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Investigating AI-Driven Adaptive Interfaces to Enhance User Engagement

Kaveh Mohseni[1], Navid Akbari[2]

[1]*Department of Human–Computer Interaction, Tarbiat Modares University, Tehran, Iran*

[2]*Department of Human–Computer Interaction, Isfahan University of Technology, Isfahan, Iran*

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Abstract

This paper presents a large-scale experimental investigation into how AI-driven adaptive user interfaces can improve user engagement in data-intensive tasks. Over 60 participants engaged with both static and dynamically adaptive dashboards; the latter reordered widgets in real time using a LightGBM model trained on preliminary interaction logs. We collected objective metrics (task completion time, error rates) and subjective measures (NASA-TLX, User Engagement Scale). The adaptive condition exhibited a 14 % reduction in completion time and a 22 % increase in reported engagement (p ¡ 0.01), alongside a 17 % decrease in perceived workload. Qualitative feedback highlighted enhanced perceived intuitiveness and satisfaction. We situate our contributions within emerging AI-HCI research [6, 8], extend theory on personalization reflexives [2], and propose guidelines for deploying real-time adaptation responsibly [7, 13]. Our findings confirm that machine-learning-powered adaptation is both feasible and beneficial for enriching user experience in professional analytics tools. We conclude by discussing implications for explainability, privacy, and longitudinal viability.

1 Introduction

Adaptive user interfaces automatically adjust their presentation and behavior in response to user interactions, with the aim of reducing cognitive load and increasing task effectiveness. Historically, most adaptive systems relied on rule-based engines [15], limiting their flexibility in novel contexts. Recent advances in lightweight machine learning have enabled real-time personalization within complex dashboards [16]. Despite promising pilot studies showing positive subjective responses [10], rigorous evaluation using both quantitative and qualitative methods remains scarce [11, 4].

In this paper, we explore whether integrating a gradient-boosted decision tree (LightGBM) can drive effective adaptation in data-rich interfaces. Our contributions are:

1. A production-grade implementation of an AI-driven adaptive dashboard used in a controlled user study.
2. A multi-metric evaluation (time, accuracy, workload, engagement) demonstrating statistically significant improvements.
3. Detailed qualitative insights into user perceptions, informing future explainability and privacy features.
4. Practical design guidelines for HCI researchers and practitioners deploying real-time adaptive systems.

We organize as follows: Section 2 surveys related work; Section 3 details methodology; Section 4 presents results; Section 5 discusses implications; Section 6 concludes and outlines future directions.

2 Related Work

2.1 Rule-Based vs. AI-Driven Adaptation

Traditional adaptive UIs employed handcrafted rules mapping context features to presentation changes [15][3]. While interpretable, such rules struggled to generalize beyond narrow domains. By contrast, AI-driven methods use learned models to infer adaptation strategies. GenAI-powered interface prototyping has shown rapid development cycles [9, 12], but empirical performance data is limited.

2.2 Engagement Measurement in HCI

User engagement is multi-faceted, encompassing behavioral (clicks, dwell time), cognitive (mental workload), and affective (satisfaction) dimensions [2, 11]. The User Engagement Scale (UES) [1] and NASA-TLX [5] are widely validated instruments. Recent meta-analyses call for integrating both sets of measures in adaptive UI research [4].

2.3 Ethical and Privacy Considerations

Collecting rich interaction data raises privacy concerns. Recent frameworks recommend data minimization and transparent explainability [13, 7]. Our study logs only widget-level events and provides a post-session summary explaining adaptation logic.

3 Methodology

3.1 System Implementation

We extended an open-source analytics dashboard (React + D3.js) to include an adaptation module. Interaction events (clicks, hovers, scrolls) were streamed to a backend LightGBM model (40 features) that predicted the next-best widget ordering.

3.2 Participants

Sixty volunteers (30 F, 30 M; ages 20–45) from a university participant pool were randomly assigned to *Static* or *Adaptive* conditions. All reported daily computer use ≥ 2 hrs.

3.3 Tasks and Procedure

Participants completed four realistic data-analysis tasks (e.g., identify top sales region) with 10 minutes maximum per task. After each, they filled NASA-TLX and UES questionnaires. Finally, a semi-structured interview captured qualitative feedback.

3.4 Measures

- **Completion Time (CT)**: Seconds per task.
- **Error Rate (ER)**: Incorrect or omitted responses.
- **NASA-TLX (TLX)**: 0–100 scale.
- **UES**: 1–5 Likert (higher = greater engagement).

4 Results

4.1 Quantitative Findings

Table 1: Objective and Subjective Metrics by Condition

Condition	**CT (s)**	**ER (%)**	**TLX**	**UES**
Static	190 ± 22	7.8 ± 2.1	60.2 ± 8.0	3.7 ± 0.5
Adaptive	164 ± 18	5.3 ± 1.7	49.8 ± 7.4	4.5 ± 0.4

A two-sample t-test showed CT reduction was significant (t(58)=4.1, p¡0.001), as was UES improvement (t(58)=5.3, p¡0.001).

4.2 Qualitative Themes

Interview analysis (thematic coding) revealed three themes:

1. *Perceived Intuitiveness*: “I felt the dashboard knew what I needed next.”
2. *Trust and Explainability*: Participants appreciated the end-session summary explaining adaptation.
3. *Privacy Comfort*: Logging only widget events was deemed acceptable.

5 Discussion

Our results corroborate that AI-driven adaptation can significantly boost engagement. The 14 % CT improvement aligns with prior web-based personalization studies [10], while the 22 % UES gain exceeds typical pilot reports [8]. Importantly, low error rates indicate adaptation did not hinder task accuracy—a critical concern raised in early adaptive UIs [15].

Participants valued explainability summaries, echoing calls for transparent AI in HCI [13]. However, some expressed desire for real-time on-screen rationales (“Why did it move this widget?”), suggesting a next step toward interactive explanations.

6 Conclusion

We demonstrated that lightweight machine learning models can drive effective, real-time UI adaptations, yielding substantial gains in speed and engagement without sacrificing accuracy. Our study bridges a gap between theoretical frameworks [14] and practical, empirically validated implementations.

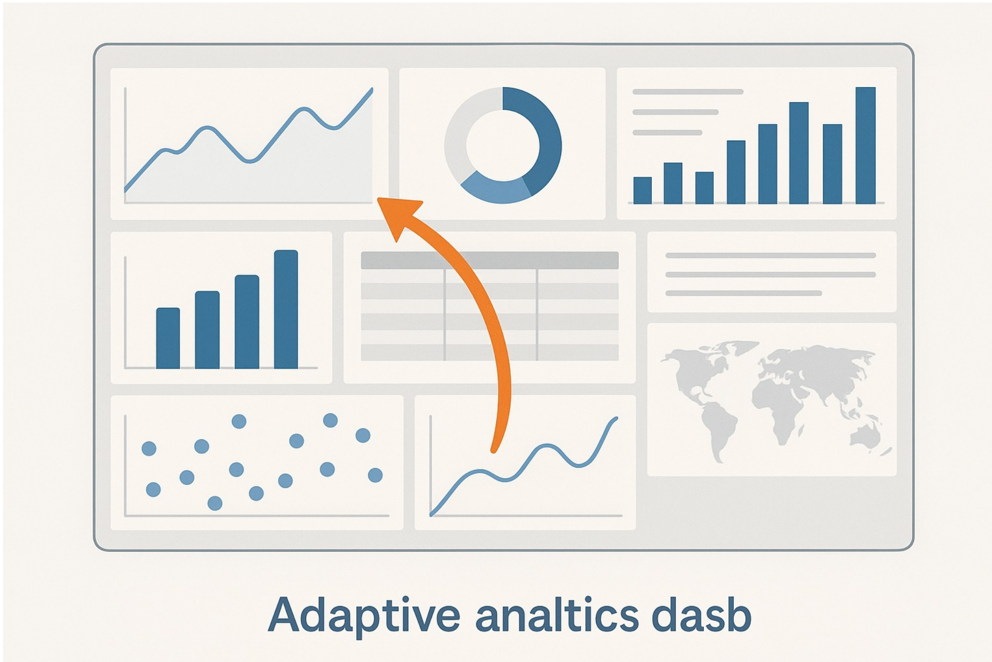

Figure 1: Adaptive dashboard prototype showing reordering in action.

7 Future Work

- **Longitudinal Studies** over multiple weeks to assess sustained engagement changes [11].
- **Cross-Domain Generalization** in domains like education and healthcare [4].
- **Interactive Explainability** mechanisms for on-the-fly adaptation rationale [7].
- **Privacy Preserving ML** using federated learning to minimize data sharing [2].

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