International Journal of Scientific Research and Modern Technology (IJSRMT) *ijsrmt.com*
Volume 2, Issue 11, 2023
***DOI:* https://doi.org/10.5281/zenodo.14942964**

Advanced Approaches to Achieve Adaptive Ethical and AI-Driven Human-Centric Software Engineering

Shahidur Rahoman Sohag[1]; Syed Muroza Mushrul Pasha[2]; Muhammad Mahin Ali[3]

[1]Department of Computer Science, University of Idaho, Idaho, USA
[2]College of Computer Science, Chongqing University, Chongqing, China
[3]School of Computer Science, Taylor's University, Subang Jaya, Malaysia

Publication Date: 2023/11/28

Abstract

Adapting the diversity and modified user requirements, particularly personalization, adaptability and ethics cannot be satisfied by the modern software engineering approaches. This study provides a novel foundation of an adaptive, AI driven, user facing software engineering. It leverages AI to tailor software systems in the moment, factoring in diverse human elements ranging from emotional state to cognitive load to accessibility requirements to dynamically shifting user preferences. At the core of this framework is an active feedback loop from users, where software systems can continuously adapt, evolve, and respond to dynamic user needs throughout their lifecycle. It also involves a complete suite of ethical guidelines that make sure values such as equity, transparency, and inclusion are considered at all stages of the design and development process. In this respect, the ethical emphasis tries to minimize the chances of bias, intrusion into privacy, and exclusionary practices that may arise with the integration of AI into software. This approach offers a robust, responsible solution to software system creation in a manner that is not only technically effective but also socially responsible, merging AI-driven adaptability with a staunch commitment to ethical principles. Designed for various industry verticals, such as healthcare, education, smart cities, and public services, the framework provides scalable solutions to the multivariate challenges associated with human-centered software engineering.

Keywords: *Adaptive Software Engineering, User-Centric Design, Ai-Driven Systems, Real-Time Adaptation, Continuous Feedback*

I. INTRODUCTION

The incredible progressions of AI [1] have made a significant shift in software engineering and its utilization in ordinary. Also, it is paving the way for more adaptive and user-oriented systems. On the contrary, the traditional software engineering practices struggle to cope with the multidimensional and dynamic that is required of an users in terms of flexibility, personalization and responsibility [2], [3]. This is exacerbated by the increased complexity in users' interactions since emotional and cognitive states increasingly affect the usability and effectiveness of software use [4], [5]. More recently, a greater number of works have pointed to the embedding of machine learning algorithms that support improved human status detection for a responsive and highly personalized user experience.

Recent Machine learning, in identifying these states, whether affective or cognitive, will directly contribute to the adaptation of the software in its application [2]. Moreover, the measurement of cognitive load in software development underlines the important relation of cognitive demands with the performance of the software itself [3]. The evaluation of self-adaptive software systems is necessary to understand the efficacy of their responses to user needs [4]. Besides, AI-driven personalization in digital platforms shows how personalized experiences can lead to improved user engagement [5]. This is important because a strong ethical framework for AI and digital technologies creates fairness, accountability, and transparency in software systems [6]. However, the use of AI is also subject to a variety of societal and ethical challenges that call for integrated approaches among stakeholders for the challenges that these technologies present [7]. This consideration regarding the ethical way of handling AI refers to the responsible construction of AI [8].

Moreover, investigative insights from the study on operationalizing ethics of AI present barriers and enablers for conducting ethical AI deployment [9]. Results of this study brought in a framework which embedded ethical considerations into several stages-requirements gathering, design, coding, testing, and deployment-to make sure adaptations powered by AI respect user needs and rights while maintaining inclusivity in the software development process itself [10], [11].

This paper proposes an advanced framework that is focused on achieving adaptive, ethical, and AI-driven human-centric software engineering. The emphasis of our work will go to the integration of real-time user feedback mechanisms and machine learning techniques in providing systems that are able to adapt to changing users' needs while following ethical standards. It includes the major contributions of providing an overall adaptive framework that drives the design toward user-centric conceptions, providing a set of ethics for guiding AI in software engineering, and insisting on integrated continuous user feedback for enhancing the adaptability of software [2,4].

This paper presents a novel framework for adaptive ethical human centric AI software engineering. By focusing on the integration of real-time active user feedback mechanisms and machine learning techniques, we seek to provide systems that meet dynamic user needs while considering ethical guidelines. The contribution of this work is the holistic adaptive framework that encourages user-centered design, establishment of ethical guidelines regarding AI in software engineering, and continuous integration of user feedback in order to make software more adaptable [2], [4]. Furthermore, both challenges and opportunities presented by AI-driven personalization across a variety of contexts are discussed, also reflected by the research into applying cognitive load assessment and emotional recognition techniques [5]. In this paper, we detail our proposed framework, going into the components in detail, and relate it to the challenges found in state-of-the-art software engineering tasks [6].

II. RELATED WORK

Related work on adaptive, ethical, and human-centric software engineering has focused so far on user-centered design, AI-driven personalization, and ethical AI frameworks. While the early efforts aimed at the design of better user experience and accessibility, recent works put more stress on real-time adaptation to human factors such as emotions and cognitive load, ethical aspects such as fairness and transparency [12]. However, most of the existing approaches are not dynamically adaptable and lack unified frameworks integrating continuous feedback with comprehensive ethical guidelines. Our proposed framework aims at providing a more holistic solution for diverse domains than that available in [13].

A. Human-Centric Software Engineering

Human-centered software engineering has evolved to address the changing and diverse needs of users by making software design adaptable, responsive, and inclusive [2]. Initial methods, such as UCD and participatory design, were developed to enhance UX by actively engaging end-users in the design process to develop intuitive interfaces and improve usability [14]. As the field evolved, advances in Human-Computer Interaction [15] introduced adaptation of interfaces and personalization of experiences by considering user features such as age, cultural background, and cognitive load. This development enabled software behavior to be adapted for individual users, driven by the analysis of interaction patterns and preferences. However, most of these works still lacked the real-time adaptation mechanism for continuous feedback provided by the users and had challenges in establishing systems that evolve autonomously on dynamic data received from users [16].

Additionally, other related fields that advanced this idea were model-driven engineering (MDE) [17], emotion-oriented computing [18] and accessibility-oriented design [19]. MDE had the capacity of embedding high-level, user-centric requirements into software models, but limited support for real-time adaptations [20]. Emotion-oriented computing opened the door for making software behaviour sensitive to user emotions in diverse fields including eHealth where emotion-aware interventions are offered to the user [21].

While accessibility research expanded the scope towards a wide range of users including those with disabilities, dynamic adaptations based on real-time behaviour are still limited. Though agile practices brought continuous feedback loops into the software lifecycle, systematic frameworks that integrate cognitive, emotional, and ethical factors consistently at all stages are still missing [22]. As AI becomes more embedded in software systems, ethical considerations such as fairness, transparency, and inclusivity are crucial, but comprehensive guidelines for ethical AI integration remain underdeveloped [23].

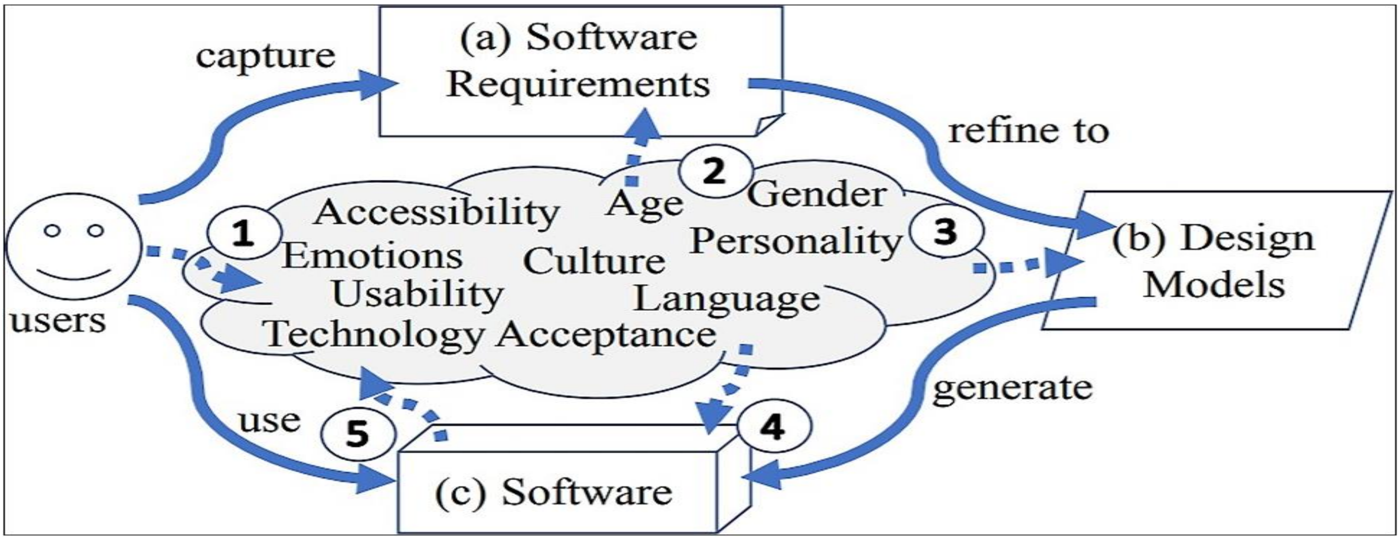

Fig 1 Incorporating “Human-Centric” Software Issues into Model-Driven Software Engineering [24].

The figure-1 illustrates the integration of human-centric considerations into Model-Driven Software Engineering (MDSE) [25]. It shows a process where user-related factors such as accessibility, emotions, usability, technology acceptance, age, culture, language, gender, and personality are captured from the users (Step-1) and incorporated into the software requirements (Step-2). These requirements are then refined into design models (Step-3) that represent user characteristics and preferences. These models are then used to construct the software, Step-4, which will be implemented and utilized by the users of said software, at Step-5. The cycle, in turn, becomes vicious: users keep feeding their view continuously in terms of the requirement for the software so that the system dynamically adapts to changes in the user's needs and contexts [24], [26].

B. Software Fundamentals in AI-Driven Adaptation

Artificial Intelligence algorithms have matured to be one of the most disruptive technologies for Software engineering in terms of personalization and adaptiveness. AI-driven adaptation allows polymorphic software systems-behavior and APIs that dynamically change according to heterogenous user characteristics, environments, and feedback collected [27].In order to drive better user satisfaction, efficiency, and accessibility, you want this software to be more responsive to the individual needs and preferences of the individual.

- *AI Techniques for Personalization:*

AI-based personalization refers to the customization of software functionalities [28], interfaces, and content using key techniques such as machine learning (ML) [29], natural language processing (NLP) [30], and deep learning [31]. ML algorithms, such as supervised and unsupervised learning [32], analyze historical data to understand user preferences and thus enable adaptive interfaces and feature recommendations, as in recommender systems like Netflix [33] or Spotify [34]. Therefore, NLP can have software deliver user experiences in conformance with users' linguistic preferences and communication style through real-time query processing, personalized to users' intent and sentiment. Deep learning models, such as neural networks, identify complex patterns in user behaviour and are hence ideal for detecting subtle changes in preference and the prediction of future actions to achieve more accurate personalization [35].

- *Real-Time Adaptation Based on Human Factors:*

AI-driven adaptation surpasses personalization in that it may make software react to real-time human factors, such as cognitive load, emotional state, physical conditions, and accessibility needs [27]. Techniques such as sentiment analysis and facial recognition enable the detection of emotional states [36], allowing systems to adapt the difficulty of content or empathetic responses based on user emotions. Cognitive load management may involve monitoring user interactions to decrease information overload by simplifying interfaces or navigation [37]. Wearable devices and also IoT sensors provide information about physical states and environmental conditions, enabling AI-driven software to automatically adjust settings such as screen brightness or the frequency of notifications. This enables applications in fitness, smart homes, and assistive technologies to gain from such data [38].

These practices are illustrated in figure-2, which shows a human-centered process that begins with understanding user needs and then translates them into model requirements. We start by using User Needs to identify Model Needs that need to be satisfied by the AI system. After this, there are the stages of Data collection which is used to collect the data to assist in training and improving AI models.

The AI system goes through Explainability and Trust phase as it matures, where it is imperative for users to understand the reasoning of the model behind its decisions. The system is equipped with Feedback and Control interfaces [40] enabling users to engage with the AI’s real-world usage and adjust its behaviour accordingly [39].

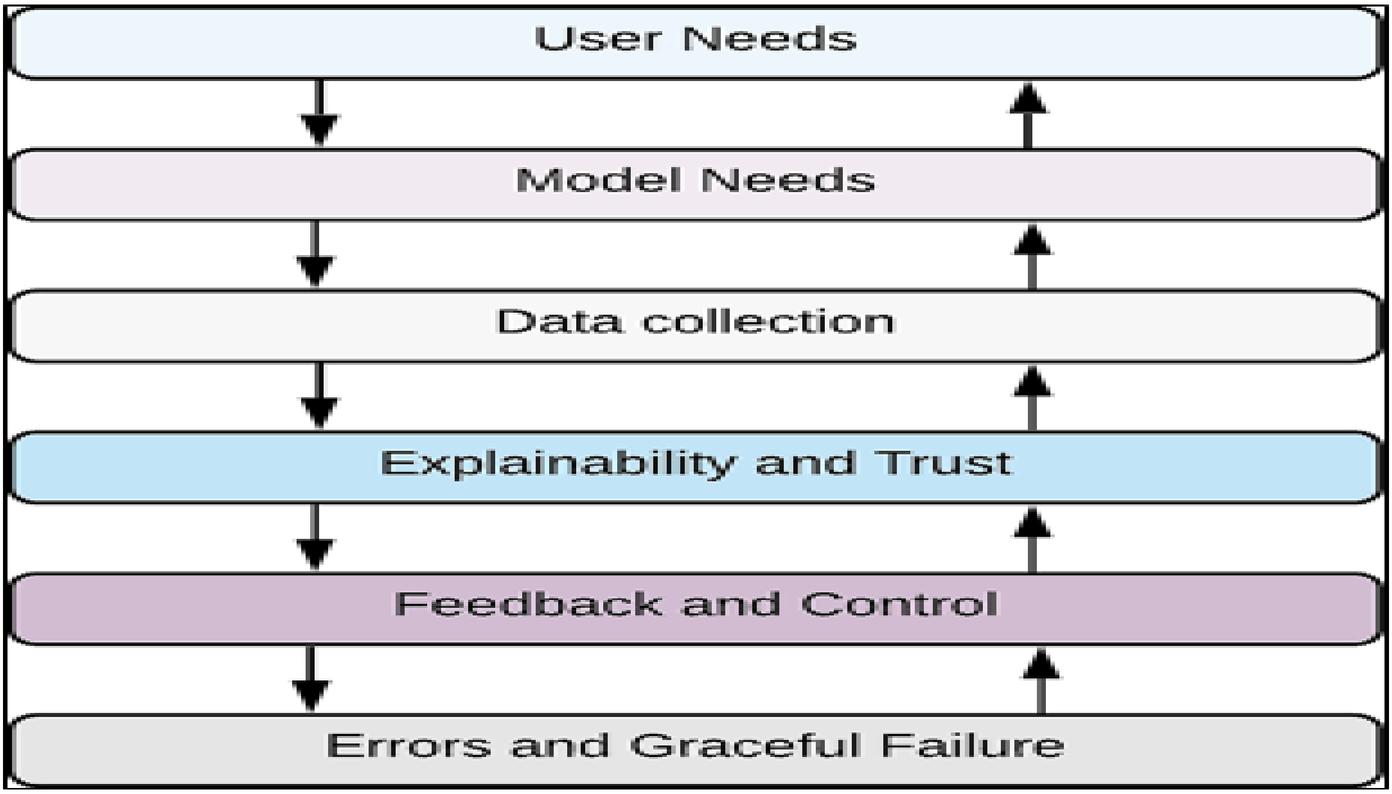

Fig 2 Stages in Developing Human-Centric AI Systems [39]

- *AI-Driven Adaptation in Specific Domains:*

Different domains are leveraging adaptive capacities to create personalized solutions, as well as enabling the possibility to respond on time. EHealth systems [41], for instance, analyze data from users on physical activities, heartbeat, sleep patterns, etc., to recommend personalized health recommendations on chronic disease management and daily monitoring [21]. Mental health apps are capable of recognizing symptoms of anxiety or stress and adapting mindfulness exercises for the user accordingly [42].In the field of education (eLearning) [43], adaptive learning platforms adapt due to individual evolution and preferences [27], such as Coursera [44] and Khan Academy [45], which recommend learning materials based on quiz results, learning styles, and engagement. Smart city and public services like traffic management, public transportation, and energy usage are streamlined for the update based on real-time data through such adaptive behaviors while keeping in mind the different accessibility needs, language preferences, and individual service needs of the user [46].

- *Challenges in AI-Driven Adaptation:*

While AI-powered adaptation is a feature with several advantages, however, this aspect brings a few challenges. This large amount of required data makes the adaptability of AI systems an issue of user privacy and data security, particularly when software adapts according to sensitive information, like health or emotional data [47]. Moreover, bias in AI algorithms would arise if some training data is corrupted, leading to adaptations that can be unfair and discriminatory; hence, there is a critical need to apply methods for detecting and mitigating bias 48. Besides, the problem of user trust also comes up since the user may not like AI to take decisions on behalf of him/her, particularly where it matters more, like health care. Providing transparency, control of personalization by users, and clear explanations of AI decisions are necessary for the development of trust in AI-driven systems [49].

C. Ethical Considerations in Software Engineering

With the proliferation of AI-driven software in nearly every aspect of life, the ethical consideration has emerged as a primary component of software engineering. Similar to academic scholarship, using AI as a core component of software systems brings up concerns about fairness, transparency, privacy, inclusivity, and accountability. In recent years, multiple ethical frameworks and guidelines were proposed to address these problems, which are mostly centered around the need for AI-directed systems to be socially responsible [50].

Table-I Internal and external ethical values and issues related to software engineering The three principles include privacy (responsible data processing and how user consent is obtained), sustainability (considering energy usage when developing software) and transparency (spelling out how mutual decisions are made transparently and in public ethical guidelines) [51]. It also covers diversity in development teams, work ethics regarding bug fixes and code quality [52], and business ethics with respect to revenue models and user communication. The table also emphasizes accountability for software-caused harm, dependability with respect to product maintenance, and the promotion of common goods, such as open-source software. These ethical values shall guide the development of responsible AI-driven systems [51].

Table 1 Example of Ethics Issues in Software Engineering

Value	Issue
Privacy	Handling, storing, sharing user data only under the circumstances and for the purposes that the user sets
Sustainability	Energy consumption of the software artifact, caring about energy throughout the SE process and in the documentation
Transparency	Transparent decision-making procedures of intelligent systems, publicly available ethics policies by software development organizations
Diversity	Gender, race, and age distribution of professionals in a development team
Work ethics	Decisions on which bugs to fix and how quickly, ensuring quality of the code before release
Business ethics	Informing users of a changed business model, including revenue models
Accountability	Who should be held responsible for the harm caused by software?
Dependability	Decision to maintain and/or keep a software product in the market
Common goods	Contributing to, using, promoting open source software

This brings out the necessary requirement of adaptive and ethical approaches in software engineering. Much literature emphasizes the potential benefits that accrue with integrating machine learning techniques to better user engagement and cognitively adequate load assessments [37]. In this context, ethical considerations towards AI take center stage, as they call for a model that enables fairness and transparency in the implementation of technology. However, the actual embedding of these principles into existing software engineering practices is nontrivial. The objective of our research is to respond to such a challenge by providing an extensive framework that prioritizes adaptability, ethics and user-centricity in order to advance responsible software systems [28].

III. PROPOSED FRAMEWORK

The motivation behind the provider of this framework is to create a customized and individualized experience in software engineering through real-time AI-based adaption and feedback at all levels while taking users features into account. Architecturally, as illustrated in the diagram, we divide this Tripartite approach into three core components: Human-User Interaction, AI-Driven adaptation and Feedback Loop, each performing a critical function in maintaining the responsiveness of the system while evolving with the user.

A. Framework Overview

The proposed framework presents an original approach for an adaptive, ethical, and human-centered software engineering powered by artificial intelligence. By integrating real-time monitoring of both user emotional state and cognitive loads, personalized adaptation and a feedback loop to refine user interactions.

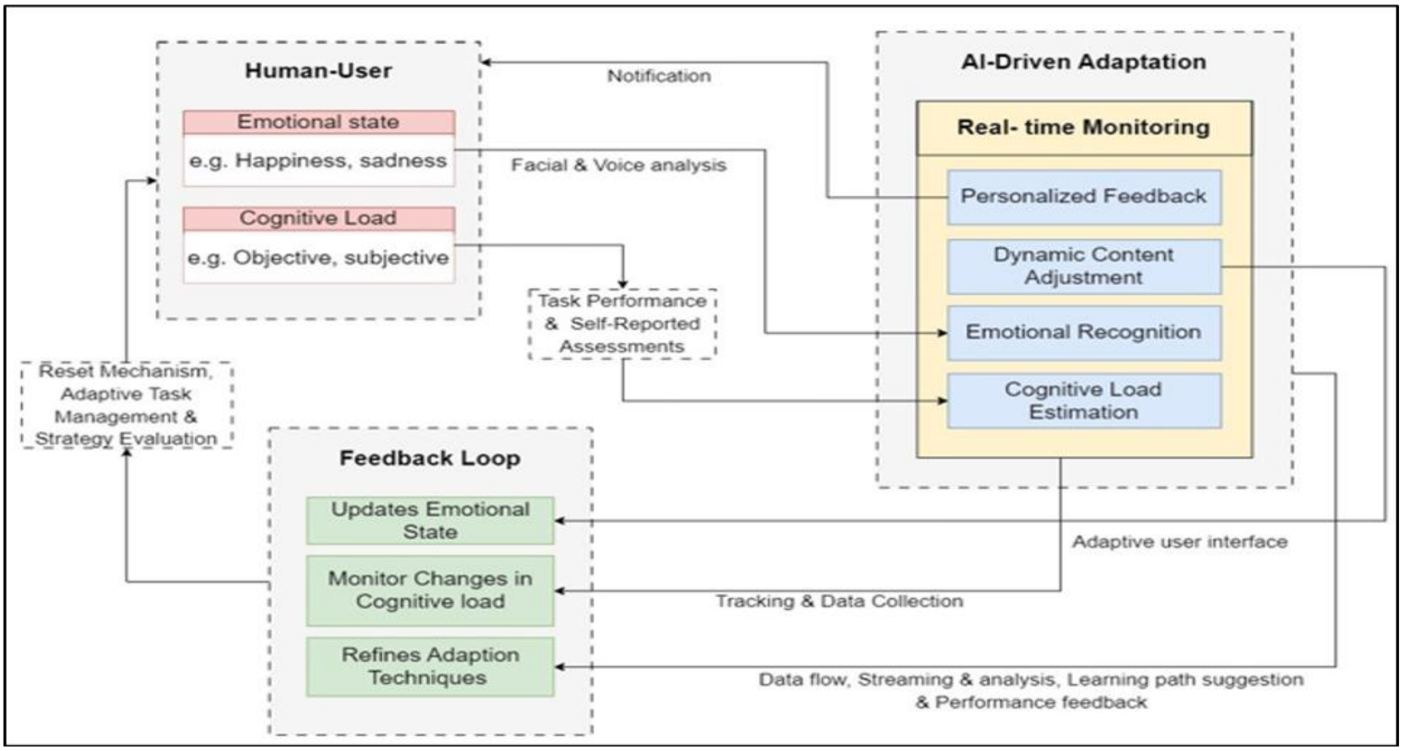

Fig 3 AI-Driven Adaptive Framework for Ethical Human-Centric Software Engineering

The AI-Adaptation element of the proposed framework actively learns and personalizes the software experience in real-time based on user characteristics (i.e., emotional state, cognitive load, or accessibility needs). Then it adapts its behavior to enhance the user experience through seamless monitoring of these factors coupled with data from facial expressions, voice tone, physiological indicators, and task performance through the system.

Machine learning models make use of analyzed data through techniques such as supervised learning to classify emotions or unsupervised learning to find patterns in user behavior. This enables the system to recognize changes in the user state and make decisions for adaptation in real time, which may regard adaptation of the interface layout, modification of the complexity of content, or giving personalized feedback. For example, in case of the detection of an elevated cognitive load, the system can simplify navigation options or reduce information density to avoid user fatigue. On the other hand, emotional recognition algorithms tune the tone or type of feedback by making it either empathetic or motivational, in accordance with the user's state. The following table-II presents examples of real-time adaptations based on different human factors:

Table 2 Examples of Human Factors, Monitoring Methods, and Real-Time Adaptations.

Human Factor	**Monitoring Method**	**Real-Time Adaptation**
Emotional State	Facial expression analysis, voice tone	Adjusts feedback tone (e.g., supportive vs. motivating) based on detected emotion (e.g., frustration vs. excitement) [53].
Cognitive Load	Eye-tracking, task performance metrics	Simplifies the user interface or reduces the number of steps for a task when high cognitive load is detected [54].
Accessibility Needs	User interaction data, self-reported data	Adjusts font size, color contrast, or enables voice control based on user accessibility preferences [55].
Fatigue Detection	Physiological signals (e.g., heart rate)	Reduces screen brightness or increases break reminders when signs of fatigue are detected [56].
Engagement Level	Click frequency, gaze tracking	Provides more interactive content or rewards (e.g., gamified elements) when engagement levels are low [54].
Stress Level	Skin conductance, heart rate variability	The pace of content delivery or adds calming visual elements when elevated stress levels are detected [53].
Environmental Conditions	Ambient noise levels, lighting changes	Adapts audio output volume or adjusts screen brightness for better visibility in changing environments [55].
Mobility Constraints	Accelerometer data, wheelchair usage	Adjusts navigation options for users with limited mobility or offers voice-command-based controls [57].
Time of Day	System clock data	Switches to dark mode during nighttime or adjusts task schedules based on the time of day for better productivity [55].
Learning Style Preferences	Self-reported data, quiz performance	Adjusts instructional methods (e.g., visual aids vs. text) based on preferred learning style or past performance [58].

The proposed framework in table-II demonstrates how real-time AI-driven adaptations depending on various human aspects facilitate user adoption and enhance their experience. This creates a responsive, user-centred system that changes with any additional user factors. This work lays the groundwork for establishing a composite model of human factors in forming adaptive software considering the diversity, on an interdisciplinary axis leading to a wide range of human-centric models for software engineering.

B. Iterative User Feedback Incorporation

Continuous user feedback, for example user-centered design can be embedded into the proposed framework to capture software evolution over time with respect to changing user needs and preferences. User data will be captured in real-time directly within the system through the various channels in which the user interacts, whether that be through user input, behavioral data, biometric/physiological signals, or task performance metrics (proctor matches).Continuous feedback analysis will support the identification of patterns, changes in user state, and assessment of the effectiveness of ongoing adaptations. Figure-4 illustrates the working of a feedback loop in terms of how information flows from user input to software adaptation and back again to the user. It analyzes the feedback to extract insights or identify issues, performs necessary updates, and refines the system to enhance the user experience.

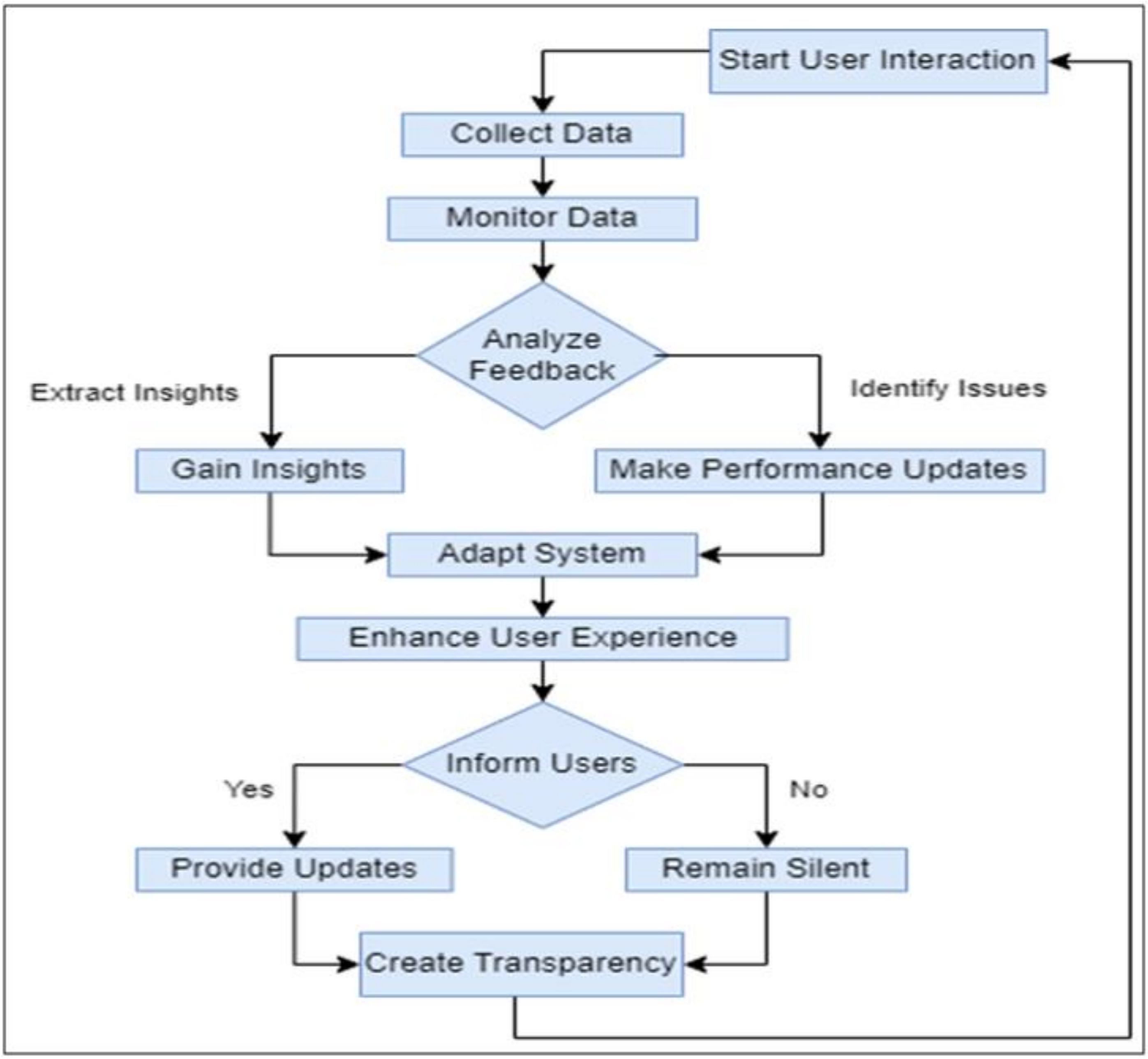

Fig 4 Continuous Feedback Loop for Adaptive Software Development

The captured feedback is used to inform the software development life cycle by feeding directly into an iterative process in which the system refines its adaptation techniques and updates its learning models. This approach makes it possible for the framework to change its strategies dynamically and to add new user preferences, adapt emerging needs without disrupting existing functionalities. This feedback loop continuously improves the system in real time, bringing the software into line with the user's dynamic needs and allowing the system to remain relevant, user-centric, and responsive.

C. Adaptive Software Design Models

The adaptive software design models do evolve over time, accommodating diverse user needs and dynamic requirements through the integration of flexibility and adaptability into the software development process. These models apply a modular architecture, dynamic user profiling, and context-aware adaptations to ensure that a system can make adaptations based on real-time feedback and changing user contexts.

Continuous integration of user feedback, combined with automated updates or evolutionary algorithms, allows the software to evolve seamlessly. This enables the creation of personalized experiences that can be tailored to different user preferences and accessibility needs.

Table 3 highlights six important steps of development related to the proposed framework that details a step-by-step approach toward adaptive, ethical, and AI-driven human-centric software engineering. Each phase leads to and extends the previous one, from an initial modular architecture to dynamic user modeling, then to context-aware adaptations, continuous feedback integration, evolutionary algorithms, and automated updates.

Table 3 DEVELOPMENT PHASES OF THE PROPOSED FRAMEWORK

Phase	Overview
Phase 1: Initial Development with Modular Architecture	Creating a robust and flexible architecture for the software system.
Phase 2: Integration of Dynamic User Modeling	Incorporating dynamic user modeling techniques for real-time adaptation.
Phase 3: Introduction of Context-Aware Adaptations	Implementing context-aware adaptations that respond to situational factors.
Phase 4: Continuous Feedback Integration	Establishing mechanisms for continuous user feedback collection.
Phase 5: Incorporation of Evolutionary Algorithms	Integrating evolutionary algorithms to optimize adaptation strategies.
Phase 6: Automated Updates and Personalization Refinement	Automating updates and refining personalization features.

A structured progression that is consistent with the objective of our research, which was to fill in the gaps within software engineering regarding embedding adaptability, real-time personalization, and ethical considerations within the process of development.

IV. APPLICATIONS AND CASE STUDIES

A. *Adaptive Smart Home System for Human-Centric Monitoring and Control*

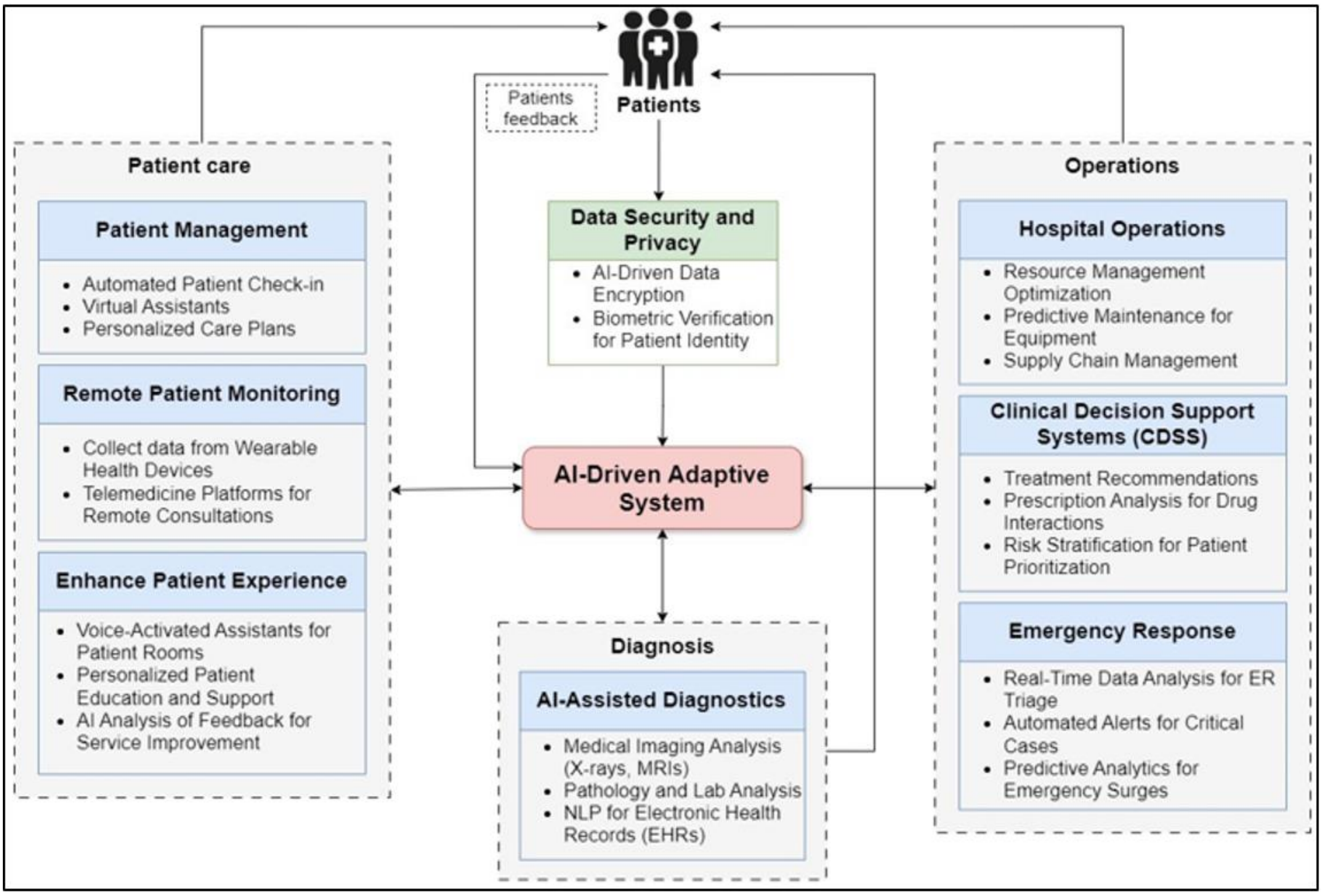

Fig 5 AI-Driven Smart Home System for Real-Time Monitoring and Adaptive Control.

The Figure 5: Smart home system where a variety of monitoring and control functionalities are connected via a central information collection and processing unit.The system integrates multiple components: health monitoring, emergency assistance (e.g., fall detection, emergency call buttons), air quality monitoring, security alerts, activity/remote monitoring, and environmental control (e.g., temperature, humidity, and lighting).

Data from such components is piped in, processed in real time, and used to achieve intelligent decision-making and alerts. The central processing unit is supposed to respond to various types of inputs and bring about appropriate actuations, like sending security alerts to family members or adjusting the environmental settings pertaining to sensor readings.

The smart-home system can be an optimal process for the applications of adaptive, AI-driven, and user-centric software engineering principles in practice. Its modular architecture allows various components, such as health monitoring, environmental control, and security protocols in order to operate independently so that it can seamlessly integrating into a unified system. Dynamic user modeling and context-aware adaptations are demonstrated in the system through changes in user status, which may be brought about by changes in health conditions or environmental factors. The capacity for evolution and optimization of the system over time can be enhanced by incorporating evolutionary algorithms that would refine adaptation strategies based on user behavior and sensor data trends. Besides, automatic updates and personal refinement would make the system responsive to the dynamic needs of users in the smart home environment [59].

B. AI-Driven Adaptive Healthcare System

Figure-6 illustrates an Adaptive AI system on a healthcare environment, connecting patient care, hospital operational efficiency, diagnosis, and data security. The system combines a number of capabilities to enhance delivery of care: automated check-ins, data gathering from wearable devices, and personalized care plans support improved patient management and patient monitoring

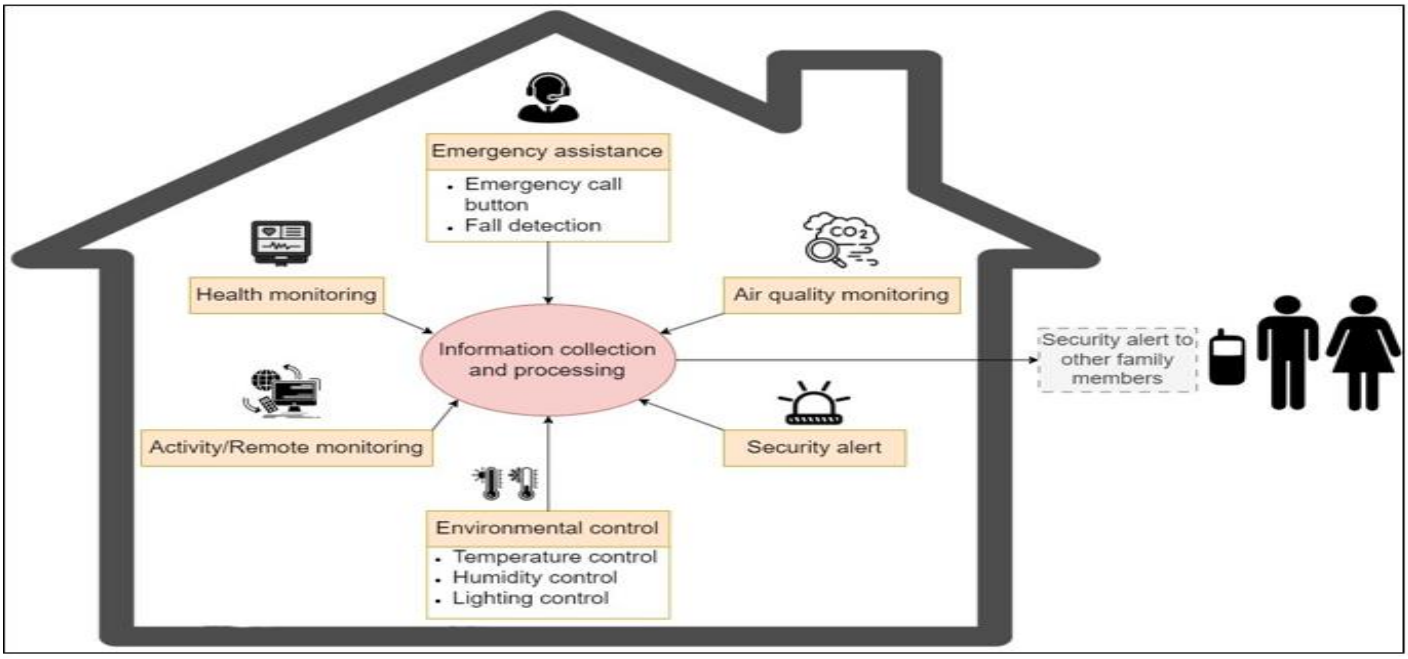

Fig 6 AI-Driven Adaptive System for Enhancing Healthcare Delivery and Hospital Operations.

Additionally, the AI system leverages natural language processing and medical imaging analysis to assist in diagnostics, providing insights from electronic health records and lab results. The continuous feedback loop from patients helps refine services, while voice-activated assistants and educational tools further enhance patient experiences.

From an operational perspective, This architecture will optimize a hospital's workflows of resource management, predictive maintenance while supporting clinical decisions with treatment suggestions, risk stratification, and analysis of interactions of drugs taken. Besides this, data will be secured via AI-driven encryptions along with biometric verification to provide patient privacy in a seamless process without any loss of data through the system itself [1]. Emergency response will be enhanced by real-time data analysis, predictive analytics, and automated alerts of critical cases [1, 41].

C. AI-Driven Integration in Educational Institutes

The platform also tackles security and safety issues with face recognition and anomaly detection for providing a secure learning environment. The personalized learning component allows adaptive learning systems and recommendation engines to meet the needs of individual students. Third, virtual tutors and chat-bots provide dynamic intelligent tutoring and personalized support, which ensure student access to personalized help. This pervasive embedding of AI capabilities aligns with the vision of adaptive, user-centric software engineering in essence with its focus on personalization, automatization and overall responsiveness to learning needs [27].

Figure-7 represents an AI integration platform for educational institutes, covering applications, tools and processes that improves administrative, academic and student support processes. This enhances administrative automation by facilitating grading and attendance [2], while AI-enhanced content creation provides interactive and gamified learning environments [60]. Also that it use the predictive analytics and monitor the student performance which help the educator and design the platform with data-driven decision-making.

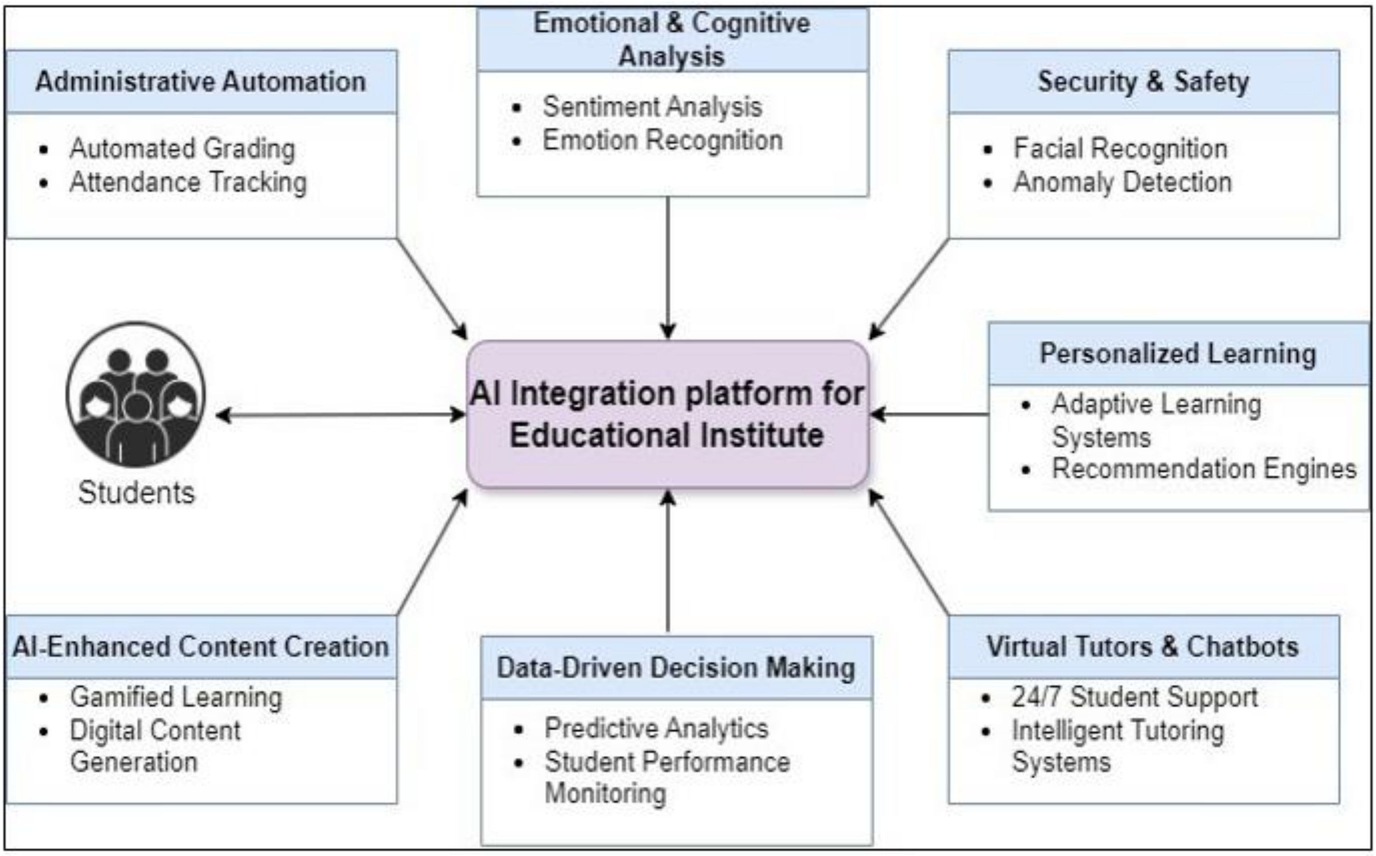

Fig 7 AI Integration Platform for Enhancing Administrative, Academic, and Student Support in Educational Institutes.

The various examples and case studies presented in this section identify domains where the proposed AI-based framework can be applied effectively, such as smart homes, healthcare, and learning environments. Each example also embodies the key ideas in our framework, including modular structure, dynamic user modelling, real time alterations and feedback loop. By addressing particular requirements in various settings, such as personalized healthcare management, emergency management, adaptive learning, and education administration automation, the framework illustrates its flexibility and adherence to the research goals.

V. DISCUSSION AND CONCLUSION

The suggested framework has tremendous potential for developing adaptive, user-centered, and ethically aware AI-based software systems. The framework overcomes the shortcomings of conventional software engineering through the incorporation of modular design [61], dynamic user modeling, real-time adaptation, and ongoing feedback mechanisms that enable the system to effectively cater to evolving user requirements in diverse areas like smart homes [62], [46], healthcare [41], and education [63]. Nonetheless, on-going adaptation and data-driven personalization demand a considerable amount of effort, raising issues on system overload, latency, validity of AI models, and their ability to capture subtleties of user states. They are being solved through an iterative addressing of feedback loops and improvements in algorithmic processing to drive robust scalable solutions.

The approach places the ethics at the center, integrating fairness, transparency, and inclusivity in the software development process. Formal ethical principles are used to minimize risks of bias, privacy, and users' consent in adaptive systems. The approach is in line with the overall objectives of human-centered software engineering in the manner it accorded AI-facilitated technology respect for the autonomy of users and society's norms. As AI takes on a larger role in decision-making and personalization, these ethical issues will be critical to building trust, sustaining user involvement, and ensuring sustainable adoption throughout applications. The emphasis of the framework on accountable AI practices makes it a complete solution to drive intelligent system advancement while addressing technical along with ethical issues. The architecture delivers a viable approach to adaptive, user-centered, and ethically aware AI-driven software development by integrating modular design, dynamic user modeling, real-time adaptation, ongoing feedback, and ethicality.

It solves fundamental limitations of conventional software engineering and facilitates customized, responsive apps in areas such as smart homes, healthcare, and education. Incorporating ethical standards mitigates issues of bias, privacy, and transparency, establishing trust in AI systems. Highlighted by the practical applications, the framework's flexibility highlights its potential to drive smart systems forward while conforming to the research agenda of human-centered design, ethical AI use, and green technology adoption. Not only does the framework find practical use with effective user experiences, but it also opens the path to upcoming AI-driven systems with priority on ethics and inclusivity. Future research will continue to increase real-time adaptation, improving emotion and cognition recognition algorithms and developing capabilities towards emerging technologies such as edge computing and IoT so that the framework finds itself effective and adaptable in evolving technological contexts.

REFERENCES

[1]. F. A. Batarseh, L. Freeman, and C. H. Huang, "A survey on artificial intelligence assurance," Journal of Big Data 2021 8:1, vol. 8, pp. 1–30, 4 2021.

[2]. S. K. Sardar, N. Kumar, and S. C. Lee, "A systematic literature review on machine learning algorithms for human status detection," IEEE Access, vol. 10, pp. 74366–74382, 2022.

[3]. L. J. Gonc¸ales, K. Farias, and B. C. da Silva, "Measuring the cognitive load of software developers: An extended systematic mapping study," Information and Software Technology, vol. 136, p. 106563, 2021.

[4]. I. Gerostathopoulos, T. Vogel, D. Weyns, and P. Lago, "How do we evaluate self-adaptive software systems?: A ten-year perspective of seams," in 2021 International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS), pp. 59–70, 2021.

[5]. J. S. Lim and J. Zhang, "Adoption of AI-driven personalization in digital news platforms: An integrative model of technology acceptance and perceived contingency," Technology in Society, vol. 69, p. 101965, 2022.

[6]. M. Ashok, R. Madan, A. Joha, and U. Sivarajah, "Ethical framework for artificial intelligence and digital technologies," International Journal of Information Management, vol. 62, p. 102433, 2022.

[7]. L. Vesnic-Alujevic, S. Nascimento, and A. Po´lvora, "Societal and ethical impacts of artificial intelligence: Critical notes on european policy frameworks," Telecommunications Policy, vol. 44, no. 6, p. 101961, 2020. Artificial intelligence, economy and society.

[8]. A. B. Brendel, M. Mirbabaie, T. B. Lembcke, and L. Hofeditz, "Ethical management of artificial intelligence," Sustainability 2021, Vol. 13, Page 1974, vol. 13, p. 1974, 2 2021.

[9]. J. Morley, L. Kinsey, A. Elhalal, F. Garcia, M. Ziosi, and L. Floridi, "Operationalising AI ethics: barriers, enablers and next steps," AI and Society, vol. 38, pp. 411–423, 2 2023.

[10]. E. Henrichs, V. Lesch, M. Straesser, S. Kounev, and C. Krupitzer, "A literature review on optimization techniques for adaptation planning in adaptive systems: State of the art and research directions," Information and Software Technology, vol. 149, p. 106940, 2022.

[11]. J. Zhang, C. Mihai, L. Tu¨shaus, G. Scebba, O. Distler, and W. Karlen, "Wound image quality from a mobile health tool for home-based chronic wound management with real-time quality feedback: Randomized feasibility study," JMIR mHealth and uHealth, vol. 9, p. e26149, 7 2021.

[12]. K. Sharma and M. Giannakos, "Sensing technologies and child–computer interaction: Opportunities, challenges and ethical considerations," International Journal of Child-Computer Interaction, vol. 30, p. 100331, 2021.

[13]. O. Gheibi, D. Weyns, and F. Quin, "Applying machine learning in self-adaptive systems: A systematic literature review," ACM Trans. Auton. Adapt. Syst., vol. 15, Aug. 2021.

[14]. S. Helman, M. A. Terry, T. Pellathy, A. Williams, A. Dubrawski, G. Clermont, M. R. Pinsky, S. Al-Zaiti, and M. Hravnak, "Engaging clinicians early during the development of a graphical user display of an intelligent alerting system at the bedside," International Journal of Medical Informatics, vol. 159, p. 104643, 2022.

[15]. A. Dix, "Human–computer interaction, foundations and new paradigms," Journal of Visual Languages Computing, vol. 42, pp. 122–134, 2017.

[16]. I. Alfonso, K. Garce´s, H. Castro, and J. Cabot, "Self-adaptive architectures in iot systems: a systematic literature review," Journal of Internet Services and Applications, vol. 12, pp. 1–28, 12 2021.

[17]. A. Bucchiarone, J. Cabot, R. F. Paige, and A. Pierantonio, "Grand challenges in model-driven engineering: an analysis of the state of the research," Software and Systems Modeling, vol. 19, pp. 5–13, 1 2020.

[18]. M. Alipour, S. Dupuy-Chessa, and E. Ce´ret, "An emotion-oriented problem space for ui adaptation: From a literature review to a conceptual framework," in 2021 9th International Conference on Affective Computing and Intelligent Interaction (ACII), pp. 1–8, 2021.

[19]. K. Sonka, C. McArdle, and L. Potts, "Finding a teaching a11y: Designing an accessibility-centered pedagogy," IEEE Transactions on Professional Communication, vol. 64, no. 3, pp. 264–274, 2021.

[20]. C. M. Sosa-Reyna, E. Tello-Leal, and D. Lara-Alabazares, "Methodology for the model-driven development of service oriented iot applications," Journal of Systems Architecture, vol. 90, pp. 15–22, 2018.

[21]. S. Yang, P. Zhou, K. Duan, M. S. Hossain, and M. F. Alhamid, "emhealth: Towards emotion health through depression prediction and intelligent health recommender system," Mobile Networks and Applications, vol. 23, pp. 216–226, 4 2018.

[22]. Z. Masood, R. Hoda, K. Blincoe, and D. Damian, "Like, dislike, or just do it? how developers approach software development tasks," Information and Software Technology, vol. 150, p. 106963, 2022.

[23]. B. Shneiderman, “Bridging the gap between ethics and practice: Guidelines for reliable, safe, and trustworthy human-centered AI systems,” ACM Trans. Interact. Intell. Syst., vol. 10, Oct. 2020.
[24]. J. Grundy, H. Khalajzadeh, and J. Mcintosh, “Towards human-centric model-driven software engineering,”
[25]. M. Snoeck and Y. Wautelet, “Agile merode: a model-driven software engineering method for user-centric and value-based development,” Software and Systems Modeling, vol. 21, pp. 1469–1494, 8 2022.
[26]. S. B. Pandi, “Artificial intelligence in software and service lifecycle,” 2023.
[27]. T. Kabudi, I. Pappas, and D. H. Olsen, “AI-enabled adaptive learning systems: A systematic mapping of the literature,” Computers and Education: Artificial Intelligence, vol. 2, p. 100017, 2021.
[28]. N. Chabane, A. Bouaoune, R. Tighilt, M. Abdar, A. Boc, E. Lord, N. Tahiri, B. Mazoure, U. R. Acharya, and V. Makarenkov, “Intelligent personalized shopping recommendation using clustering and supervised machine learning algorithms,” Plos one, vol. 17, no. 12, p. e0278364, 2022.
[29]. I. H. Sarker, “Machine learning: Algorithms, real-world applications and research directions,” SN Computer Science, vol. 2, pp. 1–21, 5 2021.
[30]. J. F. Allen, Natural language processing, p. 1218–1222. GBR: John Wiley and Sons Ltd., 2003.
[31]. I. H. Sarker, “Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions,” SN Computer Science, vol. 2, pp. 1–20, 11 2021.
[32]. R. H. Jhaveri, A. Revathi, K. Ramana, R. Raut, and R. K. Dhanaraj, “A review on machine learning strategies for real-world engineering applications,” Mobile Information Systems, vol. 2022, 2022.
[33]. K. van Es, “Netflix big data: The strategic ambivalence of an entertainment company,” https://doi.org/10.1177/15274764221125745, vol. 24, pp. 656–672, 9 2022.
[34]. J. Li, “Analysis of the trend of spotify,” BCP Business Management, vol. 34, pp. 919–926, 12 2022.
[35]. C. Ninness, M. Rumph, L. Clary, D. Lawson, J.T. Lacy, S. Halle, R. Mcadams, S. Parker, D. Forney, and C. Ninness, “Neural network and multivariate analyses: Pattern recognition in academic and social research,” Behavior and Social Issues 2013 22:1, vol. 22, pp. 49–63, 2013.
[36]. D. Zhang and Q. Tian, “A novel fuzzy optimized cnn-rnn method for facial expression recognition,” Elektronika ir Elektrotechnika, vol. 27, no. 5, pp. 67–74, 2021.
[37]. I. Reychav and D. Wu, “The interplay between cognitive task complexity and user interaction in mobile collaborative training,” Computers in Human Behavior, vol. 62, pp. 333–345, 2016.
[38]. D. Nahavandi, R. Alizadehsani, A. Khosravi, and U. R. Acharya, “Application of artificial intelligence in wearable devices: Opportunities and challenges,” Computer Methods and Programs in Biomedicine, vol. 213, p. 106541, 2022.
[39]. K. Ahmad, “Human-centric requirements engineering for artificial intelligence software systems,” in 2021 IEEE 29th International Requirements Engineering Conference (RE), pp. 468–473, 2021.
[40]. F. J. Coelho, H. Evanschitzky, C. M. Sousa, H. Olya, and B. Taheri, “Control mechanisms, management orientations, and the creativity of service employees: Symmetric and asymmetric modeling,” Journal of Business Research, vol. 132, pp. 753–764, 2021.
[41]. H. Wang, X. Yu, H. Wang, and X. Yu, “A review of e-health research in information system,” Journal of Biomedical Science and Engineering, vol. 15, pp. 198–205, 7 2022.
[42]. T. McCloud, R. Jones, G. Lewis, V. Bell, E. Tsakanikos, et al., “Effectiveness of a mobile app intervention for anxiety and depression symptoms in university students: randomized controlled trial,” JMIR mHealth and uHealth, vol. 8, no. 7, p. e15418, 2020.
[43]. R. E. Galang and A. D. Hallar, “The impact and effectiveness of e-learning on teaching and learning,” International Journal of Computing Sciences Research, vol. 5, pp. 383–397, 2021.
[44]. L. Q. Nguyen, “Learners’ satisfaction of courses on coursera as a massive open online course platform: A case study,” Frontiers in Education, vol. 7, 12 2022.
[45]. L. Q. Nguyen, “Learners’ satisfaction of courses on coursera as a massive open online course platform: A case study,” Frontiers in Education, vol. 7, 12 2022.
[46]. T. Yigitcanlar, R. Mehmood, and J. M. Corchado, “Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures,” Sustainability, vol. 13, no. 16, p. 8952, 2021.
[47]. G. Karimian, E. Petelos, and S. M. Evers, “The ethical issues of the application of artificial intelligence in healthcare: a systematic scoping review,” AI and Ethics, vol. 2, no. 4, pp. 539–551, 2022.
[48]. S. Akter, Y. K. Dwivedi, S. Sajib, K. Biswas, R. J. Bandara, and K. Michael, “Algorithmic bias in machine learning-based marketing models,” Journal of Business Research, vol. 144, pp. 201–216, 2022.
[49]. G. Wagner, R. Lukyanenko, and G. Pare´, “Artificial intelligence and the conduct of literature reviews,” Journal of Information Technology, vol. 37, no. 2, pp. 209–226, 2022.
[50]. H. Siala and Y. Wang, “Shifting artificial intelligence to be responsible in healthcare: A systematic review,” Social Science & Medicine, vol. 296, p. 114782, 2022.

[51]. F. B. Aydemir and F. Dalpiaz, "A roadmap for ethics-aware software engineering," 2018.
[52]. J. Gogoll, N. Zuber, S. Kacianka, T. Greger, A. Pretschner, and J. NidaRu¨melin, "Ethics in the software development process: from codes of conduct to ethical deliberation," Philosophy and Technology, vol. 34, pp. 1085–1108, 12 2021.
[53]. R. Rajendran, S. Iyer, and S. Murthy, "Personalized affective feedback to address students' frustration in its," IEEE Transactions on Learning Technologies, vol. 12, pp. 87–97, 1 2019.
[54]. E. Novak, K. McDaniel, and J. Li, "Factors that impact student frustration in digital learning environments," Computers and Education Open, vol. 5, p. 100153, 2023.
[55]. E. E. Kossek, M. Perrigino, and A. G. Rock, "From ideal workers to ideal work for all: A 50-year review integrating careers and work-family research with a future research agenda," Journal of Vocational Behavior, vol. 126, p. 103504, 2021. 50th Anniversary Issue.
[56]. Z. Tan, N. Dai, Y. Su, R. Zhang, Y. Li, D. Wu, and S. Li, "Human–machine interaction in intelligent and connected vehicles: A review of status quo, issues, and opportunities," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 9, pp. 13954–13975, 2022.
[57]. S. Khan, S. Nazir, and H. U. Khan, "Analysis of navigation assistants for blind and visually impaired people: A systematic review," IEEE Access, vol. 9, pp. 26712–26734, 2021.
[58]. U. Ocepek, Z. Bosnic´, I. Nancˇovska Sˇerbec, and J. Rugelj, "Exploring the relation between learning style models and preferred multimedia types," Computers Education, vol. 69, pp. 343–355, 2013.
[59]. J. F. DeFranco and M. Kassab, "Smart home research themes: An analysis and taxonomy," Procedia Computer Science, vol. 185, pp. 91– 100, 2021. Big Data, IoT, and AI for a Smarter Future.
[60]. A. Dom´ınguez, J. S. de Navarrete, L. de Marcos, L. Ferna´ndez-Sanz, C. Page´s, and J.-J. Mart´ınez-Herra´iz, "Gamifying learning experiences: Practical implications and outcomes," Computers Education, vol. 63, pp. 380–392, 2013.
[61]. M. S. Thaiya, K. Julia, and S. Mbugua, "On software modular architecture: Concepts, metrics and trends," International Journal of Computer Organization Trends, vol. 12, pp. 3–10, 4 2022.
[62]. J. Shin, Y. Park, and D. Lee, "Who will be smart home users? an analysis of adoption and diffusion of smart homes," Technological Forecasting and Social Change, vol. 134, pp. 246–253, 2018.
[63]. H. Li, T. Xu, C. Zhang, E. Chen, J. Liang, X. Fan, H. Li, J. Tang, and Q. Wen, "Bringing generative AI to adaptive learning in education,"