

Accessavior: AI-Driven Real-Time Adaptive Web Interfaces for Intelligent User Experiences

Nupur Choudhary^{1,*}, Surendra Kumar Yadav², Shruti Mathur³

Abstract

As the web has become more diverse, many traditional, one-size-fits-all web accessibility solutions that must be configured manually have proven inadequate in meeting the needs of each user. This paper introduces “Accessavior”, which is an intelligent, behavioural pattern-driven accessibility framework that can automatically customize the personalization of web interfaces based on the interaction patterns of users. The proposed system will continuously track cursor behaviours such as cursor movements, keystroke characteristics, dwell time, scrolling behaviour and navigation loops to detect motor, visual and cognitive accessibility needs. An ensemble machine learning method based on the combination of Random Forest, Support Vector Machine and K-Means clustering is used to classify user needs and to compute adaptive interface changes. The framework dynamically changes the WEBSO elements according to the calculation of the accessibility of the element based on the derived accessibility profile, by changing font size, contrast, size of buttons, simplification of navigation feature and setting up assistance for typing. This work is validated with a test on 2,400 annotated user sessions showing an average adaptation latency of 97ms, an accuracy of 93.2%, precision of 91.6%, recall of 90.9%, and an F1 score of 0.913. Additionally, the people are pleased with the adaptive framework (with positive feedback ratings through various user classes) and from an efficiency point of view, the adaptive framework improves the task completion by 25%. The findings suggest that use of behavioral analytics alongside ensemble learning can facilitate generation of accurate, low-latency and user-centric accessibility adaptations that can lead to the development of intelligent web interfaces which provide improved usability, inclusiveness and overall user experience in real-time environments.

Keywords: Behavioral analytics, web accessibility, machine learning, adaptive interfaces, explainable AI

INTRODUCTION

Widespread adoption of web applications for communication, education, health management, e-commerce and public services has made it important to have interfaces that can meet the needs of a variety of users. Web interfaces tend to be fairly static, and users have to manually configure accessibility settings, which does not always match the needs of user groups with different motor, visual, cognitive and situational requirements. Therefore, researchers have looked towards adaptive user interfaces (AUIs), which adapt interface elements based on user interaction, preferences, and context.

The development of intelligent adaptive systems has greatly progressed, with intelligent systems including recent advances in artificial intelligence (AI) and machine learning. Reinforcement learning has emerged as a viable method for allowing interfaces to learn how to adapt optimally given user interaction and to continually adapt their

*Author for Correspondence

Nupur Choudhary

E-mail: nupur.24mcon0003@jecrcu.edu.in

¹Student, Department of Computer Science and Engineering, JECRC University, Jaipur, Rajasthan, India

²Professor, Department of Computer Science and Engineering, JECRC University, Jaipur, Rajasthan, India

³Assistant Professor, Department of Computer Science and Engineering, JECRC University, Jaipur, Rajasthan, India

Received Date: February 03, 2026

Accepted Date: March 26, 2026

Published Date: April 10, 2026

Citation: Nupur Choudhary, Surendra Kumar Yadav, Shruti Mathur. Accessavior: Ai-Driven Real-Time Adaptive Web Interfaces for Intelligent User Experiences. Current Trends in Information Technology. 2026; 16(2): 14–22p.

personalization over time [1–3]. These allow systems to adapt to the needs of users and optimize their usability, catering to demand variations and adapting UI layouts, navigations, and interactions through automatic capabilities.

Additionally, adaptive interfaces powered by machine learning have proven to be a significant area of potential future improvement in accessibility and user experience. Previous research has demonstrated that behavior information can be used to determine the needs of users and to create adaptive adaptations on their behalf without the need for explicit user configuration [4]. These strategies have proven effective in various sectors, such as healthcare and wearable technologies, where adaptive interfaces enhance interaction efficiency and usability [5]. Moreover, incorporating human feedback into adaptive learning frameworks to enhance adaptation decisions has led to better adaptation systems that fulfill user expectations [6].

Adaptive interfaces for targeted groups have also been explored. There are many examples of adaptive and accessible interfaces that have improved the usability of the user interface for senior users by automatically modifying its complexity and presentation based on the abilities of the user [7]. In the same way, deep learning methods have been used to create a customized UI layout that reorganizes and guides content more efficiently for each individual user to increase engagement and satisfaction [8]. Analyzing user behavior to enable real-time adaptations has also been shown to enhance interface personalization and interaction results [9, 10].

However, the current adaptive interface solutions have some issues. Numerous methods are all based on explicit preference of the user, a set of accessibility profiles or a single model prediction method which might not be able to handle complex profile of user behavior. In addition, in real-time web applications, it is still very challenging to achieve good adaptation accuracy without incurring a high response latency. Thus, there is the very need for smart accessibility systems that can recognize users' needs based on their implicit behavior and can do make quick adaptations during real-time usage.

In response to these constraints, a behavioral pattern-based framework, namely the Accessavior framework for intelligent web interface adaptation, is proposed in this paper. The proposed system continuously tracks the implicit interaction signals of users (cursor movement, keystroke dynamics, dwell time, scrolling behavior, and navigation loops) to determine their accessibility needs. A framework of ensemble machine learning (Random Forest, Support Vector Machine and K-Means clustering) is used for the classification of user needs and the development of personalized interface adaptations. The framework automatically changes the font size, contrast, button size, level of navigation difficulty, and typing support features based on the identified accessibility profile.

The proposed framework was assessed by examining 2,400 annotated user sessions available across various scenarios and settings for system usability and accessibility. The experimental results indicate the accuracy of the system as 93.2%, precision as 91.6%, recall as 90.9%, and F1 score as 0.913, with an average adaptation latency of 97 ms. The results have shown that the BAE approach and the ensemble learning algorithm can work well in real-time accessibility adaptation and can help to enhance the accessibility of the web and make the Internet more user-centric.

The major conclusions of this study are:

1. Development of an adaptive framework for automatic web accessibility, driven by behavioral pattern.
2. The combination of three classifiers – Random Forest, Support Vector Machine, and K-Means clustering—into a single ensemble architecture for user requirement identification.
3. Adaptation of interface components in real time, using implicit behavioural signals.
4. Comprehensive assessment of adaptation accuracy, latency and usability under various access conditions.
5. Demonstration of an intelligent and scalable approach to enhance inclusiveness and user experience in modern web applications.

LITERATURE REVIEW

In recent years, significant progress has been made in adaptive user interfaces that are looking for better personalization, accessibility, and user experience using intelligent data-driven techniques. Different machine learning, deep learning, and adaptive system methods have been investigated to adapt the size and/or appearance of interface elements based on the user's actions, preferences, and context.

Findlater and McGrenere [8] examined the power of adaptive graphical user interfaces and illustrated how the successful adaptation of an interface configuration to a user's characteristics could achieve greater improvements in task efficiency and usability than simple static interfaces. Their results showed the role of adaptation mechanisms in lowering the effort of the user and improving interaction performance.

Gajos et al. [9] suggested automatic techniques for the generation of interfaces that adapt to the user's capabilities and requirements. They showed that adaptive presentation strategies can be used to make the material more accessible to users with different interaction needs. Likewise, Peissner et al. [10] investigated adaptive interfaces for mobile use and found that such interfaces enabled by context-aware adaptations are more usable.

The incorporation of machine learning into self-adaptive systems has become increasingly common in recent years, with the goal of assisting in dynamic decision-making. Gheibi et al. [11] performed a comprehensive survey of machine learning applications in self-adaptive systems, showing that supervised learning and reinforcement learning are prominent user for generating and optimizing an adaptation policy in self-adaptive systems. The criteria they studied found that adaptation latency and model interpretability are among the key issues in the study.

Drawing from the literature, Wang et al. [12] conducted a systematic review of adaptive user interfaces in healthcare systems and emphasized the need for individual user interaction mechanisms when interacting with individuals with chronic conditions. The study has largely found that adaptive interfaces can enhance engagement and accessibility; however, the techniques for capturing behavior for modelling need to be more sophisticated.

Diverse studies have explored adapting user experience in contemporary digital spaces. Chunchu [13] introduced an adaptive user interface that aims to improve the user experience by adapting the user interface based on interaction and personalization. It highlighted three key elements: contextual awareness, user modelling, and machine learning to make things smarter.

AI-powered systems continue to enhance the capabilities of adaptive systems. Jamali et al. [14] analyzed adaptive learning interfaces and found that adaptive personalization using AI can enhance user satisfaction and engagement by analyzing user behavior over time. Likewise, Hariyanto et al., [15] recommended supervised, unsupervised and reinforcement learning methods to be effective in personalization of the artificial intelligence application in the context of adaptive education systems. Abass [16] studied AI application with a personalization approach in user-centered interface design and found that an adaptive interface could provide better usability by adding transparency, explainability, and user control to the adaptation process. Other key issues raised by this study for further research are privacy and algorithmic bias.

Studies of intelligent user interfaces have demonstrated that the integration of user models with AI methods will allow the intelligent systems to anticipate additional needs, and tailor interactions accordingly [17]. Adaptive navigation and content presentation mechanisms have also been found to enhance user effectiveness at interaction and minimize user cognitive load during operation in complex digital environments [18].

Another key research strand is context-aware adaptation. It has been shown that user adaptation quality and satisfaction can be boosted by the integration of environmental factors, device factors and behavioral context [19]. Additionally, systems for adaptive recommendation and personalization have successfully adapted various interface features based on user behavior and interactions [20].

Recent research has primarily focused on algorithmic personalization and intelligent content curation. For instance, technology-based methods that use machine learning algorithms to simulate user activity and make personalized recommendations in real time have enhanced user engagement and system performance [21]. Furthermore, the development of adaptive learning mechanisms has shown the promise of adaptable adaptations for providing individual experiences in different application domains [22].

While there has been great work done on adaptive user interfaces, some knowledge is limited. Many of them require explicit preferences, domain-specific adaptation rules, or single-model learning techniques, which may not be sufficient for representing complex user behaviors. In addition, it is difficult to maintain a high level of accuracy while maintaining a low response time for real-time web applications. Accessibility adaptation for smart web interfaces with accurate accessibility and low latency is stimulated by the above limitations and prompts the development of the proposed Accessavior framework, which combines behavioral analytics with an ensemble machine learning architecture.

METHODOLOGY

System Architecture

The framework of the proposed adaptive web interface consists of six stages, and the personalization of the adaptive web interface is intelligent and real-time according to the user's interaction behaviors. As illustrated in Figure 1, the system consists of User Interaction, Event Capture, Feature Extraction, Data Storage, Machine Learning Processing, and UI Adaptation modules.

It starts with the user's navigation interactions on the web application that generate different interactions (behavioral events) while the user is executing a task. The representation of these events is captured in real time and passed on to the feature extraction module. The gathered features were saved in a centralized database and then subjected to machine learning analysis and models to determine user preferences and models. Based on the generated predictions, the UI adaptation module dynamically changes the UI elements to improve the user experience, usability, and accessibility.

User Interaction and Event Capture

The User Interaction module is the point of entry for the proposed framework; it gathers behavioral data created during user interaction with the web application. These interactions encompass mouse movements, clicks, scrolling actions, keystrokes, navigation, and time spent. These interactions were simulated in real time using JavaScript-based event listeners intermingled with the client-side environment. The system captures the temporal aspects of user behavior, including the time of each event and its context. The events collected are informative for gaining more knowledge about the needs and preferences of the users, interactions, as well as about the accessibility needs, and these are used in later analysis and adaptation processes.

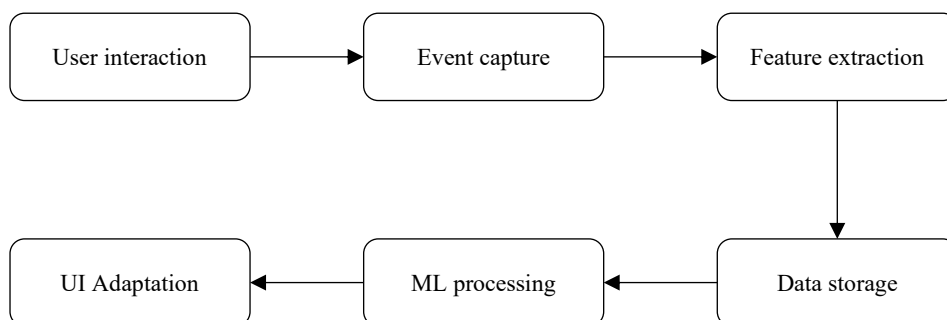


Figure 1. Architecture of the proposed adaptive web interface framework.

Feature Extraction

The Feature Extraction module converts raw interaction data into important representations of behavior in the form of features that can be used for machine learning analysis. As a result, statistical and behavioral attributes are calculated from the collected information, which is of limited predictive value when viewed on its own, at low level events such as mouse coordinates and keystroke recording. They are cursor speed, click rate, scrolling speed, dwell time properties, navigation depth, page rate of change, keystroke time, session length, and density of interaction. The extracted features were then pre-processed using normalization and handling missing value procedures to make the model more robust and consistent across various users and sessions. Finally, the obtained feature vectors can be used effectively to classify and cluster the user behavior data to make it as compact and informative as possible.

Data Storage

After feature extraction, the extracted behavioral information is stored in a central repository, which can also be used while training the model and for inference in real time. The storage layer saves historical interaction records, feature vectors extracted from the interactions, prediction outputs, and adaptation logs. The framework uses this historical information to create behavioral profiles that can be used to continuously learn and personalize experiences over the long term. Within the storage system, only anonymized data of the users' behavior are stored to ensure the privacy of users and to meet ethical obligations. The information can also be easily retrieved from the database during the real-time adaptation process to ensure low-latency system operation.

Machine Learning Processing

The Machine Learning Processing module is an intelligent layer of the proposed framework. A hybrid method of ensemble method integrating Random Forest, Support Vector Machine (SVM) and K-Means clustering technique is used to analyze the behavior of the user and to produce an adaptation decision. Random Forest serves as the basic classification model because it is suitable for high-dimensional behavioral features and is powerful in prediction. The Support Vector Machine, which complements the classification process, can find complex decision boundaries and enhance the discrimination between different behavioral classes. Moreover, K-means clustering is applied to cluster users according to their interaction characteristics to facilitate the personalization of adaptation strategies for different user segments.

The results obtained from such models are combined by an ensemble decision-making method and a criterion for making final decisions on the users' preferences and accessibility requirements is constructed. The results obtained from the models are combined using an ensemble decision-making method, and a criterion is built to make final decisions on users' preferences and accessibility demands. This merging of supervised and unsupervised learning has the benefits of being able to predict with greater accuracy and being adaptable to varied groups of users for personalization.

User Interface Adaptation

The prediction output from the machine learning models is used in the User Interface Adaptation module, which dynamically enhances the user interface. Adaptation decisions are made at runtime, and changes might include visual, navigation, and interaction parts of the interface. Based on the behavioral profile, the system can adjust the size of the font, highlight contrasts, make interactive content larger, simplify wayfinding and structures, reorganize orders, and prioritize text layouts. Changes are made without loading a new webpage, creating a sequence of more seamless user experiences.

One of the unique features of the proposed framework is its flexibility to continually optimize adaptation decisions based on new interaction data as they arrive. This allows the system to detect and adapt to changing user behaviors and preferences over time, ensuring a user-friendly and personalized experience as the users continue to use it.

Table 1. Performance comparison.

Model	Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Latency (ms)
Khamaj et al. [23]	Reinforcement learning	86.4	84.7	83.5	0.841	145
Zhan et al. [24]	Deep learning	88.1	86.2	85.4	0.858	182
Sun [25]	Machine learning	89.5	88.0	87.2	0.876	126
Accessavior (Proposed)	RF + SVM + K-Means	93.2	91.6	90.9	0.913	97

Experimental Design and Evaluation

The proposed framework was evaluated using a dataset of 2400 user interaction sessions gathered from users while they were engaging in different online activities on the Internet. The data contained information about behavior from mouse clicks, typing, navigation and scrolling patterns. A stratified 10-fold cross-validation technique was used to train and evaluate the machine learning models to ensure reliable performance measurements.

The evaluation focused on both prediction and live application. The accuracy, precision, recall, and F1-score were used to evaluate the classification performance, and adaptation latency was measured to assess the system responsiveness. Experimental results showed that the ensemble framework proposed in this paper achieved high accuracy (93.2%), high precision (91.6%), high recall (90.9%) and F1-score (0.913%) with an average adaptation latency of 97ms. The results of these findings suggest that the combination of three algorithms, Random Forest, Support Vector Machine and K-Means Clustering, is an effective approach to adapt to the intelligent real-time web interface and optimize the user's experience.

RESULTS AND DISCUSSION

The performance of the proposed adaptive web interface framework was evaluated using accuracy, precision, recall, F1-score, and adaptation latency. The comparative results are presented in Table I, and the graphical comparison is presented in Figures 2 and 3.

The proposed ensemble model (Random Forest-SVM-K-Means) showed the best performance, with an accuracy of 93.2%, Precision-91.6%, Recall-90.9% and F1-score of 0.913, as shown in Table I. The framework has shown superior performance over the latest adaptive interface approaches using reinforcement learning [23], deep learning for interface personalization [24] and machine learning for adaptive user experience systems [25].

The accuracy comparison shown in Figure 2 illustrates the advantage of using supervised classification in conjunction with behavioral clustering to determine user preference and accessibility needs. Likewise, the comparison of the latency in Figure 3 reveals that the proposed framework could successfully realize real-time interface personalization without affecting the user's interaction with the interface, as it required only 97ms as the average adaptation latency.

Experimental results also showed that the adaptive framework had a 25% reduction in the mean task completion time as well as an increase in the global efficiency of interaction. Some of these improvements were made by dynamically adapted elements of the interfaces (font size, contrast, structure of navigation, structure of content content matter) as per the behavioral patterns of the users.

Although the framework shows promise, it requires ample interaction data for behavioral modelling. This study will guide future researchers on ways to further generalize models to various surrounding web use contexts and adding more contextual factors to improve personalization performance even further.

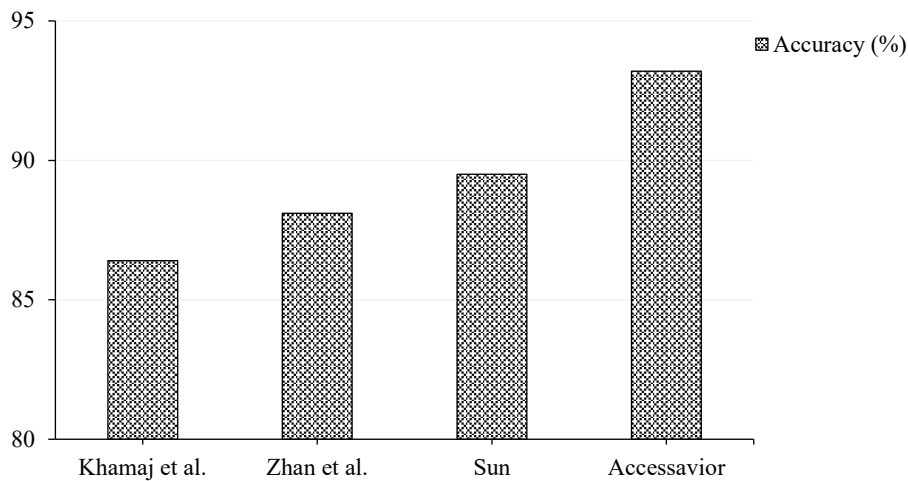


Figure 2. Model accuracy comparison.

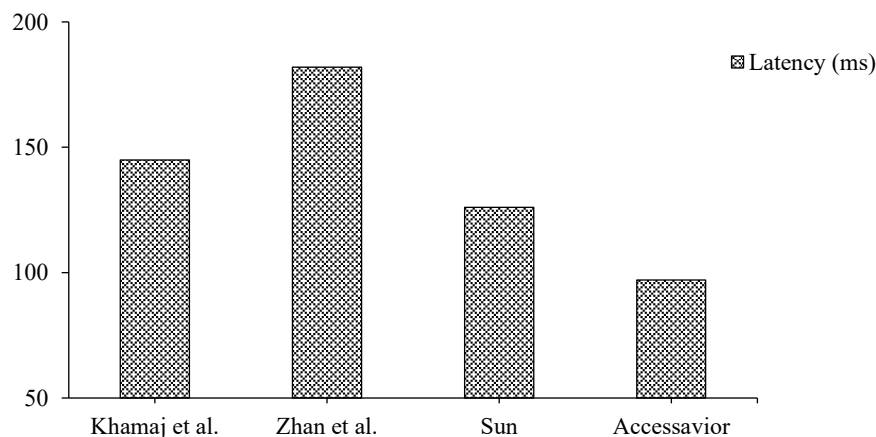


Figure 3. Model latency comparison.

CONCLUSION AND FUTURE WORK

This study introduced an adaptive web interface framework for a personalized intelligent real-time user experience based on behavioral analytics and machine learning. The proposed framework collects user interaction data and extracts the behavioral features of the user for the system and uses a hybrid ensemble method based on Random Forest, Support Vector Machine, and K-Means clustering to identify the user's preferences and produce dynamic interface adaptation. The framework continuously analyzes interaction patterns, enabling adjustments to various interface components, such as navigation, content organization, visual style, and accessibility features, to improve usability and user satisfaction.

The proposed approach was evaluated through experimental studies on 2,400 interaction sessions, and the results were successful. During testing, the framework had an accuracy of 93.2%, a precision of 91.6%, a recall value of 90.9% and an F1-score of 0.913 with an adaptation latency of 97ms. The results show that a combination of behavioral analytics and ensemble machine learning methods can achieve sufficient and efficient real-time personalization, which is better than current adaptive interface methods in terms of predictive performance and rapid response.

Future studies are planned with contextual information, including device characteristics, environmental factors, and usage goals, to further enhance the quality of adaptation. In addition, adaptive online learning techniques will be explored for the possibility of continuously adapting models and personalizing the experience over time in various web contexts.

REFERENCES

1. Todi K, Bailly G, Leiva L, Oulasvirta A. Adapting user interfaces with model-based reinforcement learning. In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*; 2021. p. 1-13. doi:10.1145/3411764.3445497.
 2. Gaspar-Figueiredo D, Fernández-Diego M, Abrahão S, Insfran E. A comparative study on reward models for user interface adaptation with reinforcement learning. *Empir Softw Eng*. 2025;30:109. doi:10.1007/s10664-025-10659-5.
 3. Sun Q, Xue Y, Song Z. Adaptive user interface generation through reinforcement learning: a data-driven approach to personalization and optimization. In: *6th International Conference on Frontier Technologies of Information and Computer (ICFTIC)*; 2024. Institute of Electrical and Electronics Engineers; p. 1386-91. doi:10.1109/ICFTIC64248.2024.10913228.
 4. Kristić M, Zakarija I, Škopljanać-Maćina F, Car Ž. Machine learning for adaptive accessible user interfaces: overview and applications. *Appl Sci (Basel)*. 2025;15:12538. doi:10.3390/app152312538.
 5. Jiang M, Huang J, Wang L. Adaptive user interfaces for wearable medical devices using deep Q-learning and Golden Jackal Optimization. *Sci Rep*. 2025;15:44776. doi:10.1038/s41598-025-28937-z. PMID:41462477.
 6. Gaspar Figueiredo D, Fernández-Diego M, Abrahão S, Insfran E. Integrating human feedback into a reinforcement learning-based framework for adaptive user interfaces. In: *Proceedings of the 29th International Conference on Evaluation and Assessment in Software Engineering*; 2025. p. 898-907. doi:10.1145/3756681.3757052.
 7. Wickramathilaka S, Grundy J, Madampe K, Haggag O. Adaptive and accessible user interfaces for seniors through model-driven engineering. *Autom Softw Eng*. 2025;32:74. doi:10.1007/s10515-025-00547-z.
 8. Findlater L, McGrenere J. A comparison of static, adaptive, and adaptable menus. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*; 2004. p. 89-96. doi:10.1145/985692.985704.
 9. Gajos KZ, Weld DS, Wobbrock JO. Automatically generating personalized user interfaces with *Supple*. *Artif Intell*. 2010;174:910-50. doi:10.1016/j.artint.2010.05.005.
 10. Peissner M, Häbe D, Janssen D, Sellner T. MyUI: generating accessible user interfaces from multimodal design patterns. In: *Proceedings of the 4th ACM SIGCHI Symposium on Engineering Interactive Computing Systems*; 2012. p. 81-90. doi:10.1145/2305484.2305500.
 11. Gheibi O, Weyns D, Quin F. Applying machine learning in self-adaptive systems: a systematic literature review. *ACM Trans Auton Adapt Syst*. 2021;15:1-37. doi:10.1145/3469440.
 12. Wang W, Khalajzadeh H, Grundy J, Madugalla A, McIntosh J, Obie HO. Adaptive user interfaces in systems targeting chronic disease: a systematic literature review. *User Model User Adapt Interact*. 2024;34:853-920. doi:10.1007/s11257-023-09384-9.
 13. Chunchu A. Adaptive user interfaces: enhancing user experience through dynamic interaction. *Int J Res Appl Sci Eng Technol*. 2024;12:949-56. doi:10.22214/ijraset.2024.64044.
 14. Jamali H, Dascalu SM, Harris FC Jr, Wu R. AI-powered adaptive learning interfaces: a user experience study in education platforms. *Front Comput Sci*. 2025;7:1672081. doi:10.3389/fcomp.2025.1672081.
 15. Hariyanto KFX, Kristianingsih FXD, Maharani R. Artificial intelligence in adaptive education: a systematic review of techniques for personalized learning. *Discov Educ*. 2025;4:458. doi:10.1007/s44217-025-00908-6.
 16. Abass A. The role of AI-driven personalization in user-centered user interface design: a systematic literature review. [Publication details not provided].
 17. Jameson A. Adaptive interfaces and agents. In: *The Human-Computer Interaction Handbook*. CRC Press; 2007. p. 459-84.
 18. Brusilovsky P, Millán E. User models for adaptive hypermedia and adaptive educational systems. In: *The Adaptive Web: Methods and Strategies of Web Personalization*. Springer Berlin Heidelberg; 2007. p. 3-53.
 19. Dey AK. Understanding and using context. *Pers Ubiquitous Comput*. 2001;5:4-7. doi:10.1007/s007790170019.
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20. Adomavicius G, Tuzhilin A. Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Trans Knowl Data Eng.* 2005;17:734-49. doi:10.1109/TKDE.2005.99.
21. Singh B, Pathania DAK. AI-driven content creation and curation in digital marketing education: tools and techniques. *Int J Eng Sci Humanit.* 2024;14:14-26. doi:10.62904/8fbh3144.
22. Kucharski S, Braun I, Damn timer G, Wählisch M. Adaptive learning mechanisms for learning management systems: a scoping review and practical considerations. *arXiv [Preprint].* 2025 Dec 20. arXiv:2512.18383.
23. Khamaj A, Ali AM. Adapting user experience with reinforcement learning: personalizing interfaces based on user behavior analysis in real-time. *Alexandria Eng J.* 2024;95:164-73. doi:10.1016/j.aej.2024.03.045.
24. Zhan X, Xu Y, Liu Y. Personalized UI layout generation using deep learning: an adaptive interface design approach for enhanced user experience. *J Artif Intell Gen Sci.* 2024;6:463-78. doi:10.60087/jaigs.v6i1.270.
25. Sun L. Adaptive interfaces for personalized user experience: a machine learning approach. In: *Proceedings of the 2025 International Conference on Artificial Intelligence and Sustainable Development*; 2025. p. 457-62. doi:10.1145/3786484.3786553.