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The Impact of the Immediate Interaction Systems in User Experience of Traditional Digital Interfaces

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ABSTRACT The present study explores how exposure to immediate interaction systems, specifically short-form content platforms and Large Language Model (LLM) based assistants, may influence user experience within traditional digital interfaces in terms of tolerance, efficiency, and satisfaction. The study aims to contribute to the understanding of how contemporary digital technologies may be reshaping users' cognitive and behavioral expectations when interacting with traditional digital systems, representing an increasingly relevant topic for future UX, HCI, and cognitive computing research. To achieve this, a quantitative and comparative approach based on performance and perception metrics commonly used in usability and user experience research is proposed. The results reveal consistent behavioral tendencies across usability, cognitive workload, and efficiency measures, supporting the proposed research hypothesis. In particular, exposure level showed a strong negative relationship with perceived usability while positive correlations were identified between exposure level and cognitive workload-related dimensions such as frustration, effort, and temporal demand. The obtained findings contribute exploratory evidence suggesting that exposure to contemporary digital interaction habits may influence how users perceive, process, and interact with conventional digital systems. From a practical perspective, the study highlights potential implications for interface design, particularly in systems that require sustained attention, sequential navigation, or prolonged interaction processes.

INDEX TERMS User experience, Human-computer interaction, Cognitive workload, Usability metrics, Digital interface design

I. INTRODUCTION

IN recent years, the digital ecosystem has become increasingly dominated by technologies designed to provide rapid interactions, immediate responses, and continuous information consumption. Short-form content platforms such as TikTok, Instagram Reels, and YouTube Shorts have transformed digital interaction patterns through highly personalized recommendation systems and constant streams of short-duration audiovisual stimuli. Simultaneously, the accelerated growth of Large Language Model (LLM)-based assistants, such as ChatGPT and Gemini, has enabled users to obtain immediate responses for tasks traditionally associated with sequential processes of information search and analysis.

Recent studies suggest that frequent exposure to digital systems optimized for immediate interaction may influence cognitive processes related to sustained attention, working memory, and executive control. Research on short-form content platforms has identified associations between intensive consumption of short-duration videos and reduced sustained attention capacity due to constant context switching, instant gratification mechanisms, and cognitive overstimulation [12]. Similarly, studies on digital consumption and instant gratification indicate that continuous social media usage promotes scanning behavior patterns and fragmented information processing, making tasks that require deep reading and prolonged concentration more difficult [11].

From the perspective of Cognitive Load Theory (CLT), modern interfaces are increasingly designed to reduce extraneous cognitive load through automation, simplified navigation, and immediate feedback [13], [16]. Within the field of Human-Computer Interaction (HCI), this tendency has promoted the development of systems focused on minimizing cognitive friction and accelerating result acquisition, particularly in mass-consumption digital platforms and artificial intelligence-based assistants.

Recent HCI and web usability studies have demonstrated that cognitive load directly influences user experience metrics such as task completion time, abandonment rate, permanence, and perceived satisfaction [8]. Complementarily, studies focused on cognitive workload measurement in HCI emphasize the importance of behavioral and perceptual metrics, such as NASA-TLX, task completion time, and usability indicators, to evaluate user performance during interaction with digital interfaces [14].

In the context of artificial intelligence assistants, recent investigations suggest that immediate conversational interactions may promote cognitive offloading processes, where users delegate cognitive tasks to automated systems, reducing the mental effort required for activities involving analysis, problem solving, and information retrieval [5]. Similarly, research on LLM-based interfaces indicates that these technologies can significantly reduce perceived cognitive workload and simplify interaction with complex systems [4].

Despite the growing body of evidence regarding sustained attention, cognitive workload, and immediate interaction systems, there is still limited understanding of how these interaction patterns may influence user experience within traditional digital interfaces. In particular, a research gap exists regarding whether frequent exposure to short-form content platforms and LLM-based assistants may be associated with changes in user tolerance toward prolonged tasks, interaction efficiency, and satisfaction when interacting with conventional digital systems.

Therefore, the present study proposes evaluating how exposure to immediate interaction systems, specifically short-form content platforms and LLM-based assistants, influences user experience within traditional digital interfaces in terms of tolerance, efficiency, and satisfaction. To achieve this, a quantitative and comparative approach based on performance and perception metrics commonly used in usability and user experience research is proposed.

The study seeks to contribute to the understanding of how contemporary digital technologies may be reshaping users' cognitive and behavioral expectations when interacting with traditional digital systems, providing relevant evidence for future research in Human-Computer Interaction, user experience, cognitive workload, and cognitively-centered interface design.

II. METHODOLOGY

A. RESEARCH DESIGN

The present study was developed under a quantitative approach with a correlational-comparative experimental and cross-sectional design, oriented toward the analysis of user experience within traditional digital interfaces according to the level of exposure to immediate interaction systems.

The study focuses on evaluating how frequent use of short-form content platforms and Large Language Model (LLM)-based assistants may influence variables related to tolerance, efficiency, and satisfaction during interaction with conventional digital interfaces.

The experimental design was structured through a task-based usability test complemented with standardized cognitive workload and perceived usability evaluation instruments.

The research process was organized according to the following evaluation model:

1) Digital exposure pre-test using an adapted Social Media Usage Scale (SMUS).
2) Task-based usability evaluation.
3) Task-specific cognitive workload assessment using NASA-TLX.
4) Global usability evaluation using the System Usability Scale (SUS).

The main objective of the experimental design was to identify possible behavioral and cognitive differences between participants with different levels of exposure to immediate interaction systems.

B. PARTICIPANTS

The sample consisted of 13 university students enrolled in engineering and digital technology-related programs.

Participants were selected through non-probabilistic convenience sampling considering accessibility and availability within the experimental environment.

1) Inclusion Criteria

- Being an active university student.
- Regular use of digital devices.
- Voluntary acceptance to participate in the study.
- Completion of all evaluation instruments.

2) Exclusion Criteria

- Participants who abandoned the experimental session.
- Incomplete questionnaire responses.
- Duplicate or inconsistent records.

To preserve confidentiality, each participant was identified through a unique participant ID.

C. RESEARCH VARIABLES

1) Independent Variable

The independent variable corresponds to the level of exposure to immediate interaction systems, understood as the frequency, duration, and intensity of use of short-form content platforms and artificial intelligence-based assistants.

This variable represents the potential factor associated with behavioral changes during interaction with traditional interfaces.

2) Exposure Metrics

- Daily usage hours.
- Weekly frequency of use.
- Frequency of LLM-based assistant usage.
- Preference for immediate interaction mechanisms.
- Short-form digital consumption habits.

3) Dependent Variables

The dependent variables of the study were tolerance, efficiency, and user satisfaction during interaction with traditional digital interfaces.

a: Tolerance

Tolerance refers to the user's ability to maintain interaction during prolonged tasks requiring sustained attention.

Metrics:

- Task permanence time.
- Task abandonment rate.

b: Efficiency

Efficiency represents the participant's ability to complete tasks successfully within the interface.

Metrics:

- Task completion time.
- Number of errors.
- Task success rate.

c: Satisfaction

Satisfaction evaluates the subjective perception of the user regarding the interaction experience.

Metrics:

- System Usability Scale (SUS).
- Perceived difficulty.
- Frustration level.

D. MEASUREMENT INSTRUMENTS

1) Adapted SMUS Questionnaire

To evaluate digital exposure levels, an adapted version of the Social Media Usage Scale (SMUS) was used, incorporating additional questions related to the use of generative artificial intelligence assistants.

The instrument included questions regarding:

- Frequency of short-form content consumption.
- Daily usage time.
- Usage of platforms such as TikTok, Reels, and Shorts.
- Frequency of use of assistants such as ChatGPT or Gemini.
- Preference for immediate responses.
- Digital interaction habits.

Responses were measured through Likert scales and frequency-based metrics.

An exposure index was later generated to classify participants into:

- Low exposure group.
- High exposure group.

2) NASA-TLX

To evaluate perceived cognitive workload during each experimental task, the NASA Task Load Index (NASA-TLX) was used in its Raw TLX version [15].

The instrument was applied immediately after each task.

The evaluated dimensions included:

- Mental demand.
- Temporal demand.
- Effort.
- Perceived performance.
- Frustration.
- Perceived complexity.

Each dimension was evaluated using a 5-point Likert scale.

The use of NASA-TLX enabled quantitative measurement of cognitive workload generated during the interaction process, which has been widely used in Human-Computer Interaction and cognitive workload studies [14].

3) System Usability Scale (SUS)

Global usability perception was evaluated through the standardized System Usability Scale (SUS).

The questionnaire consisted of 10 alternating positive and negative statements evaluated using a 5-point Likert scale.

The final SUS score was calculated using the standard scoring procedure:

- Positive statements: response - 1.
- Negative statements: 5 - response.
- Final sum multiplied by 2.5.

This instrument allowed the evaluation of perceived ease of use, consistency, and overall usability of the interface.

E. EXPERIMENTAL ENVIRONMENT

The experimental evaluation was conducted using a web-based interface called "CleanMindset," designed to simulate a traditional digital system involving sequential navigation, multiple-step processes, and sustained attention tasks.

The experimental environment was configured under homogeneous conditions for all participants.

1) Environment Configuration

- Device: Laptop computer.
- Browser: Google Chrome.
- Interaction through mouse and keyboard.
- Stable internet connection.
- Uniform application of instructions.

All participants completed the experiment under the same interaction flow.

F. EXPERIMENTAL TASKS

The experimental evaluation consisted of five tasks designed to generate different levels of cognitive workload, sustained attention, and interaction complexity.

1) T1 – Service Identification Under Ambiguity

This task evaluated the participant's ability to correctly identify a service under conditions of ambiguity and information overload.

Related variables:

- Sustained attention.
- Cognitive workload.
- Information selection.

2) T2 – Availability Verification in Restricted Zone

This task evaluated navigation efficiency and rapid information localization within the interface.

Related variables:

- Efficiency.
- Response time.
- Directed navigation.

3) T3 – Opinion Credibility Evaluation

This task measured analytical capability, contextual comparison, and inconsistency detection.

Related variables:

- Sustained attention.
- Contextual memory.
- Cognitive evaluation.

4) T4 – Service Reservation with Distractors

This task was designed to evaluate working memory, tolerance, and sequential task performance under multiple distractors.

Related variables:

- Cognitive workload.
- Frustration.
- Tolerance.
- Working memory.

5) T5 – Payment Completion and Error Detection

This task evaluated logical reasoning, information validation, and error detection before transaction completion.

Related variables:

- Attention to detail.
- Cognitive verification.
- Sequential processing.

G. EXPERIMENTAL PROCEDURE

The experimental procedure was conducted sequentially according to the following stages:

1) Stage 1 – Informed Consent

Participants received information regarding the purpose of the study and participation conditions before beginning the experiment.

2) Stage 2 – Adapted SMUS Application

Participants completed the digital exposure questionnaire to determine their level of exposure to immediate interaction systems.

3) Stage 3 – Participant Classification

Based on the obtained exposure scores, participants were classified into high- or low-exposure groups.

4) Stage 4 – Task-Based Usability Evaluation

Participants completed the five experimental tasks within the CleanMindset interface.

During this stage, the following metrics were recorded:

- Task completion time.
- Number of errors.
- Abandonment rate.
- Task success rate.

5) Stage 5 – NASA-TLX Application

After each task, participants completed the corresponding NASA-TLX evaluation.

6) Stage 6 – SUS Application

After completing all tasks, participants answered the System Usability Scale questionnaire.

H. DATA ORGANIZATION AND ANALYSIS

Collected data were organized using Microsoft Excel spreadsheets and CSV files compatible with Python-based analysis.

Each row represented a participant and each column corresponded to a specific metric or variable.

1) Descriptive Analysis

The following descriptive statistics were calculated:

- Mean.
- Median.
- Standard deviation.
- Frequencies.
- Percentages.

2) Group Comparison

Results were compared between:

- High exposure participants.
- Low exposure participants.

3) Statistical Techniques

Due to the reduced sample size, the study was approached from an exploratory perspective.

The proposed statistical techniques included:

- Spearman correlation.
- Mann-Whitney U test.
- Comparative descriptive analysis.

I. ETHICAL CONSIDERATIONS

The research was conducted following ethical principles related to:

- Informed consent.
- Voluntary participation.
- Data confidentiality.
- Participant anonymity.
- Academic-only use of collected information.

Participants were allowed to withdraw from the experiment at any moment.

J. METHODOLOGICAL LIMITATIONS

The primary methodological limitations of the study include:

- Reduced sample size.
- Non-probabilistic sampling.
- Partially adapted exposure instrument.
- Cross-sectional design.
- University-specific experimental context.

Despite these limitations, the study provides relevant exploratory evidence regarding the influence of immediate interaction systems on user experience within traditional digital interfaces.

III. RESULTS

This section presents the findings obtained from the analysis of exposure to immediate interaction systems, perceived usability, cognitive workload, and task efficiency. The results are reported through descriptive and inferential analyses supported by selected figures and tables that best represent the observed behavioral and cognitive trends.

A. EXPOSURE LEVEL DISTRIBUTION

Participants were classified into *Low Exposure* and *High Exposure* groups according to their SMUS/EESII exposure scores. The obtained scores presented moderate variability and an approximately balanced distribution between groups, allowing comparative analysis between participant profiles.

The overall exposure score mean was 3.08, while the median threshold used for group separation was 3.35. No extreme outliers or severe skewness were identified in the distribution.

Fig. 1 presents the exposure score distribution obtained from the adapted SMUS/EESII instrument.

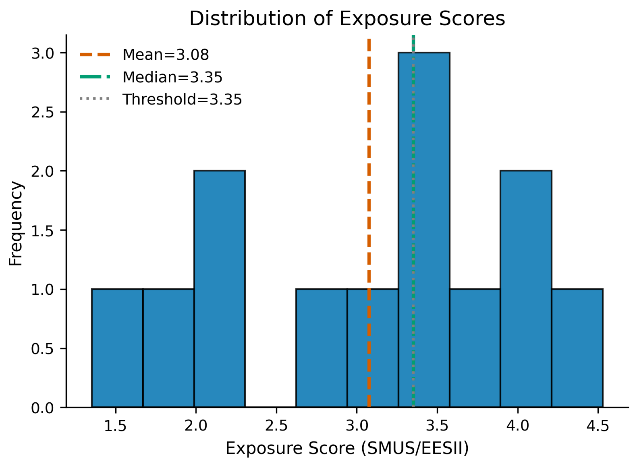

FIGURE 1. Distribution of exposure scores based on the adapted SMUS/EESII questionnaire.

B. SYSTEM USABILITY SCALE (SUS) RESULTS

The usability analysis revealed noticeable differences between exposure groups. Participants classified within the *Low Exposure* group consistently reported higher perceived usability scores compared to participants with higher exposure to immediate interaction systems.

As summarized in Table 1, the *Low Exposure* group obtained a mean SUS score of approximately 76, corresponding to a "good" usability range according to standard SUS interpretation models. In contrast, the *High Exposure* group obtained a mean score near 66, indicating lower perceived usability during interaction with the evaluated interface.

Fig. 2 illustrates the SUS score distribution for both exposure groups.

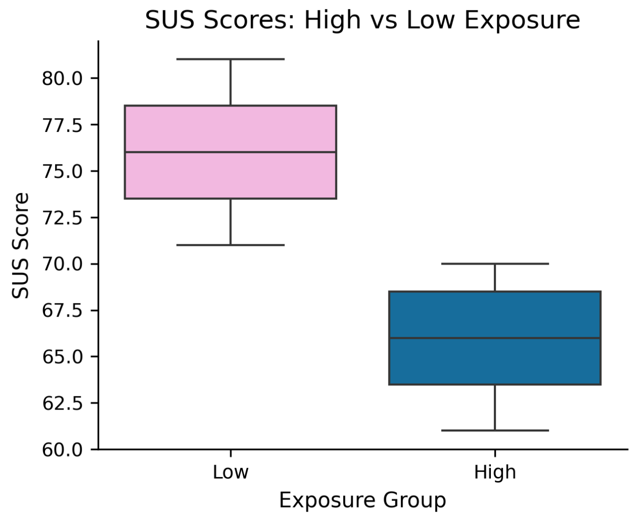

FIGURE 2. Distribution of SUS scores by exposure group.

ExposureGroup	High	Low
n	6.00	7.00
mean	65.83	76.00
sd	3.49	3.56
median	66.00	76.00
min	61.00	71.00
max	70.00	81.00

TABLE 1. Descriptive statistics of SUS scores by exposure group.

Table 2 summarizes the results of the inferential analysis.

Variable	n_High	n_Low	Median_High	Median_Low	U	p	r	d
SUS	6	7	66.00	76.00	0.00	0.00	1.00	-2.88
NASA Mental Demand	6	7	3.70	2.80	42.00	0.00	-1.00	3.68
NASA Temporal Demand	6	7	3.75	2.40	41.00	0.01	-0.95	2.56
NASA Effort	6	7	3.45	2.40	39.50	0.01	-0.88	2.20
NASA Performance	6	7	2.15	3.60	0.00	0.00	1.00	-4.43
NASA Frustration	6	7	3.85	2.40	42.00	0.00	-1.00	5.49
NASA Complexity	6	7	4.30	2.60	42.00	0.00	-1.00	6.53
Completion Time	6	7	244.00	217.60	42.00	0.00	-1.00	3.62
Abandonment	6	7	9.00	0.00	28.00	0.30	-0.33	0.71

The observed results suggest that participants with higher exposure to immediate interaction systems perceived lower usability and demonstrated greater cognitive difficulty during task execution.

C. COGNITIVE WORKLOAD ANALYSIS (NASA-TLX)

NASA-TLX results revealed consistent differences between exposure groups across multiple workload dimensions. Participants in the *High Exposure* group reported higher levels of mental demand, temporal demand, effort, frustration, and perceived complexity compared to participants with lower exposure levels.

Conversely, the *Low Exposure* group generally reported lower workload values and better perceived task performance.

Fig. 3 presents the workload distributions for each NASA-TLX dimension across exposure groups.

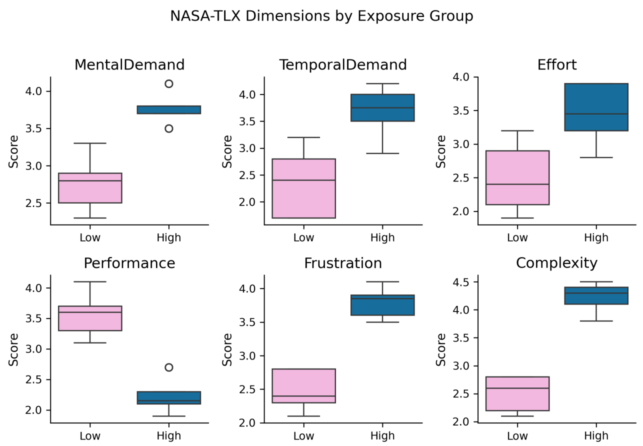

FIGURE 3. NASA-TLX workload dimension distributions by exposure group.

Among the evaluated dimensions, frustration and perceived complexity showed the clearest separation between groups, suggesting that participants with higher exposure levels experienced greater cognitive strain during prolonged interaction tasks.

Table 3 summarizes the descriptive statistics obtained from the NASA-TLX evaluation.

	n	mean	sd	median	min	max
MentalDemand	65.00	3.20	0.57	3.30	2.30	4.10
TemporalDemand	65.00	2.95	0.85	2.90	1.70	4.20
Effort	65.00	2.92	0.65	2.90	1.90	3.90
Performance	65.00	2.94	0.73	3.10	1.90	4.10
Frustration	65.00	3.08	0.71	2.80	2.10	4.10
Complexity	65.00	3.31	0.90	2.80	2.10	4.50

TABLE 2. Descriptive statistics of NASA-TLX dimensions (collapsed across tasks).

Overall, the workload analysis indicates that exposure to highly stimulating digital environments may be associated with increased cognitive demand during interaction with traditional digital interfaces.

D. TASK EFFICIENCY AND COMPLETION TIME

Task efficiency analysis showed moderate differences between groups regarding task completion time and interaction consistency.

Participants within the *High Exposure* group generally required more time to complete the assigned tasks, particularly during tasks involving sequential navigation, information validation, and sustained attention processes.

Fig. 4 presents the mean completion time comparison between groups across the evaluated tasks.

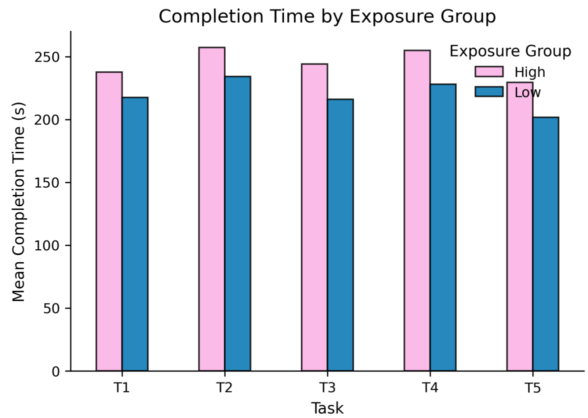

FIGURE 4. Mean completion time comparison between exposure groups across tasks.

Although the observed differences were moderate rather than extreme, participants with higher exposure levels exhibited greater variability and lower interaction consistency during task execution.

E. CORRELATION ANALYSIS

To further examine the relationships among exposure, usability, workload, and efficiency variables, a Spearman correlation analysis was conducted.

The obtained results revealed coherent behavioral relationships among the evaluated variables. In particular, exposure level showed a strong negative relationship with perceived usability, while positive correlations were identified between exposure level and workload-related dimensions such as frustration, effort, and temporal demand.

Similarly, higher workload levels were associated with longer task completion times and lower perceived usability.

Fig. 5 presents the Spearman correlation matrix obtained from the experimental data.

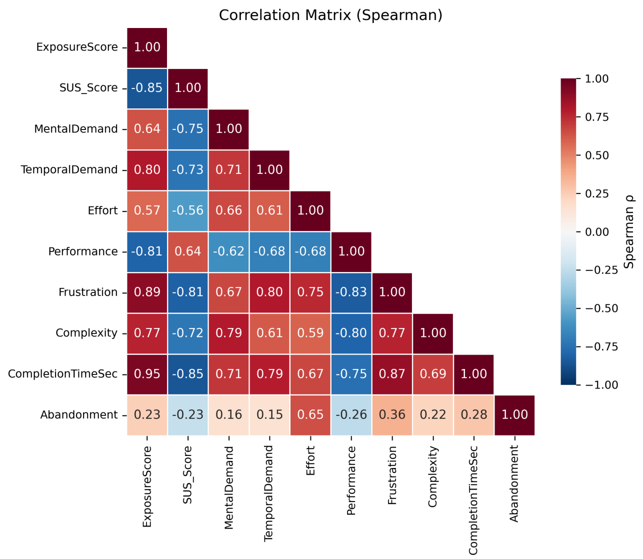

FIGURE 5. Spearman correlation matrix among exposure, usability, workload, and efficiency variables.

The observed relationships followed consistent behavioral tendencies and aligned with the patterns identified throughout the descriptive analyses.

F. SUMMARY OF FINDINGS

Overall, the obtained results indicate that participants with higher exposure to immediate interaction systems tended to:

- report lower perceived usability scores,
- experience higher cognitive workload levels,
- exhibit increased frustration and perceived effort,
- and require more time to complete interaction tasks.

Although the observed differences were moderate rather than extreme, the consistency across usability, workload, and efficiency measures suggests the presence of meaningful behavioral tendencies associated with exposure to immediate interaction systems.

IV. DISCUSSION

The present study explored how exposure to immediate interaction systems, specifically short-form content platforms and LLM-based assistants, may influence user experience within traditional digital interfaces. The obtained results revealed consistent behavioral tendencies across usability, cognitive workload, and efficiency measures, supporting the proposed research hypothesis.

Participants classified within the *High Exposure* group generally reported lower perceived usability scores, higher workload levels, greater frustration, and longer task completion times compared to participants with lower exposure levels. Although the observed differences were moderate rather than extreme, the consistency across multiple variables suggests that prolonged exposure to highly stimulating digital environments may influence user expectations and interaction behavior during sustained digital tasks.

One of the most notable findings was the difference observed in perceived usability. Participants with lower exposure levels obtained higher SUS scores overall, while participants with higher exposure levels consistently reported lower usability perception during interaction with the evaluated interface. These findings may suggest that users accustomed to rapid-response systems and highly optimized interaction flows could exhibit lower tolerance toward interfaces requiring sequential navigation, delayed feedback, or prolonged attention processes.

This tendency aligns with previous research regarding short-form digital consumption and sustained attention. Lin *et al.* [12] identified that continuous exposure to short-form video platforms may negatively affect sustained attention capabilities due to constant context switching and rapid stimulus consumption. Similarly, Mokry [11] discussed how environments driven by instant gratification can promote fragmented information processing behaviors and reduce tolerance for cognitively demanding activities.

The workload analysis also revealed important patterns. Participants within the *High Exposure* group reported higher levels of mental demand, effort, temporal demand, frustration, and perceived complexity across multiple tasks. These findings are consistent with principles derived from Cognitive Load Theory (CLT), which suggests that interfaces generating excessive cognitive friction or requiring prolonged processing may negatively affect user performance and experience [16].

From a Human-Computer Interaction perspective, the results support arguments proposed by Oviatt [13], who emphasized that interface design increasingly prioritizes cognitive load reduction and interaction simplification. Modern digital systems, particularly social media platforms and AI-driven interfaces, are optimized to minimize interaction effort and accelerate information acquisition. Consequently, users frequently exposed to these environments may gradually adapt to interaction models centered around immediacy and reduced cognitive resistance.

The observed workload patterns are also coherent with findings reported by Akintunde [8], who highlighted the direct relationship between cognitive load and web usability metrics such as task completion time, frustration, and user satisfaction. In the present study, participants with higher exposure levels not only perceived greater workload but also demonstrated lower perceived usability and reduced interaction efficiency.

Another relevant finding concerns the relationship between exposure level and frustration. Frustration consistently emerged as one of the workload dimensions showing the clearest separation between groups. This result may indicate that highly exposed users experience greater resistance when interacting with systems requiring sustained navigation or delayed information retrieval.

This interpretation is reinforced by Hertzum and Hornbæk [6], who argued that frustration remains one of the most common negative experiences in user interaction, particularly when interfaces fail to align with user expectations regarding efficiency and responsiveness. In the context of the present study, exposure to systems optimized for immediate gratification may contribute to reduced tolerance toward interaction friction within traditional interfaces.

The results also suggest potential relationships between exposure to LLM-based assistants and cognitive offloading behaviors. Participants with higher exposure levels demonstrated tendencies associated with reduced tolerance for prolonged analytical interaction processes, which may be partially explained by increasing reliance on automated systems for information retrieval and problem-solving tasks.

These findings are coherent with discussions presented by Muñoz and Flavio [5], who emphasized that generative artificial intelligence systems may promote reduced cognitive engagement during learning and problem-solving activities. Similarly, Nittala [4] highlighted how LLM-based interfaces significantly reduce perceived workload and simplify interaction processes within complex digital systems.

Despite the observed behavioral tendencies, the present study should be interpreted within the context of its methodological limitations. First, the sample size was relatively small and restricted to university students within technology-related academic programs, limiting the generalizability of the findings. Second, the adapted SMUS/EESII instrument incorporated additional AI-related items, which, although theoretically justified, may require further psychometric validation in future studies.

Additionally, the study followed a cross-sectional and exploratory design, preventing causal interpretation of the observed relationships. While the results suggest meaningful associations between exposure level and interaction behavior, it cannot be concluded that exposure to immediate interaction systems directly causes reduced usability tolerance or increased cognitive workload.

Another important limitation concerns the simulated experimental environment. Although the designed tasks attempted to reproduce realistic interaction scenarios, the evaluated interface does not fully represent the diversity and complexity of real-world digital ecosystems. Future studies could incorporate larger samples, longitudinal designs, adaptive interfaces, eye-tracking technologies, physiological workload measurements, or EEG-based cognitive state analysis to obtain more robust evidence regarding the cognitive effects of immediate interaction systems.

From a practical perspective, the findings highlight important implications for interface design and user experience research. As digital ecosystems continue evolving toward highly optimized and automated interaction models, designers may need to reconsider how traditional interfaces accommodate users increasingly habituated to immediate-response environments.

This becomes particularly relevant in educational, governmental, and enterprise systems, where interaction processes frequently require prolonged attention, sequential navigation, and sustained cognitive engagement. The growing divergence between modern interaction expectations and traditional interface structures may represent an emerging challenge for future Human-Computer Interaction research.

Overall, the obtained findings contribute exploratory evidence suggesting that exposure to immediate interaction systems may influence user experience, cognitive workload perception, and interaction behavior within traditional digital interfaces. Although additional research is required to validate and expand these findings, the study provides an initial framework for understanding how contemporary digital interaction habits may reshape cognitive and behavioral expectations during human-computer interaction.

V. CONCLUSION

This study explored the relationship between exposure to immediate interaction systems and user experience within traditional digital interfaces. Specifically, the research analyzed how frequent interaction with short-form content platforms and LLM-based assistants may influence usability perception, cognitive workload, and task efficiency during prolonged digital interaction processes.

The obtained results revealed consistent behavioral tendencies across the evaluated variables. Participants with higher exposure levels generally reported lower perceived usability, higher cognitive workload, greater frustration, and longer task completion times compared to participants with lower exposure levels. Although the observed differences were moderate rather than extreme, the consistency of the findings across multiple usability and workload measures suggests the presence of meaningful relationships between exposure to highly stimulating digital environments and interaction behavior within traditional interfaces.

The study also demonstrated the usefulness of combining behavioral metrics, usability instruments, and cognitive workload measurements within exploratory Human-Computer Interaction research. The integration of the adapted SMUS/EESII instrument, NASA-TLX, SUS, and task-based usability testing allowed a multidimensional analysis of user interaction, connecting subjective perception with observable interaction behavior.

From a theoretical perspective, the findings support discussions related to Cognitive Load Theory and cognitive adaptation within modern digital ecosystems. The results suggest that continuous exposure to systems optimized for immediacy, automation, and reduced interaction friction may gradually shape user expectations regarding responsiveness, interaction speed, and cognitive effort during digital experiences.

From a practical perspective, the study highlights potential implications for interface design, particularly in systems that require sustained attention, sequential navigation, or prolonged interaction processes. As users become increasingly accustomed to highly optimized and instant-response digital environments, traditional interfaces may require new design strategies capable of reducing unnecessary cognitive friction while maintaining usability and task clarity.

Despite its exploratory nature and methodological limitations, the present research provides an initial framework for studying the cognitive and behavioral implications of immediate interaction systems within Human-Computer Interaction research. The obtained findings may contribute to future investigations involving larger populations, longitudinal studies, adaptive interfaces, physiological workload measurements, eye-tracking systems, or neuroadaptive interaction models.

Future work may also explore how different types of AI-assisted interaction, recommendation systems, and algorithmically optimized platforms influence sustained attention, cognitive persistence, and interaction tolerance across diverse digital contexts.

Overall, the study contributes preliminary evidence suggesting that contemporary digital interaction habits may influence how users perceive, process, and interact with traditional digital systems, representing an increasingly relevant topic for future UX, HCI, and cognitive computing research.

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