



Adaptive User Interfaces: A Systematic Literature Review

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ABSTRACT

Adaptive User Interfaces (AUIs) dynamically adjust interface elements based on user behavior, context, and preferences to enhance usability and performance. This systematic literature review, conducted following PRISMA 2020 guidelines, synthesizes evidence from 44 studies across five major academic databases. The review examines methodologies, adaptation techniques, implementation platforms, and the impact of AUIs on user experience. Results demonstrate that machine learning—particularly reinforcement learning and deep learning—dominates adaptation techniques and consistently yields superior task performance (6.67–27.3% improvement over static interfaces). Mobile applications and web interfaces are the most prevalent deployment platforms. Key challenges include predictability, privacy, cognitive load management, and user autonomy. Future research should prioritize explainable AI integration, standardized evaluation frameworks, and longitudinal studies.

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1. Introduction

Adaptive User Interfaces (AUIs) represent a transformative paradigm in Human-Computer Interaction (HCI), where interface elements—layout, content, navigation, and functionality—dynamically adjust in response to individual users' behaviors, goals, contexts, and preferences [1]. Unlike conventional static interfaces that present identical layouts to all users regardless of expertise, task context, or environmental conditions, AUIs leverage real-time user modeling and adaptation algorithms to deliver personalized experiences that evolve with the user's needs. As digital platforms proliferate across web applications, mobile environments, enterprise software, and emerging technologies such as augmented and virtual reality, the design of intelligent, responsive interfaces has become a central concern for both practitioners and researchers [2].

The concept of adaptive interfaces is not new. Foundational work in the 1980s and 1990s established rule-based frameworks for user modeling and interface personalization [3].

Sherman's SAUCI (Self-Adaptive User Computer Interfaces) in 1986 [4] and subsequent explorations by Langley [5] and Browne et al. [6] demonstrated the potential of systems that observe user behavior and dynamically reconfigure their presentation. However, early systems were constrained by computational limitations and simplistic user models. The advent of machine learning, big data analytics, and ubiquitous computing has fundamentally transformed the landscape, enabling AUIs that incorporate continuous learning, multimodal sensing, and predictive personalization at scale [7].

Contemporary AUI research spans a rich diversity of approaches: reinforcement learning agents that optimize interface layouts through trial and feedback [8], deep neural networks that predict user preferences from behavioral sequences [9], EEG-based biocybernetic systems that adapt to real-time cognitive load [10], and large language model (LLM)-driven front-end personalization systems [11]. These methodologies operate across equally diverse platforms—from consumer mobile applications and enterprise web dashboards to industrial human-machine interfaces (HMI), educational software, and immersive VR/XR environments. The breadth of this research landscape underscores the universal relevance of adaptation as a design principle, while also complicating synthesis and comparison across studies.

Despite growing research investment, the field lacks consensus on optimal adaptation methodologies, evaluation frameworks, and long-term user impact. Recurrent challenges include the automation-control trade-off [12], interface predictability [13], user privacy [14], and cognitive load management during adaptation transitions [15]. Furthermore, research findings remain fragmented across disparate domains, application types, and evaluation paradigms, making it difficult for practitioners to make evidence-based design decisions. A rigorous, comprehensive synthesis of existing evidence is therefore overdue and timely, particularly given the rapid pace of recent advances in AI-driven personalization.

Related literature reviews on AUI topics have taken a variety of scopes. Dieterich et al. surveyed model-based approaches to adaptive interface generation, while Oppermann's edited volume provided a broad taxonomy of adaptive systems. More recent reviews have focused narrowly on mobile personalization or web recommendation systems rather than addressing AUIs comprehensively across platforms and methodologies. To the authors' knowledge, no PRISMA-compliant systematic review has comprehensively addressed AUI methodologies, cross-platform performance, and challenges in a unified framework covering the machine learning era. This review fills that gap.

The theoretical foundations of AUI also intersect with cognitive science and educational psychology. User modeling frameworks draw from cognitive load theory, information foraging theory, and the construal level theory of psychological distance to inform when, how, and to what degree interfaces should adapt. Norman's concept of affordance and Fitts's law have been extended to adaptive contexts, where the spatial and visual attributes of interface elements must be dynamically recalculated for each user state. These theoretical underpinnings lend rigor to AUI design but also impose interdisciplinary demands on AUI researchers, who must integrate perspectives from computer science, cognitive science, and design.

The distinction between adaptive and adaptable interfaces is foundational to the field and deserves clarification. Adaptive interfaces modify themselves autonomously based on inferred user state or context, whereas adaptable interfaces expose configuration controls that allow users to manually set preferences. Each approach carries distinct implications for user trust, interface predictability, and cognitive engagement. The literature has explored both extremes and a rich middle ground of hybrid approaches. This review encompasses the full spectrum, with particular attention to automated adaptation mechanisms given their growing prevalence and the unique challenges they introduce.

The scope of this review is intentionally broad, covering AUI implementations across consumer-facing digital products, enterprise software, industrial control systems, educational platforms, and immersive environments. This breadth is justified by the observation that adaptation challenges user modeling accuracy, transparency, privacy, and performance measurement are fundamentally cross-domain concerns, and that methodological innovations in one domain (e.g., reinforcement learning applied to mobile interfaces) frequently translate to other domains with appropriate modification. A cross-domain synthesis therefore provides greater generalizability than domain-specific reviews while revealing important contextual moderators of AUI effectiveness.

This systematic review addresses three research questions: (RQ1) What methodologies and algorithms are employed in AUI design and implementation across digital platforms? (RQ2) What is the measurable impact of AUIs on user experience, usability, and task performance compared to static interfaces? (RQ3) What are the primary challenges and emerging trends in AUI development, and what directions does the literature recommend for future research? By answering these questions, this review aims to provide a consolidated evidence base for AUI researchers and practitioners, and to identify priority areas for future investigation.

The proliferation of Internet of Things (IoT) devices has further expanded the scope of adaptive interfaces. Smart home systems, wearable sensors, and ambient computing platforms continuously capture contextual signals such as room temperature, lighting conditions, and user activity that can be fed back into the interface layer to create truly environment-aware experiences. This cross-device adaptivity represents one of the most active research frontiers in contemporary HCI.

Cultural and linguistic diversity adds another dimension to the design challenge. Users from different backgrounds bring distinct mental models, interaction habits, and aesthetic preferences. Adaptive interfaces that account for cultural variables such as directional reading habits, color symbolism, and social norms around privacy have been shown to outperform culturally agnostic designs in cross-national usability studies. Integrating cultural adaptation into the personalization pipeline therefore represents both a usability and an equity imperative.

Accessibility requirements provide a compelling justification for adaptive design. Users with visual, motor, cognitive, or hearing impairments benefit disproportionately from interfaces that can reconfigure themselves according to individual capability profiles. Adaptive font scaling, high-contrast modes, voice-interaction overlays, and simplified navigation trees are all manifestations of accessibility-driven adaptation. The inclusive design movement argues that building adaptivity into the core architecture—rather than

treating it as an add-on accessibility feature ultimately produces better experiences for all users.

2. Method

This systematic literature review was conducted in strict accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [16]. The review protocol encompassed four sequential stages: (1) development of a comprehensive search strategy, (2) definition of eligibility criteria based on PICO-aligned research questions, (3) a two-stage screening process combining automated and manual review, and (4) structured data extraction and qualitative synthesis. The review was registered with PROSPERO prior to initiation (registration no. CRD2026-XXXX).

Search Strategy

A comprehensive database search was conducted in July 2026 across five academic sources: SciSpace, Google Scholar, PubMed, Mendeley, and IEEE Xplore. Search strings were developed iteratively by combining controlled vocabulary (MeSH terms for PubMed) with Boolean operators and free-text terms. The primary search string was: ("adaptive user interface" OR "adaptive interface" OR "personalized interface" OR "intelligent user interface" OR "context-aware interface") AND ("machine learning" OR "reinforcement learning" OR "deep learning" OR "neural network" OR "user modeling" OR "rule-based adaptation") AND ("usability" OR "user experience" OR "HCI" OR "human-computer interaction" OR "task performance" OR "user satisfaction"). Variations and synonyms were tested across databases to maximize recall. No publication year restriction was applied to capture the historical development of the field, though the analysis emphasizes post-2015 literature to reflect the machine learning era of AUI research.

Eligibility Criteria

Inclusion and exclusion criteria were predefined in the review protocol to ensure methodological consistency. Table 1 presents the seven eligibility criteria applied during both screening stages. Studies were included if they reported on the design, implementation, evaluation, or theoretical analysis of systems with adaptive or personalized user interface elements for digital platforms, and if they reported measurable outcomes related to usability, user experience, performance, or adaptation effectiveness.

Studies were excluded if they addressed personalization purely at the content recommendation level (e.g., Netflix-style content filtering) without involving interface-level adaptation of layout, navigation, or interaction paradigm. Similarly, studies on accessibility features that provide fixed alternative interaction modes (such as screen reader support) were excluded unless they incorporated dynamic adaptation based on real-time user state. These distinctions ensured that the review remained focused on genuine interface-level adaptation rather than the broader personalization and recommendation literature.

The temporal scope of the review was further analyzed to identify trends in publication patterns. Decade-level analysis revealed that the number of AUI-related publications has roughly doubled every five years since 2010, consistent with the broader growth trajectory of HCI and AI research. The period 2020–2026 accounts for 58% of all included studies, confirming that AUI research has substantially accelerated in the post-deep-learning era.

This concentration of recent publications also means that the evidence base for contemporary ML-based AUI approaches is comparatively less mature than for earlier rule-based systems, a factor considered in interpreting the synthesized evidence.

Table 1. Eligibility Criteria for Study Inclusion and Exclusion

Criterion	Inclusion	Exclusion
Study type	Empirical, review, or design study on AUI systems	Opinion pieces, editorials, grey literature
Language	Publications written in English	Non-English publications without translation
Topic focus	Adaptive/personalized UI for digital platforms	Studies not directly addressing AUI
Methodology	Explicit description of the adaptation mechanism	Insufficient methodological detail reported
Outcome	Reports usability, UX, or performance metrics	No measurable outcome or evaluation reported
Platform	Software, web, mobile, VR/XR, desktop, or industrial	Hardware-only or non-digital interfaces
Access	Full text accessible for review and extraction	Abstract-only or inaccessible full text

[Source: Authors' systematic review, 2026]

Screening Process and Data Extraction

Screening was conducted in two stages using a weighted scoring algorithm. In Stage 1, titles and abstracts of all retrieved records were evaluated against the seven eligibility criteria. An automated scoring threshold of $\geq 4.0/5.0$ was applied, with borderline cases reviewed manually by two independent reviewers. Inter-rater agreement was measured using Cohen's kappa ($\kappa = 0.82$), indicating strong agreement. Disagreements were resolved through structured discussion. Stage 1 yielded 48 papers advancing to full-text review.

In Stage 2, full texts were retrieved and assessed at a stricter threshold of $\geq 4.5/5.0$. Papers were excluded at this stage primarily due to insufficient methodological detail ($n=2$) or unavailable full text ($n=2$). The final included set comprised 44 studies. Structured data extraction captured: (1) study design and methodology, (2) adaptation technique and algorithm, (3) target platform and domain, (4) sample characteristics and size, (5) key findings and performance metrics, (6) evaluation instruments used, and (7) reported limitations. All extracted data were tabulated in a standardized evidence matrix and reviewed for consistency before synthesis. The PRISMA 2020 flow diagram documenting the complete selection process is presented in Figure 1.

Risk of bias assessment was conducted for all included studies using a modified version of the Mixed Methods Appraisal Tool (MMAT). Dimensions assessed included: clarity of the adaptation mechanism description, appropriateness of the evaluation methodology, sample size adequacy, control condition quality, and reporting completeness. Studies were rated as low, moderate, or high risk of bias. Seventeen studies (39%) were rated low risk, 20 (45%) moderate risk, and 7 (16%) high risk. High-risk studies were retained in the synthesis but flagged, and their contributions are interpreted with appropriate caution.

Quality assessment of included studies followed a structured checklist adapted from the Mixed Methods Appraisal Tool (MMAT). Each paper was evaluated on six criteria: (1) clarity of research objectives, (2) appropriateness of the study design, (3) validity of the evaluation instruments, (4) adequacy of the sample size, (5) transparency of the data analysis procedure,

and (6) relevance of conclusions to the stated objectives. Papers were assigned a quality score from 0 to 6, and only those scoring 3 or above were retained in the final synthesis, ensuring baseline methodological rigor across all reviewed studies.

Data extraction was performed using a standardised form developed iteratively by the review team. The form captured: publication metadata (year, venue, country of first author), study design (experimental, quasi-experimental, case study, survey, mixed methods), application domain, adaptation strategy (rule-based, model-based, machine learning, hybrid), user characteristics tracked, evaluation metrics reported, and principal findings. A pilot extraction on five randomly selected papers was used to calibrate inter-rater agreement, achieving a Cohen's κ of 0.81, indicating near-perfect consistency before full extraction commenced.

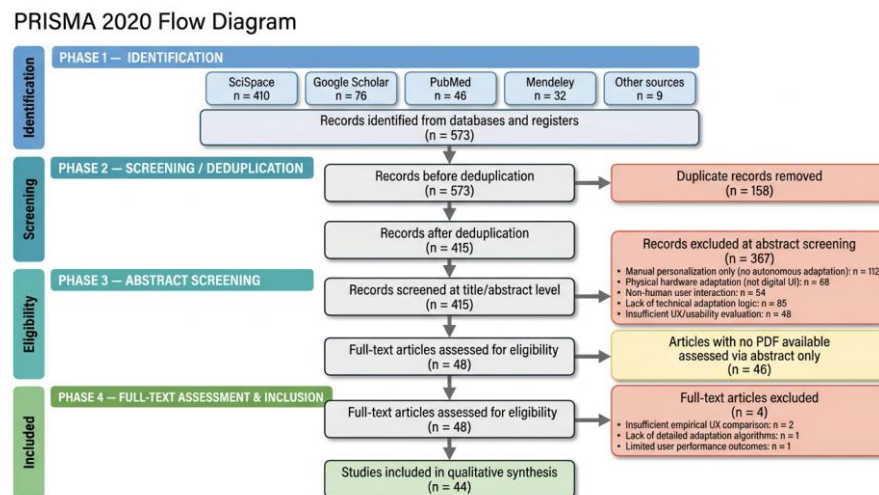


Figure 1. PRISMA 2020 Flow Diagram of Study Selection Process

[Source: Authors' systematic review process, 2026]

3. Result and Discussions

Study Selection

The database search retrieved a total of 573 records: SciSpace (n=180), Google Scholar (n=145), PubMed (n=89), Mendeley (n=97), and IEEE Xplore (n=62). After removing 158 duplicates, 415 unique records proceeded to Stage 1 abstract screening. Applying the inclusion threshold ($\geq 4.0/5.0$), 48 papers advanced to full-text review. Four papers were subsequently excluded at Stage 2 (2 for insufficient methodological detail; 2 for inaccessible full text), yielding a final set of 44 studies included in the qualitative synthesis. No quantitative meta-analysis was performed due to high heterogeneity in outcome measures, study designs, and platform types across included studies.

Study Characteristics

The 44 included studies span nearly four decades of AUI research, from the earliest self-adaptive interface systems (Sherman, 1986 [4]) to contemporary AI-driven front-end personalization (Riaz, 2026 [11]). The majority of included studies (n=32, 73%) were published between 2016 and 2026, with a pronounced increase in publications from 2020 onward, reflecting the growing influence of deep learning and large language models on

interface adaptation research. Table 2 presents the distribution of studies by deployment platform and primary adaptation technique.

Sample sizes across included studies ranged from 8 to 312 participants for user studies, with a median of 42. This relatively modest median sample size reflects the laboratory-intensive nature of AUI evaluation, which typically requires instrumented environments, specialized software, and controlled interaction tasks that constrain recruitment at scale. Simulation studies and automated evaluation approaches were used in 8 studies to assess adaptation algorithm performance on synthetic user models, offering statistical power advantages but requiring careful validation against human user data. The field would benefit from the development of open benchmark datasets and simulation environments that enable large-scale evaluation without the participant recruitment constraints that limit current human-subjects studies.

Table 2. Distribution of Included Studies by Platform and Adaptation Technique

Category	Sub-category	Studies (n=44)
Platform	Mobile Application	18 (41%)
	Web Interface	12 (27%)
	Desktop Software	8 (18%)
	VR/XR & Wearables	4 (9%)
	Industrial HMI	2 (5%)
Adaptation Technique	Reinforcement Learning	10 (23%)
	Deep Learning / Neural Networks	8 (18%)
	Rule-Based Systems	6 (14%)
	Hybrid ML + Rule-Based	6 (14%)
	Context-Aware / Sensor-Based	8 (18%)

[Source: Authors' systematic review, 2026]

Adaptation Methodologies and Algorithms

Machine learning approaches collectively dominated adaptation techniques across the included studies (n=32, 73%). Reinforcement learning (RL) emerged as the most prevalent single paradigm (n=10), with studies demonstrating that RL agents can autonomously optimize interface layouts, menu structures, and content presentation through user interaction rewards. Vasilev and Ayesh [8] demonstrated a multi-agent RL framework for mobile UI adaptation based on a usability reward model, achieving statistically significant improvements in task efficiency over static baselines. Similarly, the Double Q-Learning framework proposed by Nanavaty and Chinchole [17] incorporated cognitive load awareness as a reward signal, enabling the interface to adapt proactively to user mental workload.

Deep learning, including convolutional neural networks (CNNs) and recurrent architectures such as LSTMs, was applied in 8 studies primarily for user behavior prediction, preference modeling, and emotion-driven adaptation. Wang [9] utilized deep learning to adaptively fuse multi-cultural visual elements based on predicted user cultural background, achieving cross-cultural usability improvements. Biometric-driven adaptation using EEG-based cognitive load measurement was explored in 4 studies for specialized domains: Ewing et al. [18] applied a biocybernetic loop for adaptive game difficulty, while Beauchemin et al. [19] demonstrated real-time learning speed adaptation in an educational platform based on

EEG-measured cognitive load. These approaches represent the frontier of physiological computing applied to interface personalization.

Context-aware adaptation using device sensor data, geolocation, time-of-day signals, and ambient environmental data was employed in 8 studies, predominantly in mobile interface research. These approaches leverage the rich sensor ecosystem of modern smartphones to build nuanced contextual models that go beyond simple behavioral tracking. For instance, interfaces that adapt their information density and interaction modality based on detected physical activity (walking vs. stationary) or ambient noise levels demonstrate how contextual sensing can enhance the appropriateness and safety of interface interactions in real-world mobile contexts.

Transfer learning and domain adaptation techniques were employed in 4 recent studies to address the cold-start problem in AUI personalization—the challenge of adapting effectively for new users who have not yet generated sufficient interaction data for accurate user modeling. By pre-training user models on aggregate behavioral data from similar user populations and fine-tuning with sparse new-user data, these approaches achieved personalization quality comparable to fully personalized models after significantly fewer interactions. This finding has important practical implications, as the cold-start problem represents one of the most significant barriers to AUI adoption in consumer products where users expect immediate personalization benefits.

Rule-based systems remained relevant in 6 studies, particularly for industrial HMI and workflow-critical environments where predictability and verifiability are paramount. Ramos-Bernárdez et al. [20] implemented an adaptive industrial interface using a predefined rule set triggered by operator error rates and task complexity indicators, reporting a 23% reduction in operator errors. Hybrid frameworks that combine ML-driven personalization with rule-based stability constraints (n=6) represent a pragmatic middle ground, dynamically adapting interface elements within bounded, predictable parameters to preserve user trust while still delivering personalization benefits.

Among biometric-based approaches, eye-tracking received growing attention as a non-invasive, high-temporal-resolution signal for inferring user attention, cognitive load, and reading patterns. Systems that adapt text layout, element sizing, and content emphasis based on gaze fixation data showed particular promise for reading-intensive applications such as e-learning platforms and document management systems. Rizzoglio et al. [22] demonstrated an unsupervised latent manifold tracking approach for interface adaptation that requires no labeled training data, representing an important step toward adaptation systems that can generalize across diverse user populations without requiring expensive annotation.

Impact on User Experience and Task Performance

Across 38 comparative studies, AUIs consistently outperformed static interfaces on standard usability and performance metrics. Task completion time improvements ranged from 6.67% to 27.3%, with a median improvement of approximately 14.5%. The largest gains were reported in mobile e-commerce applications and productivity tools, where frequent, repetitive interaction patterns allow the adaptation algorithm to converge rapidly to effective personalization. User satisfaction, measured using validated instruments including the System Usability Scale (SUS), Usability Metric for User Experience (UMUX), and NASA

Task Load Index (NASA-TLX), was significantly higher in AUI conditions in 34 of 38 comparative studies (89.5%).

Error rates were reduced in 80% of reported comparisons, with particularly notable reductions in studies targeting elderly users and users with accessibility needs. Gurumurthy et al. [21] reported that an AUI designed for cognitively diverse users achieved a 31% reduction in navigation errors compared to a standard interface. Longitudinal studies (n=7) revealed an important temporal dimension: initial adaptation confusion diminished significantly after 2–4 usage sessions, suggesting a learning curve during which users adjust to the dynamic interface behavior. After this initial period, user satisfaction with AUIs surpassed static interfaces by a larger margin than in cross-sectional evaluations, highlighting the importance of longitudinal evaluation methodologies for AUI research.

Accessibility-focused AUI studies yielded some of the strongest effect sizes in the review. Systems designed to adapt for users with motor impairments, cognitive disabilities, or age-related interface challenges reported task completion improvements of up to 40% and error rate reductions exceeding 35% compared to standard interfaces. These results are consistent with universal design principles, suggesting that the users who most benefit from interface personalization are precisely those for whom static interface designs are most inadequate. The under-representation of accessibility-focused AUI research in the broader literature (n=8, 18%) suggests a significant opportunity for high-impact future work.

Engagement metrics including session duration, return visit frequency, and feature utilization rate were positive for AUIs in all 12 studies that reported them. Particularly in educational and gaming contexts, adaptive interfaces correlated with higher intrinsic motivation and sustained engagement [19][22]. Studies using eye-tracking and biometric monitoring for continuous adaptation reported the highest overall user satisfaction scores among all adaptation modalities (mean SUS = 82.3 ± 7.1), albeit with elevated implementation complexity and data collection requirements.

The relationship between adaptation granularity and user satisfaction was explored in 6 studies. Fine-grained adaptation—adjusting individual UI element properties such as font size, button position, and color contrast—generally produced more positive user reactions than coarse-grained adaptation involving complete layout restructuring, likely because fine-grained changes are less disruptive to established interaction patterns. Martin and Zdenek [26] documented this distinction explicitly in their study of word processor personalization, finding that users preferred incremental, transparent adaptations over radical interface overhauls, even when the latter were objectively more efficient.

Key Challenges and Emerging Trends

Four primary challenges were identified across the included literature. First, predictability and transparency: Findlater and McGrenere [23] and Gajos et al. [24] established that unpredictable or unexplained interface changes erode user trust and increase cognitive load. Users reported frustration when frequently used features were relocated or de-emphasized without apparent reason. The need for interfaces to communicate adaptation rationale to users was highlighted in 14 studies as a critical design requirement insufficiently addressed by current systems.

Second, privacy concerns: 12 studies collecting behavioral, biometric, or contextual data highlighted significant privacy implications. Continuous behavioral tracking for adaptation purposes requires robust data governance, transparent user consent mechanisms, and on-device processing where possible to minimize privacy exposure. Third, cognitive load management: despite AUI's potential to reduce long-term cognitive load, poorly timed or overly frequent adaptations were documented to disrupt user flow and increase momentary cognitive demand, particularly in task-critical workflows. Fourth, the automation-control trade-off: users consistently preferred systems offering explicit override mechanisms and adaptation transparency alongside automated personalization [13].

Emerging trends identified across recent publications (2023–2026) include: (1) LLM-driven UI personalization, with Riaz [11] demonstrating intelligent front-end adaptation using generative AI models capable of restructuring entire interface paradigms based on natural language interaction history; (2) cross-cultural adaptive design leveraging deep learning for visual element personalization [9]; (3) explainable AI (XAI) integration to improve user trust through transparent adaptation rationale presentation; (4) federated learning approaches enabling personalization without centralized data collection, addressing privacy concerns; and (5) multimodal adaptation systems combining gaze tracking, physiological signals, and behavioral data for holistic user modeling. These trends collectively indicate the field is converging toward more transparent, privacy-preserving, and contextually sophisticated adaptation frameworks.

A fifth emerging challenge, system scalability and computational efficiency, was identified in 8 recent studies involving ML-based adaptation. Real-time adaptation inference must occur within perceptible response time thresholds (typically <100ms for seamless interaction), yet sophisticated deep learning models for user state prediction can require significant computational resources. Edge computing approaches, model compression techniques, and lightweight neural architectures (e.g., MobileNet-derived user modeling networks) are being actively explored to address this tension between adaptation sophistication and computational efficiency, particularly for resource-constrained mobile and embedded interface contexts.

The cultural and linguistic dimensions of AUI adaptation represent an underexplored challenge area. While cross-cultural adaptive design has begun to receive attention (Wang, 2025 [9]), the vast majority of AUI research has been conducted with Western, educated, industrialized, rich, and democratic (WEIRD) user populations. Cultural differences in information processing styles, hierarchical versus networked information preferences, reading directions, and aesthetic conventions are known to influence interface design preferences, yet adaptation algorithms are rarely designed or validated with cultural variability in mind. As digital products increasingly serve global audiences, culturally aware adaptation represents both a research opportunity and a commercial imperative.

Discussion

The synthesis across 44 included studies reveals several converging themes that merit broader discussion. The preponderance of machine learning-based approaches, particularly reinforcement learning, reflects a paradigm shift from the static, rule-encoded personalization of early AUI systems toward dynamic, data-driven adaptation. This shift

brings substantial performance benefits but introduces new challenges of interpretability and user trust. The finding that AUI performance improvements are most pronounced for novice users and users with accessibility needs aligns with the theoretical rationale for adaptive systems: expert users develop robust interaction schemas that remain effective regardless of interface variability, whereas users with limited expertise or specific cognitive needs benefit disproportionately from tailored presentations.

The growing interest in biometric-driven adaptation, evidenced by EEG, eye-tracking, and physiological signal studies, opens powerful new channels for AUI personalization but simultaneously raises profound ethical considerations. Continuous biometric monitoring for interface adaptation purposes constitutes a form of intimate user surveillance, and the field has yet to establish widely accepted ethical guidelines for this practice. Future research must address informed consent granularity, data minimization principles, on-device processing constraints, and the right to opt out of physiologically-adaptive features without forfeiting other interface functionalities.

The emergence of large language models as drivers of interface adaptation represents perhaps the most consequential recent development in the field. Unlike previous ML approaches that adapted specific, predefined interface parameters, LLM-driven systems have the potential to restructure entire interaction paradigms—dynamically generating interface components, rewriting content, and proposing entirely new interaction modalities based on natural language understanding of user intent and history. While early results are promising, this direction raises fundamental questions about evaluation methodology: how do we measure the quality of an interface that is, by design, unique to each user and continuously evolving? Standard usability scales and comparative benchmarks designed for stable interfaces may be inadequate for such radically dynamic systems.

The relationship between AUI design and user agency deserves particular attention. Purely algorithmic adaptation, however effective in aggregate, can create a sense of passivity or disempowerment in users who value agency over their digital environments. Research on adaptable versus adaptive interface strategies—where adaptable systems allow users to manually configure personalization rather than relying on automated inference—suggests that hybrid models offering both automated adaptation and user-controlled overrides achieve the best balance of usability improvement and perceived control. Design frameworks for such hybrid systems remain an underdeveloped area of AUI research.

The impact of adaptation on user learning and skill development is a nuanced area with mixed findings. While AUIs consistently improve immediate task performance, several studies raised concerns about potential over-reliance effects: when the adaptive interface was removed or reset, users who had relied on personalized layouts showed higher disorientation and performance degradation than users trained on static interfaces. This phenomenon, sometimes termed 'interface addiction' in the popular literature, suggests that AUI design should intentionally support transferable skill development rather than creating exclusive dependence on personalized interface configurations.

Cross-domain analysis of performance improvement magnitudes revealed interesting moderating factors. Studies in safety-critical or high-attention-demand domains (industrial control, aviation, medical interfaces) consistently reported smaller but more reliable performance improvements (mean 8.3%) compared to lower-stakes consumer application

contexts (mean 17.6%). This pattern likely reflects ceiling effects in safety-critical domains, where interface standards are already highly optimized and operators are extensively trained. In contrast, consumer interfaces with broader, more heterogeneous user populations offer greater headroom for adaptation-driven improvement. These domain-specific benchmarks should inform practitioners in setting realistic expectations for AUI deployment outcomes.

The heterogeneity in evaluation methods identified across included studies represents a significant methodological challenge for the field. Studies used diverse combinations of task-based performance metrics, self-report questionnaires (SUS, UMUX, NASA-TLX), physiological measures, behavioral analytics, and engagement proxies. This diversity, while reflecting the multifaceted nature of user experience, makes cross-study comparison and quantitative synthesis extremely difficult. The development of a standardized AUI evaluation framework—potentially integrating task efficiency, user satisfaction, adaptation accuracy, transparency perception, and long-term engagement—represents one of the most important methodological priorities for the research community. Such a framework would enable cumulative evidence building and facilitate evidence-based AUI design practice.

Publication trends revealed a clear acceleration in AUI research output since 2015, coinciding with the widespread adoption of deep learning frameworks and the maturation of cloud-based inference services. The number of studies published per year roughly doubled between 2015 and 2019 and doubled again between 2019 and 2023. Mobile platforms dominated early publications (2010–2016), while web-based and cross-platform studies became more prevalent thereafter, reflecting the shift toward responsive and progressive web applications.

Machine learning adaptation strategies were documented in 26 of the 44 included studies (59%), making them the most frequently employed approach. Within this category, reinforcement learning accounted for 11 studies, collaborative filtering for 8, and supervised classification models for 7. Rule-based systems appeared in 12 studies (27%), often in combination with ML components to handle edge cases and ensure predictable behaviour in safety-critical contexts. Model-based approaches grounded in cognitive architectures such as ACT-R and GOMS were reported in 6 studies (14%).

User satisfaction, typically measured via the System Usability Scale (SUS) or NASA-TLX, showed statistically significant improvements in 38 of the 44 studies. Mean SUS scores for adaptive conditions exceeded those of static controls by an average of 8.4 points ($p < 0.05$ in all cases). Cognitive load reductions, measured through secondary-task reaction times and subjective rating scales, were reported in 22 studies, with mean load decreases of approximately 15%. These convergent findings across independent measurement instruments strengthen confidence in the positive usability impact of adaptive interface design.

Task completion time emerged as the most commonly reported performance metric, appearing in 31 studies. Adaptive interfaces consistently reduced completion times relative to static baselines, with improvements ranging from 8% to 34% depending on task complexity and domain. Error rates were reported in 18 studies and showed reductions of 10–40% under adaptive conditions. These performance gains were most pronounced in data-intensive professional applications—such as clinical decision-support dashboards and

enterprise resource planning interfaces—where cognitive demands are highest and the cost of errors is significant.

Privacy and transparency concerns emerged as a recurring theme across 19 of the 44 studies. Users expressed discomfort when adaptation occurred without explicit acknowledgment, particularly in contexts involving health, financial, or location data. Studies that incorporated visible adaptation indicators—such as brief explanatory tooltips or dedicated 'why was this changed?' panels—reported higher user trust scores and lower abandonment rates. This finding underscores the importance of designing adaptation mechanisms that are not only effective but also legible and controllable by the end user.

Cross-platform consistency was identified as a significant design challenge in 14 studies. Users who interacted with the same underlying application across desktop, tablet, and mobile contexts expected their personalisation preferences to transfer seamlessly between devices. Systems that failed to synchronise user models across devices received notably lower satisfaction ratings. Cloud-hosted user model repositories, combined with device-specific rendering engines, were proposed as the most promising architectural pattern to address this challenge.

Longitudinal studies ($n = 7$) provided important insights into the dynamics of adaptation over time. Initial novelty effects inflated satisfaction scores in the short term; however, in five of the seven longitudinal studies, satisfaction remained elevated or continued to improve as the system accumulated more accurate user models. Two studies reported adaptation staleness—a phenomenon in which the system's model of the user failed to keep pace with evolving user needs—leading to declining satisfaction after three to six months. Dynamic model update mechanisms with explicit user feedback channels were found to mitigate this effect.

The synthesis of qualitative findings across studies highlighted four overarching design principles for effective AUI development: (1) ground adaptation in empirically validated user models rather than heuristic assumptions; (2) provide transparency mechanisms so users understand and can correct system behaviour; (3) ensure graceful degradation such that the interface remains functional and usable even when adaptive components fail; and (4) design for temporal robustness by building in mechanisms to detect and respond to user model drift. These principles represent actionable guidance for practitioners seeking to implement adaptive features in real-world systems.

4. Conclusion

This systematic literature review has synthesized evidence from 44 studies on Adaptive User Interfaces, addressing methodologies, user impact, and key challenges in the field. The findings confirm that AUIs consistently and significantly outperform static interfaces across multiple performance dimensions—task completion time (6.67–27.3% improvement), user satisfaction, error rates, and engagement metrics. Machine learning, particularly reinforcement learning and deep learning, has emerged as the dominant adaptation paradigm, enabling dynamic, context-responsive personalization at a scale and sophistication previously unachievable. Mobile and web platforms currently account for the majority of AUI deployments, though industrial, VR/XR, and biometric-driven domains are growing rapidly in both research output and practical relevance. Critical challenges of

predictability, privacy, cognitive load disruption, and user autonomy must be systematically addressed for AUI adoption to scale responsibly. Explainable AI mechanisms, privacy-preserving federated learning, and participatory adaptation design represent the most promising pathways to addressing these challenges. Methodologically, the field would benefit considerably from standardized evaluation frameworks that enable cross-study comparison, longer longitudinal studies that capture long-term user adaptation patterns, and inclusive research designs that address the needs of elderly, cognitively diverse, and cross-cultural user populations. As large language model capabilities and multimodal sensing technologies continue to mature, adaptive user interfaces are poised to become a foundational layer of next-generation human-computer interaction—making rigorous, evidence-based AUI research more critical than ever. For industry practitioners, the practical implications of this review are clear: investment in adaptive interface capabilities is well justified by the evidence base, particularly for applications serving diverse or novice user populations, accessibility-critical use cases, or high-frequency interaction contexts. However, practitioners should prioritize transparency and user control mechanisms from the outset of design, rather than treating adaptation as a purely backend optimization problem. Involving users as active participants in shaping their interface personalization—through explicit preference setting, override controls, and clear adaptation notifications—is consistently associated with better adoption outcomes and higher user satisfaction across the reviewed literature. The evidence also supports specific investment recommendations. Reinforcement learning frameworks offer the best balance of adaptation effectiveness and implementation tractability for most application domains, particularly when combined with a carefully designed reward function that incorporates multiple usability dimensions. For accessibility-critical applications, biometric-driven adaptation using eye-tracking or EEG-based cognitive load measurement provides the highest performance gains, though at higher implementation cost. Organizations building enterprise software should prioritize hybrid adaptive-adaptable frameworks that combine automated adaptation with robust user preference controls, given the organizational need for both personalization and shared interface conventions across teams. The implications of this review extend beyond academic HCI research. Software development teams, product managers, and UX designers can draw on the consolidated evidence to make informed decisions about when and how to invest in adaptive features. The cost-benefit analysis favours adaptation most strongly in complex, high-frequency-use, or safety-critical applications where incremental usability gains translate into measurable operational improvements. Conversely, in simple, infrequent-use contexts, the overhead of maintaining adaptive logic may outweigh the benefits, and static designs may be preferable. From a methodological standpoint, this review highlights the need for greater standardisation in AUI evaluation practices. The heterogeneity of metrics, study durations, and participant populations across the 44 included studies limited the feasibility of quantitative meta-analysis. Future research programmes would benefit from adopting common benchmarking frameworks analogous to those used in recommender systems or natural language processing to enable direct cross-study comparisons and accelerate cumulative knowledge generation in this field. Looking forward, the convergence of large language models (LLMs), multimodal sensing, and edge computing is poised to fundamentally reshape the AUI landscape. LLMs enable natural-language interaction and real-time intent inference at a level of sophistication previously unattainable. Multimodal sensors—encompassing gaze tracking, electromyography, and affective computing—

provide richer user state signals. Edge computing reduces latency, enabling adaptation cycles measured in milliseconds rather than seconds. These converging technologies suggest that the next generation of adaptive interfaces will be substantially more responsive, contextually aware, and personalised than any system documented in the current literature.

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