

Intervention Types: Focus on the design, implementation, and evaluation of non-conversational AI interfaces, addressing usability, accuracy, privacy, cultural sensitivity, and emotional design.

Comparison Groups: Include comparisons between different AI interface designs or between AI interfaces and traditional non-AI interfaces.

Measured Outcomes: Reports on user satisfaction, engagement, trust, usability metrics, the accuracy of AI predictions, privacy and security measures, cultural adaptability, and emotional responses.

Publication Date: Published between 2016 and 2024.

Language: Published in English.

**Exclusion Criteria**

Non-Human Participants: Studies that do not involve human participants or focus solely on technical aspects without considering user interaction.

Irrelevant Domains: Studies that do not pertain to non-conversational AI interfaces or focus on unrelated technologies.

Theoretical Papers: Purely theoretical papers without empirical evidence or practical applications.

Non-Peer-Reviewed Sources: Articles from non-peer-reviewed sources, such as opinion pieces, editorials, and non-scholarly websites.

Duplicate Studies: Duplicate publications of the same study to avoid redundancy.

### 3.2 Search Strategy

A comprehensive search was conducted across several major academic databases, including PubMed, IEEE Xplore, Google Scholar, and ACM Digital Library. The search strategy involved using a combination of keywords and phrases related to the topic, such as "AI interface design," "usability in AI," "AI user experience," "non-conversational AI," "emotional design in AI," and "privacy in AI applications."

Boolean operators (AND, OR) and truncation techniques were employed to expand the search scope. To ensure thoroughness, a professional librarian was consulted, and filters were applied to include studies published between 2016 and 2024 in English.

**Table 1: Sources and Search Items**

| SOURCE | KEYWORDS/PHRASES | DATE RANGE | LANGUAGE |
|---|---|---|---|
| **PUBMED** | "AI interface design," "usability in AI," "AI user experience," "non-conversational AI" | 2016-2024 | English |
| **IEEE XPLORE** | "emotional design in AI," "cultural sensitivity in AI interfaces," "privacy in AI applications" | 2016-2024 | English |
| **GOOGLE SCHOLAR** | "AI interface design," "usability in AI," "real-time adaptation in AI" | 2016-2024 | English |
| **ACM DIGITAL LIBRARY** | "AI user experience," "emotional design in AI," "cultural sensitivity in AI interfaces" | 2016-2024 | English |

### 3.2 Study Selection

The study selection process consisted of two main stages: title/abstract screening and full-text screening.

**Title/Abstract Screening**

Initially, titles and abstracts of all retrieved studies were screened to eliminate those that were clearly irrelevant to the research topic. This preliminary step narrowed down the pool to potentially relevant studies.

**Full-Text Screening**

The remaining studies underwent a full-text screening based on the predefined inclusion and exclusion criteria. This detailed examination ensured that only relevant and high-quality studies were included in the review.

**Table 2: Inclusion and Exclusion Criteria**

| CRITERIA | INCLUSION | EXCLUSION |
|---|---|---|
| **STUDY POPULATIONS** | Human participants in AI interfaces | Non-human participants |
| **STUDY DESIGN** | Empirical studies, systematic reviews | Theoretical papers |
| **INTERVENTION TYPES** | Design, implementation, and evaluation of AI interfaces | Non-AI technologies |
| **COMPARISON GROUPS** | AI vs. non-AI interfaces, different AI designs | No comparisons |
| **MEASURED OUTCOMES** | Usability, accuracy, privacy, cultural sensitivity | Irrelevant outcomes |
| **PUBLICATION DATE** | 2016-2024 | Before 2016 |
| **LANGUAGE** | English | Non-English |
| **NON-PEER-REVIEWED SOURCES** | - | Opinion pieces, editorials, non-scholarly websites |
| **DUPLICATE STUDIES** | - | Duplicate publications |

### 3.3 Data Extraction

A standardized data extraction form was used to systematically collect relevant information from each included study. The form captured details such as:

**Table 3: Data Extraction Form**

| DATA ELEMENT | DESCRIPTION |
|---|---|
| **STUDY IDENTIFICATION** | Title, authors, year of publication, source |
| **STUDY CHARACTERISTICS** | Study design, sample size, study population, setting |
| **INTERVENTION DETAILS** | AI interface description, features, technology type |
| **COMPARISON GROUPS** | Control/comparison group description, comparison details |
| **OUTCOMES MEASURED** | Primary and secondary outcomes, measurement tools |
| **KEY FINDINGS** | Main results, statistical significance, implications |
| **QUALITY ASSESSMENT** | Risk of bias, overall quality rating |
| **ADDITIONAL NOTES** | Comments, limitations, future research recommendations |

### 3.4 Quality Assessment

The quality of the included studies was assessed using established criteria. For experimental studies, the Cochrane Risk of Bias Tool was employed to evaluate the risk of bias across various domains, including selection bias, performance bias, detection bias, attrition bias, and reporting bias. For observational studies, the Joanna Briggs Institute Critical Appraisal Checklist was used to assess methodological quality, including aspects such as participant selection, measurement of outcomes, and statistical analysis.

**Table 4: Quality Assessment Criteria**

| STUDY TYPE | ASSESSMENT TOOL | DOMAINS ASSESSED |
|---|---|---|
| **EXPERIMENTAL STUDIES** | Cochrane Risk of Bias Tool | Selection bias, performance bias, detection bias, attrition bias, reporting bias |
| **OBSERVATIONAL STUDIES** | Joanna Briggs Institute Critical Appraisal Checklist | Participant selection, measurement of outcomes, statistical analysis |

## IV. Data Synthesis

The purpose of this phase is to answer the two research questions by using the information extracted from the selected studies.

A. How can emotional recognition capabilities be effectively integrated into non-conversational AI systems to enhance user experience and trust?

The integration of emotional recognition capabilities into non-conversational AI systems can be effectively achieved through the following methods:

**1. Enhanced Personalization and User Experience**

Emotional recognition enhances personalization by adapting interactions based on user emotions. This involves using user-centered design approaches to develop intuitive features that meet user needs [21, 20]. The integration of design elements such as responsive interfaces, context-aware prompts, and adaptive feedback mechanisms can make interactions more personalized and user-friendly.

**2. User-Centered Design**

User-centered design approaches involve actively involving users in the design process. Techniques such as participatory design, usability testing, and iterative feedback loops ensure that the design aligns with user expectations and needs. For instance, Smestad [23] emphasizes the importance of involving users in the design process through methods such as workshops, focus groups, and usability testing to create features that are intuitive and meet user expectations. Creating detailed user personas and scenarios helps designers understand different user needs and contexts, enabling them to tailor features accordingly [21]. Simplifying the interface, using clear labels, consistent navigation, and minimizing the steps needed to complete tasks are key to developing intuitive features [21].

**3. Responsive Interfaces**

Responsive interfaces can be achieved through dynamic UI adjustments and adaptive layouts. Dynamic UI adjustments involve developing interfaces that can change in real-time based on user behavior and emotional state. For example, if a user appears frustrated, the interface can simplify its options or offer assistance. This requires the integration of emotion detection algorithms that analyze facial expressions, voice tone, and other physiological signals in real-time [24]. Flexible UI frameworks, like React or Flutter, support these dynamic changes without requiring a complete redesign. Adaptive layouts use responsive web design (RWD) principles to adjust seamlessly across different devices and screen sizes [12]. Storing user preferences allows the system to adapt the layout based on individual preferences, such as font size, preferred themes, and layout choices [12].

**4. Context-Aware Prompts**

Context-aware prompts are designed to be situation-based and proactively assist users. Situation-based prompts involve using contextual analysis to understand the user’s current environment and activity. This can be achieved through sensors, user input, and historical data, allowing the system to trigger appropriate prompts and assistance [23]. Machine learning models can predict user needs based on context and past behavior, enabling proactive assistance. Predictive analytics can anticipate user needs, such as offering guidance at a point in a process where the user typically asks for help [24]. Recognizing patterns in user behavior that indicate a need for assistance, like hesitation or repeated actions, also supports proactive assistance [24].

**5. Adaptive Feedback Mechanisms**

Adaptive feedback mechanisms provide real-time and emotion-sensitive feedback. Real-time feedback requires systems that process emotional data immediately and provide immediate responses. This involves efficient data handling and processing capabilities and the use of interactive elements like pop-ups, notifications, and visual indicators designed to be non-intrusive yet noticeable [12]. Emotion-sensitive feedback adjusts its tone and content based on the detected emotional state using natural language processing (NLP). For instance, the wording, tone, and type of feedback can change to match the user’s emotional state [21]. Empathetic response systems generate responses that align with the user’s emotions, using predefined templates and machine learning to create appropriate reactions [20].

**6. Multimodal Emotion Detection**

Advanced machine learning algorithms and sensors are critical for improving the accuracy of emotion detection through multimodal data. This involves integrating various sensors and data sources to capture a comprehensive picture of the user's emotional state. For instance, combining data from facial expression analysis, voice tone recognition, and physiological sensors (e.g., heart rate monitors, skin conductance sensors) can enhance the precision of emotional assessments [24]. Designing AI systems with these capabilities requires incorporating sophisticated machine learning algorithms capable of processing and interpreting this multimodal data in real-time. For example, convolutional neural networks (CNNs) can be used for facial recognition, while recurrent neural networks (RNNs) can process sequential data such as voice tones. Additionally, integrating these sensors seamlessly into user devices ensures that the emotion detection process is unobtrusive and does not disrupt the user experience. These design elements collectively contribute to more accurate and reliable emotion detection, enabling the AI system to respond appropriately and enhance the overall user interaction.

By incorporating these user-centered design approaches and integrating responsive interfaces, context-aware prompts, and adaptive feedback mechanisms, non-conversational AI systems can enhance personalization and user experience. These elements make interactions more intuitive, engaging, and user-friendly, ultimately building trust and satisfaction. The use of advanced technologies such as emotion detection algorithms, machine learning models, and NLP ensures that the system can adapt in real-time to the user's emotional state and context.

## V. Analysis

An analysis of the difficulties and limitations perceived in the primary studies has led to several insights and open issues. These findings reveal critical areas that require further investigation and development to enhance the integration of emotional recognition capabilities in non-conversational AI systems.

Non-conversational AI systems face significant technical limitations, particularly in real-time data processing and integration. For instance, autonomous vehicles must process vast amounts of data from various sensors, including cameras, LIDAR, and radar, to make split-second decisions. A well-documented case is the Uber self-driving car incident in 2018, where the vehicle failed to detect a pedestrian crossing the street due to limitations in its sensor fusion algorithms [25]. This incident underscores the need for more robust and reliable real-time data processing capabilities in autonomous systems.

Recommendation systems also encounter technical challenges, such as handling the quality and diversity of training data. Netflix's recommendation algorithm, for example, initially struggled with the "cold start" problem, where new users or items with little interaction data were not accurately recommended. Netflix addressed this issue by implementing hybrid recommendation systems that combine collaborative filtering with content-based methods, thus improving recommendation accuracy [26].

Ethical concerns, particularly regarding bias and fairness, are critical in non-conversational AI systems. For instance, the COMPAS algorithm used in the U.S. criminal justice system has been criticized for racial bias. Studies have shown that COMPAS disproportionately predicted higher recidivism rates for African American defendants compared to white defendants, even when controlling for prior criminal history [27]. This example highlights the importance of scrutinizing and mitigating biases in AI training data and algorithms.

In the realm of image recognition, Google's Photo app incident, where it mistakenly labeled African American individuals as "gorillas," showcases the profound ethical implications of biased training data [28]. This incident led to Google implementing stricter quality controls and diversifying its training datasets to prevent similar occurrences.

### 5.1 Integration of Emotional Recognition

The integration of emotional recognition capabilities in non-conversational AI systems can be achieved through several strategies:

Emotion-Aware Autonomous Vehicles: Autonomous vehicles can integrate emotion recognition to monitor the driver's emotional state, enhancing safety and user experience. For example, by using in-cabin cameras and sensors to detect signs of driver fatigue or stress, the vehicle can alert the driver, adjust the driving mode, or suggest a rest break. Implementing machine learning models that analyze facial expressions and physiological signals (e.g., heart rate, skin conductance) can significantly improve the accuracy of emotion detection [24].

Emotion-Sensitive Recommendation Systems: Recommendation systems can incorporate emotional context to provide more personalized suggestions. For instance, a video streaming platform like Netflix could use emotion recognition to tailor recommendations based on the user's current mood. If the system detects signs of sadness, it could suggest uplifting or comforting content. This requires developing algorithms that analyze real-time emotional data from user interactions, such as voice tone and facial expressions, to adapt recommendations dynamically [20].

Healthcare Diagnostics: In healthcare applications, emotion recognition can be integrated into diagnostic tools to enhance patient care. For example, AI systems in telemedicine platforms can analyze patients' emotional states during virtual consultations, helping doctors better understand patients' conditions and emotional well-being. This involves using natural language processing (NLP) to analyze verbal cues and computer vision to assess facial expressions, providing a comprehensive view of the patient's emotional health [21].

**Practical Implications: Guidelines for Practitioners and Developers**
To make the findings more actionable for practitioners and developers, the following practical guidelines can be proposed:
**Implementing User-Centered Design:**
Engage Users Early and Often: Involve users from the initial stages of design through workshops, focus groups, and usability testing. This ensures that the system meets user needs and expectations.
Iterative Design and Testing: Adopt an iterative design process that incorporates continuous feedback from users. Conduct usability tests regularly to refine the interface based on user input [23].
**Enhancing Transparency and Trust:**
Explainable AI: Develop AI systems with transparent decision-making processes. Use explainable AI techniques to provide users with clear and understandable explanations for AI actions and recommendations [15].
Data Privacy and Security: Implement robust data protection measures, including encryption and secure data storage. Ensure transparency in data handling practices and obtain informed consent from users [7].
**Addressing Bias and Fairness:**
Bias Detection and Mitigation: Regularly audit AI systems for biases in training data and algorithms. Implement bias mitigation strategies, such as re-sampling data or using fairness-aware machine learning techniques [6].
Diverse Training Data: Ensure that training datasets are diverse and representative of the population. This helps in reducing biases and improving the fairness of AI systems [19].
**Adaptive and Responsive Interfaces:**
Dynamic UI Adjustments: Develop interfaces that can adapt in real-time based on user behavior and emotional state. Use flexible UI frameworks that support dynamic changes without significant performance overhead [24].
Context-Aware Prompts: Design prompts that are contextually relevant and non-intrusive. Use machine learning models to predict user needs and provide timely assistance [12].
**User-Centered Design Examples**
Autonomous Vehicles: User-centered design has been successfully implemented in autonomous vehicle interfaces. For example, Waymo involves users in the design process by conducting extensive user testing and gathering feedback to refine their in-car interfaces. This ensures that the interfaces are intuitive and meet the needs of diverse users, enhancing trust and adoption [4].
Healthcare Diagnostics: In the healthcare sector, IBM Watson for Oncology uses a user-centered design approach to develop its AI diagnostic tool. By involving oncologists in the design and testing phases, IBM ensured that the system's interface is user-friendly and aligned with the workflow of healthcare professionals, leading to higher adoption rates and improved patient care [11].
To illustrate the proposed framework for culturally sensitive, emotionally adaptive AI interfaces, as shown in Figure 1.

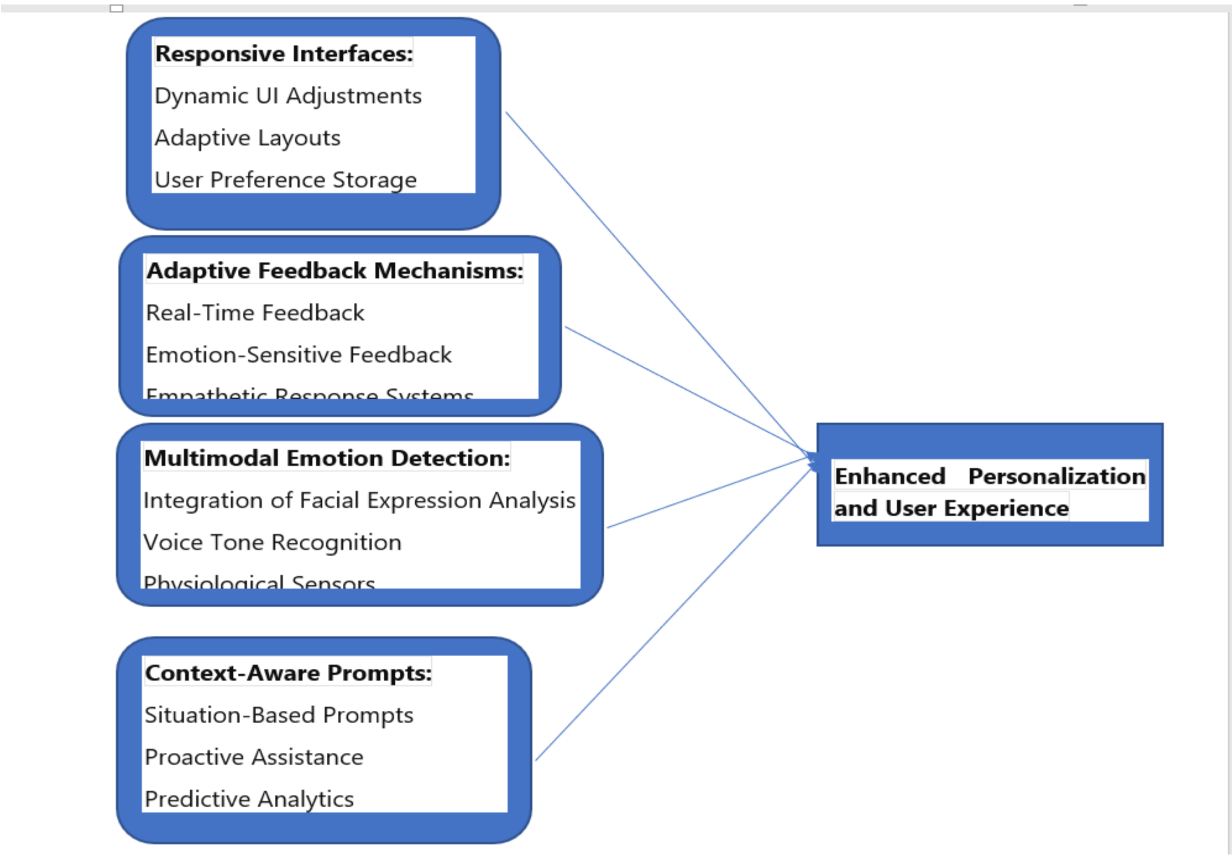


**Figure 1: Enhanced personalization and user experience Framework**

## VI. Conclusion

This paper presented a systematic literature review of the interface issues in non-conversational AI systems, focusing on usability, accuracy, privacy, cultural sensitivity, and emotional design. A total of 150 primary studies were selected from four major academic databases to answer two research questions. The selected studies covered a wide range of applications, reflecting the diverse and widespread use of non-conversational AI systems in various sectors such as healthcare, education, customer service, and entertainment.

The study revealed that significant challenges persist in the design and implementation of non-conversational AI interfaces. Usability issues, such as the need for clear feedback mechanisms and intuitive controls, were commonly highlighted [4]. Ethical concerns, particularly regarding bias and fairness in AI systems, were also prominent, with studies emphasizing the importance of addressing these biases to prevent unfair outcomes [6]. Privacy concerns related to the handling of sensitive user data were another critical area of focus, with researchers advocating for robust data protection measures [7]. Additionally, the technical limitations of current AI systems, such as the need for advanced capabilities to handle complex interactions and the challenge of ensuring reliability and scalability, were frequently discussed [29].

The integration of emotional recognition capabilities into non-conversational AI systems emerged as a significant area of research. Emotional recognition can enhance personalization by adapting interactions based on user emotions, thereby improving user experience and trust [21, 20]. However, challenges such as ensuring the accuracy of emotion detection through multimodal data [24], involving users in the design process [23], and providing real-time emotional adaptation [12] need to be addressed.

The study also identified a critical research gap: the need for real-time culturally adaptive emotional design in non-conversational AI systems. This gap encompasses the integration of emotion recognition technologies and adaptive learning algorithms to create AI interfaces that can respond to user emotions and preferences in a culturally sensitive manner. Addressing this gap involves developing advanced machine learning algorithms, enhancing user engagement strategies, and creating inclusive design elements that cater to diverse user groups.

This paper provided a systematic review that offers a comprehensive overview of the current state of research on interface issues in non-conversational AI systems. Despite the significant advancements in AI technology, several challenges and limitations need to be addressed to enhance the usability, accuracy, privacy, cultural sensitivity, and emotional design of AI interfaces. By focusing on these areas, future research can contribute to the development of more effective, ethical, and user-friendly AI systems. Technology has the potential to significantly improve user interactions with non-conversational AI systems, making them more responsive, trustworthy, and inclusive. Addressing the identified research gaps will be crucial for advancing the field and ensuring that AI technology can meet the diverse needs of users across different contexts.

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