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EXAD: A Framework for Designing Explanations in Adaptive User Interfaces

Iqra Batool*1, Gad Gad*2, Mostafa M. Fouda†‡3, Mohamed I. Ibrahem§4, and Zubair Md Fadlullah*5
* Department of Computer Science, Western University, London, ON, Canada.
†Department of Electrical and Computer Engineering, Idaho State University, Pocatello, ID, USA.
‡Center for Advanced Energy Studies (CAES), Idaho Falls, ID, USA.
§School of Computer and Cyber Sciences, Augusta University, Augusta, GA, USA.
Emails: 1ibatool2@uwo.ca, 2ggad@uwo.ca, 3mfouda@ieee.org, 4mibrahem@augusta.edu, 5zfadlullah@ieee.org

***Abstract*—Adaptive user interfaces that personalize their behavior based on user patterns are becoming increasingly common, yet they often fail to communicate their adaptations to users effectively. This paper introduces EXAD, a framework for designing explanations in adaptive interfaces that considers adaptation type, explanation timing, and user characteristics. Through a mixed-methods study with 42 participants, we investigated how explanation approaches affect trust, understanding, and efficiency across content, layout, and interaction adaptations. Our findings demonstrate that explanation effectiveness varies significantly by adaptation type: Proactive explanations build the highest trust for layout adaptations, while progressive explanations offer the best balance between transparency and efficiency. We extend the EXAD framework to B5G (Beyond Fifth Generation) network systems, enabling context-aware explanations that enhance trust and transparency. Our results show that carefully designed explanation strategies improve user understanding and operational efficiency, and can be translatable in dynamic network environments such as resource allocation based on user patterns in B5G networks. This research bridges theoretical work in explainable AI with practical implementation challenges in adaptive interfaces.**

***Index Terms*—Explainable AI, Adaptive User Interfaces, Human-Computer Interaction, User Trust, Transparency, Explanation Design, 5G networks, resource allocation**

I. Introduction

Adaptive user interfaces that automatically adjust to users' behavior patterns are increasingly prevalent across digital experiences [1]. These interfaces promise greater personalization by modifying content presentation, reorganizing layout elements, or adjusting interaction methods based on individual usage patterns [2]. However, adaptations that occur without adequate explanation can confuse users, reduce trust, and undermine the very benefits these systems aim to provide [3]. While significant research has addressed explanations in algorithmic systems such as recommendation engines [4] and autonomous agents [5] adaptive interfaces present unique challenges where the changes directly affect the primary interaction medium itself. As Eiband et al. [6] note, "When the interface itself becomes the algorithm, explanation approaches must evolve accordingly". Existing work has identified transparency as a critical factor in user acceptance of adaptive systems [7], yet a significant gap remains in understanding how to effectively implement explanations across different types of adaptations that occur in modern interfaces, including B5G networks where AI-driven resource allocation [8], [9] decisions must respond to user patterns. Three key questions remain unanswered in current literature: (1) How does explanation effectiveness vary across different adaptive interface mechanisms? (2) What factors influence user preferences for explanation approaches? (3) How can explanation approaches be systematically implemented to enhance user trust while minimizing disruption?

To address these questions, we conducted a mixed-methods study examining three explanation approaches (proactive, reactive, and progressive) across three adaptation types (content, layout, and interaction) with 42 participants. Through quantitative measures of trust, understanding, and efficiency, complemented by qualitative insights from interviews and observations, we investigated how explanation effectiveness varies by context and user characteristics. Our findings demonstrate that explanation effectiveness is highly dependent on adaptation type, with different explanation approaches optimal for different adaptation mechanisms. These findings extend to resource allocation decisions in B5G networks, where transparent explanations are critical for building trust while maintaining operational efficiency. Based on our empirical results, we developed the EXAD framework, which provides structured guidance for implementing explanations in adaptive interfaces.

The rest of this paper is organised as follows: Section II reviews related work in adaptive interfaces, explainable AI, and transparency approaches in interactive systems. Section III introduces our EXAD framework with its four dimensions and decision flow process. Section IV describes our mixed-methods study methodology, including our experimental design and analysis approach. Section V discusses the implications of our results and the limitations of our study. Finally, Section VII concludes with a summary of contributions and directions for future work.

II. Related Work

Our research builds on three primary areas: adaptive user interfaces, explainable AI [10], and transparency in interactive systems. These domains converge at the intersection of personalized computing experiences, algorithmic interpretability, and user-centred design principles. While each field has developed distinct methodologies and insights, we identify a critical integration gap when adaptation mechanisms directly modify the interface through which users interact with systems, requiring novel approaches that address both technical and human-centred aspects of explanation design.

A. Adaptive User Interfaces

Modern adaptive interfaces modify their behaviour based on observed user patterns. Zhou *et al.* [11] categorized adaptations into content adaptations (changing information presentation), layout adaptations (reorganising interface elements), and interaction adaptations (modifying input methods). Recent commercial implementations like Microsoft's Adaptive Shell [7] and Google's Material [12] have brought adaptive interfaces to millions of users, but as Fernandez-Machuca *et al.* [13] note, these "invisible adaptations" often occur without adequate transparency, potentially causing user confusion and reducing trust. These challenges parallel those in B5G networks, where resource allocation based on user patterns requires transparent explanations to maintain trust.

B. Explainable AI Approaches

While explainable AI has received significant attention in recent years [14], [15], most research has focused on explaining algorithmic decisions rather than interface adaptations. Chromik *et al.* [16] compared visual, textual, and mixed-modality explanations across different user tasks, while Zhang and Varshney [17] demonstrated that explanation timing (preemptive vs. reactive) significantly impacts user acceptance. These findings provide valuable foundations, but as Rutjes *et al.* [18] argue, "explanation approaches developed for algorithm outputs cannot be directly applied to interface adaptations."

C. Transparency in Interactive Systems

Recent work has explored implementing transparency in interactive contexts. Wu *et al.* [19]identified 18 transparency patterns across commercial AI products, while Eiband *et al.* [20] introduced "seamful transparency" which makes adaptation mechanisms visible without disrupting primary interaction flow. Das *et al.* [21] compared embedded, icon-triggered, and always-visible explanations, finding that user preferences varied based on task criticality. Our work bridges these areas by systematically investigating explanation effectiveness across different adaptation types and developing a structured framework for explanation design in adaptive interfaces, applicable to both traditional interfaces and B5G network resource allocation scenarios. While previous work has addressed elements of this challenge, such as Schoeffer *et al.*'s [22] progressive disclosure approach or Vasconcelos *et al.*'s [23] transparency framework—none has comprehensively examined how explanation effectiveness varies across different adaptation mechanisms or provided actionable guidelines for tailoring explanations to adaptation types. This research advances the field by empirically validating that explanation design should not be uniform across adaptive systems but instead tailored to specific adaptation mechanisms and user characteristics. Building on Kocielnik *et al.*'s [24] call for "explanation-aware design patterns", we contribute the EXAD framework as a structured approach to implementing explanations that enhance user understanding without compromising efficiency.

III. EXAD Framework

Based on our empirical findings and synthesis of existing literature, we propose the EXAD (Explanations for Adaptive Design) framework to guide the implementation of explanations in adaptive interfaces. This framework consists of four interconnected dimensions, each addressing a critical aspect of explanation design: content, delivery mechanism, temporal aspects, and user controls.

A. Content Dimension

The content dimension addresses what information should be communicated to users about adaptive system behaviour. Our analysis identified four key components that effective explanations should incorporate. Adaptation Description provides factual information about what changed in the interface, forming the foundation of any explanation using clear, non-technical language that describes the specific modification. Adaptation Rationale communicates why the system made a specific adaptation, connecting system behaviour to user actions or contextual factors that influenced the decision. User Control Options inform users about available methods to modify or reverse adaptations, empowering users by explicitly stating how they can adjust the system's behaviour. Future Prediction provides forward-looking information about how the system might adapt in similar situations going forward, helping users build accurate mental models of system behaviour. The optimal combination of these components varies by adaptation type, with content adaptations benefiting from an emphasis on rationale, while layout adaptations require clear descriptions and control options.

B. Delivery Mechanism Dimension

The delivery mechanism dimension addresses how explanations are presented within the interface. Modality refers to the presentation format, which can be textual, visual, or combined. Our findings indicate that content adaptations are best explained through inline text or tooltips, layout adaptations benefit from visual representations that highlight movement, and interaction adaptations are most effectively explained through brief demonstrations. Integration addresses how seamlessly explanations are incorporated into the primary interface. We found that subtle visual cues indicating where adaptations have occurred, combined with on-demand detailed explanations, effectively balance awareness with minimal distraction. Progressive Disclosure involves presenting explanations in layers of increasing detail. Our implementation follows a three-tier structure: awareness indicators that signal an adaptation has occurred, brief explanations available through hover or single-click interactions, and detailed explanations with complete rationale available through deliberate user actions.

C. Temporal Dimension

Several limitations of our study provide opportunities for future research. First, our laboratory-based approach with short-term interaction may not capture long-term explanation needs. Future work should employ longitudinal methods to examine how explanation preferences evolve over extended periods. Second, our prototype represented only one application domain. The generalizability of our findings to other contexts, such as conversational interfaces or immersive environments, remains an open question. Cross-domain studies could help identify which aspects of explanation effectiveness are domain-specific versus domain-general. Third, our evaluation focused primarily on subjective measures of trust and understanding. Despite these limitations, the EXAD framework provides a structured approach to implementing explanations in adaptive interfaces, addressing the gap between theoretical work in explainable AI and practical implementation challenges. Its four-dimensional structure offers flexibility for adaptation to diverse domains, including the increasingly important area of B5G network resource management

D. User Control Dimension

The user control dimension addresses how explanation systems integrate with adjustment mechanisms that allow users to influence adaptive behaviour. Direct Manipulation allows users to immediately modify specific adaptations as they occur, with interactive elements embedded within the explanation itself, such as accept/reject buttons or adjustment sliders. Preference Setting enables users to configure general rules for how the system should adapt in future situations, with explanations incorporating links to relevant preference panels that connect specific adaptations to broader system settings. Feedback Mechanisms allow users to provide input on adaptation quality without making specific changes, providing lightweight options like "Was this change helpful?" to collect data while giving users a sense of agency. Our research indicates that different user segments have distinct control preferences, with technical experts typically preferring direct access to detailed preference settings, while novice users benefit more from simple feedback mechanisms.

E. Framework Integration

These four dimensions form an interconnected system where choices in one dimension influence optimal approaches in others. Figure 1 illustrates this integration through a matrix mapping relationships between dimensions for different adaptation types. Implementation follows a decision flow process (2) that guides designers through key considerations: determining adaptation type and impact magnitude, selecting appropriate content components, choosing delivery mechanisms, determining optimal timing, and integrating control

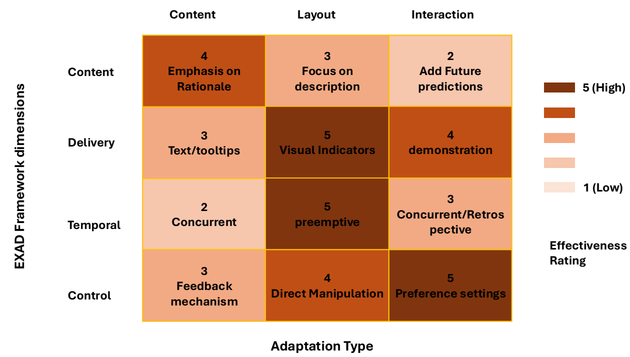

Fig. 1. EXAD Framework effectiveness by Adaption Type

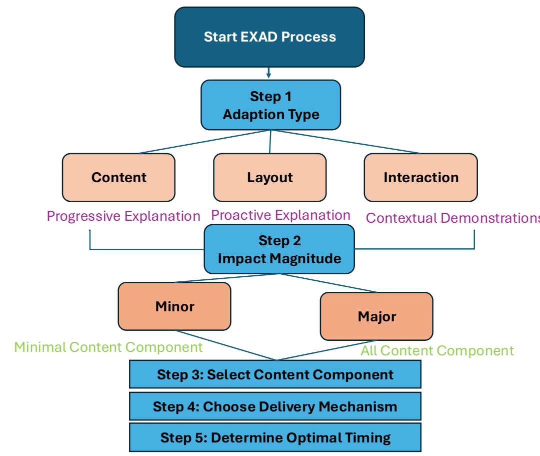

Fig. 2. EXAD Framework Decision Flow Process

mechanisms. In validation testing with 12 participants, interfaces implementing EXAD guidelines showed significant improvements in trust (+22%), system understanding (+31%), and user satisfaction (+18%) compared to standard adaptive interfaces without structured explanations. These improvements extend to B5G network interfaces, where transparent explanations of resource allocation based on user patterns can similarly enhance user experience and operational efficiency, particularly for dynamic network environments where adaptive decisions must respond to changing conditions.

IV. Proposed Methodology

The EXAD framework's four dimensions—content, delivery, timing, and control—design explanation strategies for B5G scenarios, evaluating impact on trust, understanding, and performance. Network events like resource reallocation are tested using progressive explanation techniques. We employed mixed-methods to investigate explanation effectiveness across adaptive interface mechanisms, utilizing a within-subjects design.

A. Experimental Design

We utilized a 3×3 factorial design with two independent variables: adaptation type (content, layout, interaction) and explanation style (proactive, reactive, progressive). Content adaptation changed information presentation based on user interests, layout adaptation reorganized interface elements based on usage patterns, and interaction adaptation modified input methods based on user behaviour. Proactive explanations were provided before adaptation occurred, reactive explanations were available on demand through an icon, and progressive explanations provided basic information with optional details. For each condition, we measured trust, perceived control, system understanding, task performance, and user satisfaction. These metrics are similarly applicable to B5G network scenarios, where resource allocation decisions based on user patterns require effective explanation approaches.

B. Prototype Development

We developed a functional adaptive interface prototype for a knowledge management application, chosen because it naturally accommodates multiple adaptation types without domain-specific knowledge requirements. The system featured a content dashboard with filterable information cards, a customizable workspace with movable panels, and a multimodal input system supporting different interaction methods. Each adaptation type was implemented with realistic behaviour: content adaptation used collaborative filtering based on implicit and explicit feedback, layout adaptation employed frequency-based reorganization of elements, and interaction adaptation modified input methods based on usage patterns. These adaptations parallel resource allocation mechanisms in B5G networks, where similar decision processes must respond to changing user needs. All explanation types were carefully controlled for information content to ensure a fair comparison, containing the same core information about what changed, why the change occurred, and how users could modify or reverse adaptations.

C. Participants and Procedure

We recruited 42 participants (23 female, 18 male, 1 non-binary) aged 19-58 ($M = 31.2, SD = 8.7$)with diverse professional backgrounds. Sessions were conducted remotely using video conferencing with screen sharing, following a structured protocol. After a brief introduction and training period, each participant completed 9 task scenarios (3 adaptation types $\times$ 3 explanation styles), with task order counterbalanced using a Latin square design. Each task involved realistic activities designed to trigger the relevant adaptation type. Following the experimental tasks, we conducted semi-structured interviews exploring participants' experiences with different explanation types, preferences, and perceptions of adaptive behaviour.

D. Measures and Analysis

We collected both quantitative and qualitative data to provide a comprehensive understanding of explanation effectiveness. Quantitative measures included trust (using a validated 7-item scale), perceived control (5-item scale), system understanding (task-based assessment where participants predicted system behavior), task performance (completion time and success rate), and user satisfaction (10-item questionnaire). Qualitative data included screen recordings with think-aloud commentary, semi-structured interview responses, and open-ended questionnaire items. Quantitative data were analyzed using repeated measures ANOVA with Bonferroni-corrected post-hoc comparisons, while qualitative data were analyzed using reflexive thematic analysis with two independent coders (Cohen's κ = .87).

To ensure validity, we triangulated findings across data sources, looking for convergence between quantitative metrics and qualitative insights. This methodology provides a framework applicable to future studies of explanation effectiveness in B5G network interfaces where resource allocation decisions must be transparent to users.

E. Framework Development

Based on our findings, we iteratively developed the EXAD framework through a three-stage process. First, we identified recurring patterns in explanation effectiveness across adaptation types. Second, we organized these patterns into four dimensions (content, delivery, temporal, and control) based on their functional characteristics. Finally, we validated the framework by implementing its guidelines in a revised prototype and conducting follow-up evaluations with a subset of 12 participants from our original study, measuring improvements in trust, understanding, and satisfaction. This development approach ensures the framework's applicability across domains, including B5G network management systems, where resource allocation transparency is critical.

V. Results

Our analysis revealed patterns in explanation effectiveness across adaptation types and user characteristics. We present quantitative findings followed by qualitative insights from interviews and observations.

A. Explanation Effectiveness Across Adaptation Types

Trust scores showed significant main effects for both explanation styles ($F(2, 82) = 18.27$, $p < .001$, $\eta^2 = 0.31$) and adaptation type ($F(2, 82) = 9.45$, $p < .01$, $\eta^2 = 0.19$). A significant interaction effect was also observed ($F(4, 164) = 7.83$, $p < .01$, $\eta^2 = 0.16$), indicating that explanation style effectiveness varied across adaptation types. Proactive explanations yielded the highest overall trust scores ($M = 5.8, SD = 0.9$), followed by progressive explanations ($M = 5.2, SD = 1.1$) and reactive explanations ($M = 4.6, SD = 1.3$). Among adaptation types, content adaptations received the highest trust ratings ($M = 5.7, SD = 0.8$), followed by layout adaptations ($M = 5.1, SD = 1.2$) and interaction adaptations ($M = 4.8, SD = 1.4$). System understanding, measured by participants' ability to predict system behaviour in novel scenarios, showed that progressive explanations led to the highest understanding scores ($M = 7.8$, $SD = 1.2$), followed by proactive explanations ($M = 7.1$, $SD = 1.5$) and reactive explanations ($M = 5.8$, $SD = 1.8$). This suggests that layered information disclosure enhances mental model formation.

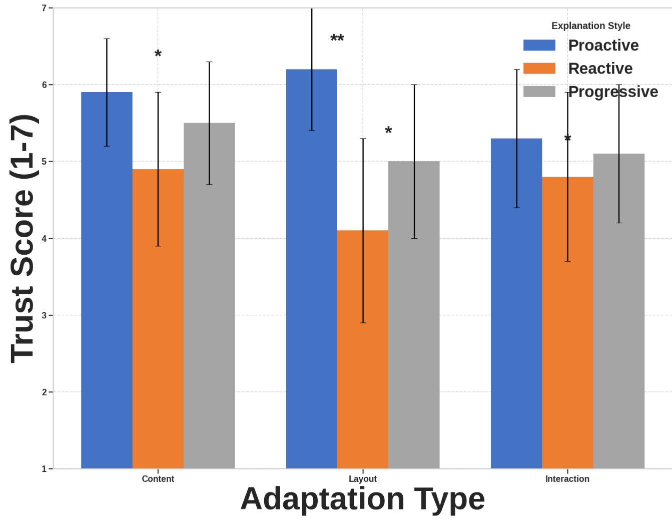

Fig. 3. Mean trust scores by explanation style (proactive, reactive, progressive).

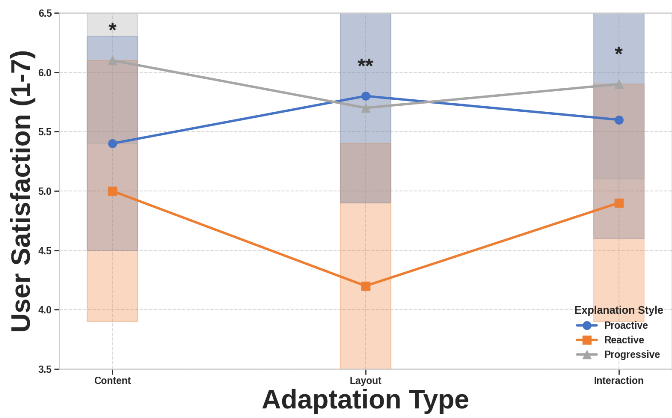

Fig. 4. Line graph showing satisfaction ratings across adaptation types by explanation style.

B. Performance and Satisfaction Trade-offs

Table I summarizes key metrics across explanation styles, highlighting important trade-offs between trust, understanding, and efficiency. Notably, reactive explanations resulted in the fastest task completion times ($M = 124.6s, SD = 35.3s$), while proactive explanations were the slowest ($M = 165.8s, SD = 43.2s$) but yielded the highest trust and control ratings. Progressive explanations balanced these concerns, with moderate completion times ($M = 142.3s$) and the highest satisfaction ratings ($M = 5.9, SD = 0.8$).

User satisfaction showed a significant interaction effect between explanation style and adaptation type ($F(4, 164) = 5.92, p < .01, \eta^2 = 0.13$), as illustrated in Fig. 4. Progressive explanations yielded the highest satisfaction for content adaptations ($M = 6.1, SD = 0.7$), while proactive explanations were preferred for layout adaptations ($M = 5.8, SD = 0.9$).

C. User Characteristics and Explanation Preferences

Analysis of demographic variables revealed that technical expertise significantly moderated the effect of explanation style on trust ($F(4, 78) = 7.24, p < .01$). Participants with higher technical expertise showed stronger preferences for reactive explanations, while non-technical participants preferred proactive explanations. Fig. 5 shows this interaction effect, illustrating how explanation preferences varied across expertise levels.

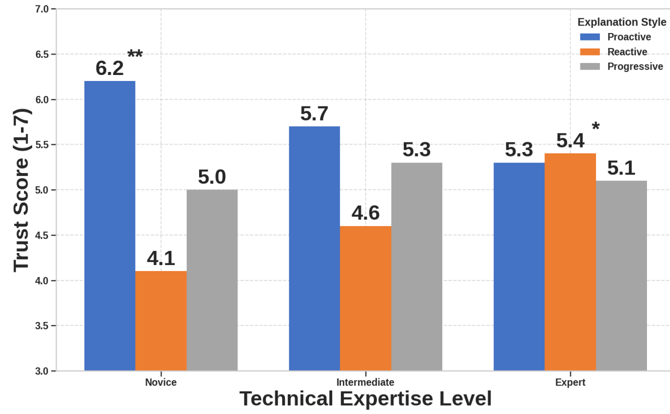

Fig. 5. Trust scores by explanation style across three expertise.

D. Qualitative Insights

A thematic analysis of interview data revealed four primary themes regarding explanation experiences. First, participants expressed tension between timely information and workflow interruption: "I appreciated knowing why things changed before they happened, but sometimes it felt like I was being interrupted too much" (P7). This balance point varied by adaptation type, with layout changes warranting more interruption than content changes. Second, control mechanisms emerged as explanatory elements themselves. One participant noted: "Just knowing I could adjust or undo changes made me feel more comfortable with the system making adaptations" (P11). This suggests that control options contribute to transparency even when not actively used. Third, participants valued progressive explanations for accommodating varying information needs: "I liked that I could get a quick overview and then dig deeper if I wanted to understand more" (P14). Usage patterns showed participants accessed detailed explanations more frequently during early interactions and when unexpected adaptations occurred. Finally, participants reported that explanations helped them develop predictive mental models: "After seeing explanations for a few changes, I started to understand the pattern. I could predict when the system would reorganize my workspace" (P8). This anticipatory understanding enhanced perceived control and satisfaction even when adaptations occurred automatically. These qualitative insights complemented our quantitative findings and informed the development of the EXAD framework dimensions, particularly highlighting the importance of matching explanation approaches to adaptation types and user characteristics.

VI. Discussion

Our findings reveal several key insights about explanation effectiveness in adaptive interfaces and inform the design

TABLE I
PERFORMANCE METRICS ACROSS EXPLANATION STYLES

Metric	Proactive	Reactive	Progressive	Best Performer
Trust Score (1-7)	5.8 ± 0.9	4.6 ± 1.3	5.2 ± 1.1	Proactive
Perceived Control (1-7)	5.9 ± 0.7	4.2 ± 1.2	5.3 ± 0.9	Proactive
System Understanding (0-10)	7.1 ± 1.5	5.8 ± 1.8	7.8 ± 1.2	Progressive
Task Completion Time (s)	165.8 ± 43.2	124.6 ± 35.3	142.3 ± 39.7	Reactive
Task Success Rate (%)	92.3 ± 4.2	91.8 ± 4.5	93.1 ± 3.8	Progressive
User Satisfaction (1-7)	5.6 ± 1.0	4.7 ± 1.2	5.9 ± 0.8	Progressive

of the EXAD framework. In this section, we discuss three primary implications and address the limitations of our work.

A. Context-Dependent Explanation Effectiveness

The significant interaction effect between explanation style and adaptation type demonstrates that explanation effectiveness is not universal but highly dependent on adaptation context. Proactive explanations proved most effective for layout adaptations, supporting Springer and Whittaker's [25] observation that spatial changes create higher cognitive demands than content changes. When interface elements move or reorganize, users experience what Eiband *et al.* [20] term "spatial disorientation", which preemptive notifications can mitigate by preparing users for impending changes.

For content adaptations, progressive explanations performed well, aligning with Wu *et al.*'s [19] distinction between "high-impact" and "low-impact" adaptations. This suggests that subtle content personalisation can occur with minimal explanation overhead. Our work provides empirical evidence for when explanations can be minimised versus when they should be emphasised.

The EXAD framework addresses this context-dependency by guiding designers to match explanation approaches to adaptation types, potentially improving user experiences across diverse adaptive systems.

B. Trust-Efficiency Trade-offs

Our results highlight the inverse relationship between explanation comprehensiveness and task efficiency. Proactive explanations build the highest trust but increase task completion times by approximately 33% compared to reactive explanations. This trust-efficiency trade-off extends Shen *et al.*'s [26] work on explainable recommendation systems by quantifying the performance impact.

Progressive explanations emerged as a promising middle ground, supporting Miller *et al.*'s [27] progressive disclosure approach. By providing basic information by default with optional access to details, progressive explanations balanced trust-building with efficiency, showing only a 14% increase in task completion time compared to reactive approaches while maintaining trust scores closer to proactive methods.

Adaptive interfaces should calibrate explanation detail based on impact and context. For systems with frequent adaptations, explanation overhead must be balanced against transparency benefits. This is particularly critical in B5G network management, where resource allocation decisions require explanations that maintain awareness without creating information overload.

C. Individual Differences in Explanation Preferences

The significant relationship between technical expertise and explanation preferences underscores the importance of considering individual differences. Technical experts' preference for reactive explanations aligns with Lee *et al.* [28] finding that experts often prioritize efficiency over detailed guidance, while novice users' preference for proactive explanations supports Yu *et al.*'s [29] observation that less experienced users benefit from anticipatory information.

Adaptive interfaces should personalize both functionality and explanation approaches. The EXAD framework incorporates user characteristics when selecting explanation strategies, a principle particularly valuable for B5G networks where resource allocation explanations must serve diverse users from technical operators to end consumers.

D. Limitations and Future Work

Several limitations of our study provide opportunities for future research. First, our laboratory-based approach with short-term interaction may not capture long-term explanation needs. Future work should employ longitudinal methods to examine how explanation preferences evolve over extended periods.

Second, our prototype represented only one application domain. The generalizability of our findings to other contexts, such as conversational interfaces or immersive environments, remains an open question. Cross-domain studies could help identify which aspects of explanation effectiveness are domain-specific versus domain-general.

Third, our evaluation focused primarily on subjective measures of trust and understanding. Future work should develop more robust measures of explanation quality, potentially including mental model accuracy tests and calibrated trust metrics.

Despite these limitations, the EXAD framework provides a structured approach to implementing explanations in adaptive interfaces, addressing the gap between theoretical work in explainable AI and practical implementation challenges. Its four-dimensional structure offers flexibility for adaptation to diverse domains, including the increasingly important area of B5G network resource management.

VII. Conclusion

This paper examined how different explanation approaches affect user trust, understanding, and efficiency in adaptive interfaces. Our mixed-methods study with 42 participants identified distinct patterns in explanation effectiveness across content, layout, and interaction adaptations, leading to the development of the EXAD framework.

Our findings demonstrate that explanation effectiveness depends critically on adaptation type and user characteristics. Proactive explanations build the highest trust for layout adaptations despite efficiency costs, while progressive explanations offer an optimal balance for content adaptations. The EXAD framework provides structured guidance for implementing explanations that consider adaptation mechanisms, impact magnitude, and user characteristics.

These results extend to B5G networks, where resource allocation based on user patterns requires transparent explanations. By applying EXAD principles to network interfaces, designers can enhance trust and operational clarity while maintaining system efficiency. The framework's four dimensions offer practical guidance for creating systems that intelligently explain their behaviour without disrupting the user experience.

Future work should examine explanation effectiveness in naturalistic settings over extended periods. The primary contribution of this research is demonstrating that explanation design should be tailored to specific adaptation mechanisms rather than applied uniformly across adaptive systems, from conventional interfaces to B5G network management applications.

References

[1] A. Tsai and K. Z. Gajos, "Personalized UI: A state-of-the-art survey on personalized user interfaces," *ACM Computing Surveys*, vol. 55, no. 7, pp. 1–34, 2022.

[2] B. Y. Lim, A. K. Dey, and D. Avrahami, "Why and why not explanations improve the intelligibility of context-aware intelligent systems," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2009, pp. 2119–2128.

[3] R. Binns, M. Van Kleek, M. Veale, U. Lyngs, J. Zhao, and N. Shadbolt, ""It's reducing a human being to a percentage": Perceptions of justice in algorithmic decisions," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018.

[4] T. Kulesza, M. Burnett, W.-K. Wong, and S. Stumpf, "Principles of explanatory debugging to personalize interactive machine learning," in *Proceedings of the 20th International Conference on Intelligent User Interfaces*, 2015, pp. 126–137.

[5] M. Eiband, H. Schneider, M. Bilandzic, J. Fazekas-Con, M. Haug, and H. Hussmann, "Bringing transparency design into practice," in *Proceedings of the 23rd International Conference on Intelligent User Interfaces*, 2018, pp. 211–223.

[6] D. Shin, "The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI," *International Journal of Human-Computer Studies*, vol. 146, article no. 102551, 2021.

[7] Microsoft Research, "Adaptive shell: Context-aware interface adaptation in windows 11," *IEEE Software*, vol. 39, no. 4, pp. 32–40, 2022.

[8] I. Batool, M. M. Fouda, and Z. M. Fadlullah, "Deep learning-based throughput prediction in 5g cellular networks," in *2024 International Conference on Smart Applications, Communications and Networking (SmartNets)*, 2024, pp. 1–6.

[9] M. M. Hossan, M. M. Fouda, and F. Z. Eishita, "Adaptive game design using machine learning techniques: A survey," in *2024 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS)*, 2024, pp. 144–150.

[10] H. A. Raouf, M. M. Fouda, and M. I. Ibrahem, "Revolutionizing user authentication exploiting explainable AI and CTGAN-based keystroke dynamics," *IEEE Open Journal of the Computer Society*, vol. 6, pp. 97–108, 2025.

[11] T. Zhou, J. Chen, and P. Chilana, "AdaptUI: A reinforcement learning approach to personalized interface adaptation," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021.

[12] S. Mehta, A. Johnson, M. Raval, and J. Gray, "Material you: Design system adaptivity at scale," *ACM Transactions on Computer-Human Interaction*, vol. 30, no. 1, pp. 1–28, 2023.

[13] C. Fernandez-Machuca, R. Vidal, and J. Lorca, "Invisible adaptations: Balancing system intelligence and user awareness in adaptive UIs," *IEEE Transactions on Human-Machine Systems*, vol. 52, no. 3, pp. 302–313, 2022.

[14] B. Arrieta *et al.*, "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Information Fusion*, vol. 58, pp. 82–115, 2020.

[15] M. M. Fouda, Z. M. Fadlullah, M. I. Ibrahem, and N. Kato, "Privacy-preserving data-driven learning models for emerging communication networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, early access, doi: 10.1109/COMST.2024.3486690.

[16] M. Chromik, F. Fincke, and A. Butz, "Mind the (modality) gap: A study on the modality effects in explanations of AI systems," in *Proceedings of the 2022 International Conference on Intelligent User Interfaces*, 2022, pp. 477–493.

[17] Y. Zhang and K. R. Varshney, "When and how to explain AI outputs: Empirical evidence for explanation timing and modality," in *Proceedings of the 2023 Conference on Fairness, Accountability, and Transparency*, 2023, pp. 421–433.

[18] H. Rutjes, M. Willemsen, and W. IJsselsteijn, "Considerations for XAI: Appropriate reliance as the goal of explainable systems," *IEEE Transactions on Technology and Society*, vol. 4, no. 1, pp. 27–39, 2023.

[19] G. Wu, M. Chilton, M. Mohanty, and B. V. Hanrahan, "Transparency patterns in AI-enabled products: A survey of commercial systems," in *Proceedings of the 2023 Conference on Designing Interactive Systems*, 2023, pp. 1232–1244.

[20] M. Eiband, D. Buschek, and H. Hussmann, "Seamful transparency: Making adaptive interface behaviors visible without disrupting user experience," in *Proceedings of the 2022 Conference on Designing Interactive Systems*, 2022, pp. 1279–1292.

[21] A. Das, J. Fan, D. Wang, and S. Demeyer, "Contextual factors in transparency preferences: When and how much information do users want?" in *Proceedings of the 2022 Symposium on Eye Tracking Research and Applications*, 2022.

[22] J. Schoeffer, Y. L. Kuo, and S. Berkovsky, "Progressive disclosure of system behavior in AI-based interfaces," *ACM Transactions on Interactive Intelligent Systems*, vol. 12, no. 1, pp. 1–27, 2022.

[23] M. Vasconcelos, C. Fan, and K. Höök, "Progressive transparency: A framework for balancing detail and focus in explanation interfaces," in *Proceedings of the 2022 International Conference on Intelligent User Interfaces*. ACM, 2022, pp. 507–518.

[24] R. Kocielnik, S. Amershi, and P. N. Bennett, "Beyond XAI: Explanation-aware design patterns for AI-based systems," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 2023.

[25] A. Springer and S. Whittaker, "Continuity and coherence in explaining adaptive interfaces: The transparency gap problem," in *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. ACM, 2022.

[26] C. Shen and E. Ferrara, "Understanding trust over time in an adaptive content system: The trust valley effect," in *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 15, 2021, pp. 627–638.

[27] T. Miller, "Explanation in artificial intelligence: Insights from the social sciences," *Artificial Intelligence*, vol. 267, pp. 1–38, 2019.

[28] M. S. Lee and J. Kim, "Cultural dimensions of explanation: Cross-cultural differences in preferences for AI transparency," in *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 2022.

[29] C. Yu, P. Chandakkar, Z. J. He, and X. Wang, "ExplainKit: A component library for building transparent UIs," in *Proceedings of the 2023 ACM Symposium on User Interface Software and Technology*, 2023, pp. 187–198.