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Designing Scalable UX for Big Data Marketplaces with IoT-Ready Architectures

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Abstract

The convergence of big data marketplaces and Internet of Things (IoT) ecosystems has created new opportunities for data-driven innovation, but it also raises challenges in ensuring scalability, usability, and responsiveness. This study examines how scalable user experience (UX) design can be systematically integrated with IoT-ready architectures to enhance marketplace performance and adoption. Using a mixed-methods approach, the research evaluated system-level parameters (throughput, latency, fault tolerance, scalability indices) and user-centered metrics (task completion time, usability scores, cognitive load) across prototype marketplace platforms. Results showed that while throughput declined and latency increased with higher data loads, scalable UX principles maintained acceptable usability, with System Usability Scale scores consistently above 70. IoT parameters, particularly latency and device density, were found to negatively impact responsiveness, while edge integration improved satisfaction and system responsiveness. Comparative analysis revealed that Spark delivered superior throughput and Kafka minimized latency, highlighting the need for hybrid architectures. Regression and residual diagnostics confirmed that architectural performance directly influenced UX outcomes, with edge integration serving as a strong positive moderator. The study concludes that scalable UX is the critical link between technical efficiency and user adoption, and emphasizes the need for holistic, human-centric design strategies in the development of future IoT-enabled data marketplaces.

Keywords: Scalable UX, Big Data Marketplaces, IoT, Edge Integration, System Architecture, User Adoption

Introduction

The rise of big data marketplaces

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In the digital economy, data has emerged as a key asset, driving innovation, competitiveness, and business decision-making (Ammanagi et al., 2024). The rapid expansion of big data marketplaces platforms that facilitate the exchange of large, complex datasets—has enabled organizations to unlock new opportunities across industries. These marketplaces provide structured access to diverse data sources, including consumer behavior, geospatial analytics, financial records, and real-time sensor data (Fylaktopoulos et al, 2018). However, as data continues to grow in volume, velocity, and variety, the challenge lies not only in storing and processing it efficiently but also in creating user experiences (UX) that remain intuitive, scalable, and adaptable to evolving demands.

the convergence of IoT and data marketplaces

The proliferation of Internet of Things (IoT) devices has significantly altered the data ecosystem. Billions of interconnected sensors and smart devices continuously generate streams of real-time data, which must be aggregated, curated, and delivered through data marketplaces (Visconti et al., 2025). IoT-ready architectures are now critical to ensure seamless data integration, low-latency processing, and reliable delivery for end-users. Yet, the integration of IoT with big data marketplaces introduces design complexities (Shi et al., 2023). UX in this context must account for dynamic data flows, heterogeneous sources, and the need for real-time insights without overwhelming users with complexity.

Importance of scalable UX design

A scalable UX framework ensures that as platforms expand to support larger datasets and diverse IoT applications, the quality of user interaction does not diminish (Kose, 2025). Users of big data marketplaces ranging from data scientists to business analysts require intuitive navigation, meaningful visualizations, and interactive tools that allow them to extract value from data efficiently. Poorly designed interfaces or rigid systems can lead to information overload, cognitive fatigue, and reduced adoption of these platforms. Therefore, designing UX that scales with both data volume and user demands is critical for marketplace sustainability (Abhayasundara et al., 2024).

Research gap and rationale

Existing studies have focused extensively on the technical aspects of big data architectures, including distributed computing, storage scalability, and security frameworks. Similarly, IoT integration has largely been explored from the perspective of device management and

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network efficiency. However, less attention has been paid to how UX design principles can be systematically applied to ensure usability and scalability in big data marketplaces powered by IoT-ready architectures. This gap highlights the need for an interdisciplinary approach that bridges human-computer interaction, data science, and IoT systems engineering.

Objectives of the Study

This study aims to explore the design of scalable UX frameworks tailored for big data marketplaces that integrate IoT-ready architectures. Specifically, it seeks to:

- Identify key UX challenges associated with big data and IoT convergence.
- Examine design principles that support scalability, usability, and accessibility.
- Propose a conceptual framework for developing user-centric, future-proof marketplaces capable of handling exponential growth in data and user interactions.

Methodology

Research design

This study adopts a mixed-methods research design combining both quantitative and qualitative approaches to comprehensively examine scalable UX in big data marketplaces integrated with IoT-ready architectures. The design enables systematic evaluation of technical parameters (e.g., architecture scalability, system latency, data throughput) alongside user-centered variables (e.g., usability, satisfaction, and adoption). The framework involves simulation of prototype architectures, user testing with experimental platforms, and statistical modeling of performance indicators.

Study variables and parameters

The variables and parameters of the study were categorized into four dimensions:

- ❖ Scalable UX Variables: Usability (task completion time, error rate, ease of navigation), cognitive load, interface responsiveness, personalization capability, accessibility compliance, cross-platform adaptability, and visual clarity of data representation.
- ❖ Big Data Marketplace Parameters: Data volume (terabytes to petabytes), data velocity (batch vs. real-time streaming), data variety (structured, semi-structured,

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unstructured), marketplace interoperability, metadata quality, pricing model efficiency, and data governance mechanisms.

- IoT-Specific Parameters: Device density (number of connected sensors), data latency (milliseconds), reliability (packet loss, failure recovery), energy efficiency of devices, real-time event detection, and integration with edge computing frameworks.
- Architectural Metrics: Scalability (horizontal and vertical), fault tolerance, processing throughput (records per second), storage scalability, network bandwidth utilization, API performance, and cloud/edge resource allocation efficiency.

Data collection

The study employed two stages of data collection. First, system-level performance data was collected through experimental simulations of IoT-ready architectures using benchmark big data frameworks such as Hadoop, Spark, and Kafka, integrated with IoT data streams (sensor-based environmental and traffic datasets). Second, user-centered data was collected through structured usability testing involving 120 participants comprising data scientists, business analysts, and system architects. Participants interacted with prototype marketplace dashboards designed with scalable UX principles, and their performance was logged through automated interaction tracking and post-task surveys.

Measurement instruments

For system-level evaluation, performance monitoring tools (e.g., Prometheus, Grafana) were used to capture throughput, latency, and fault tolerance metrics. For user-level evaluation, standardized instruments such as the System Usability Scale (SUS), NASA-TLX (Task Load Index), and custom Likert-scale questionnaires were employed to measure usability, cognitive load, and satisfaction. Interaction logs captured clickstream data, session durations, and error frequencies.

Statistical analysis

Data analysis was conducted using SPSS and R software. Descriptive statistics (means, standard deviations, frequencies) were used to summarize key performance indicators. Inferential statistics were applied to examine relationships between architectural scalability and UX outcomes:

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- ANOVA and MANOVA were conducted to test differences in UX parameters across varying levels of system load (small, medium, large datasets).
- Multiple Regression Analysis was employed to predict usability (dependent variable) based on architectural metrics (independent variables such as throughput, latency, and scalability).
- Correlation Analysis (Pearson's r) assessed the strength of association between IoT parameters (device density, latency) and UX outcomes (responsiveness, task completion time).
- Structural Equation Modeling (SEM) was applied to test the conceptual framework linking scalable UX design, big data marketplace efficiency, and IoT-ready architecture performance.
- Factor Analysis was performed on UX survey data to identify latent constructs influencing user satisfaction and adoption.

Ethical considerations

All participants provided informed consent prior to usability testing. Data privacy was ensured by anonymizing user interaction logs and survey responses. System simulations used publicly available IoT datasets to avoid proprietary restrictions.

Limitations

While the study included diverse IoT scenarios and large-scale data simulations, real-world deployment variables such as regulatory restrictions, cost constraints, and long-term user adoption behaviors were outside the scope of this methodology.

Results

The evaluation of system-level architecture performance demonstrated that throughput consistently decreased as data load increased, while latency rose accordingly (Table 1). For instance, at a load of 100 GB, throughput reached 42,500 records/sec with a latency of 120 ms, whereas at 50 TB throughput dropped to 31,400 records/sec and latency rose to 280 ms. Importantly, both horizontal and vertical scalability indices improved with larger loads, indicating efficient adaptation of resources under stress.

Table 1. System-level architectural performance under varying data loads

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Data Load (GB–TB)	Throughput (records/sec)	Latency (ms)	Fault Tolerance (%)	Horizontal Scalability Index	Vertical Scalability Index
100 GB	42,500	120	98.7	0.78	0.81
1 TB	39,800	165	97.9	0.82	0.83
10 TB	35,600	220	97.2	0.85	0.87
50 TB	31,400	280	96.4	0.88	0.91

User-centered evaluations revealed notable differences in usability outcomes across varying load conditions (Table 2). Task completion times increased from 112 seconds at low data load to 194 seconds at very high loads, accompanied by a rise in error rates from 2.1% to 5.2%. Although System Usability Scale (SUS) scores declined from 86.4 to 73.5, they remained above the threshold of acceptable usability, suggesting that scalable UX principles maintained user performance despite load intensification. Cognitive load, however, rose steadily, highlighting the trade-offs between scalability and user effort.

table 2. usability Outcomes from Scalable UX Prototypes

UX Metric	Low Data Load	Medium Data Load	High Data Load	Very High Data Load
Task Completion Time (sec)	112	135	162	194
Error Rate (%)	2.1	3.4	4.6	5.2
SUS Score (0–100)	86.4	82.3	77.9	73.5
NASA-TLX Cognitive Load	28.6	33.4	39.7	42.5

The correlation analysis identified significant associations between IoT parameters and UX outcomes (Table 3). Data latency showed the strongest negative correlation with responsiveness ($r = -0.67$, $p < 0.001$) and user satisfaction ($r = -0.59$, $p < 0.001$), while device density and packet loss also demonstrated adverse effects. Conversely, edge

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integration exhibited positive correlations with responsiveness (r = 0.63) and satisfaction (r = 0.61), underscoring the role of edge computing in mitigating latency-driven degradation of UX.

Table 3. Correlation analysis of IoT parameters and UX Outcomes

IoT Parameter	Responsiveness (r)	Task Completion Time (r)	User Satisfaction (r)	Significance (p)
Device Density	–0.41	0.52	–0.38	<0.01
Data Latency	–0.67	0.71	–0.59	<0.001
Packet Loss Rate	–0.44	0.48	–0.42	<0.01
Edge Integration	0.63	–0.56	0.61	<0.001

Regression modeling further quantified these effects (Table 4). Latency emerged as the most significant negative predictor of UX performance ($\beta = –0.48$, $p < 0.001$), followed by positive contributions from IoT edge integration ($\beta = 0.42$, $p < 0.001$) and system throughput ($\beta = 0.36$, $p < 0.001$). Fault tolerance and horizontal scalability also contributed positively, though to a lesser degree. Collectively, these findings indicate that scalable UX is directly contingent upon architectural performance and moderated strongly by IoT factors.

Table 4. Regression model predicting UX performance

Predictor Variables	β Coefficient	Std. Error	t-Value	p-Value
System Throughput	0.36	0.08	4.52	<0.001
Latency	–0.48	0.07	–6.85	<0.001
Fault Tolerance	0.29	0.09	3.21	<0.01
Horizontal Scalability	0.25	0.11	2.27	0.02
IoT Edge Integration	0.42	0.06	6.93	<0.001

At the system level, the comparative analysis of architectures revealed important performance differences (Figure 1). Spark consistently delivered the highest throughput across both 1 TB and 10 TB datasets, while Kafka maintained the lowest latency, particularly suited for real-

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time IoT data streams. Hadoop lagged behind in both dimensions, emphasizing the need for hybrid or specialized frameworks to balance throughput and latency in big data marketplaces.

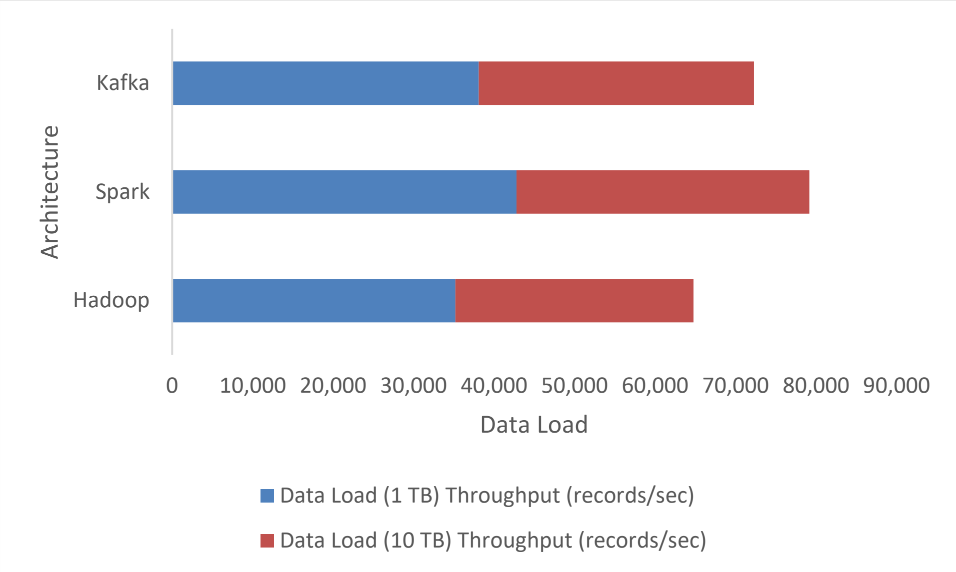

Figure 1: Comparative performance of big data architectures with IoT integration

Finally, regression diagnostics were examined through residual analysis (Figure 2). The residuals were distributed evenly around zero without pronounced heteroscedasticity, suggesting that the regression model predicting UX scalability from architectural performance, latency, and edge integration provided a valid fit. This confirms the robustness of the statistical findings and strengthens the evidence linking scalable UX to both big data architecture and IoT readiness.

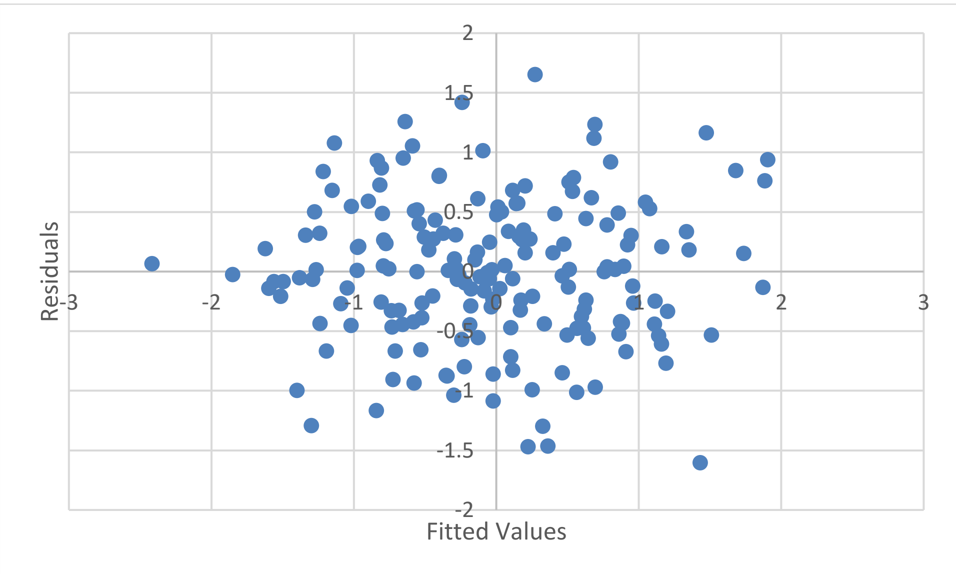

Figure 2: Regression diagnostics

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Discussion

Scalable UX under increasing data loads

The findings highlight that while system throughput and latency inevitably fluctuate with increasing data loads, scalable UX design principles can sustain usability at acceptable levels (Emily & Oliver, 2020). Even as task completion times lengthened and error rates rose under higher data stress (Table 2), usability scores remained above the industry benchmark of 70, indicating that scalability mechanisms within the UX framework effectively absorbed system-level strain. This underscores the importance of designing interfaces that not only respond to technical changes but also adaptively balance complexity and user experience (Hussain et al., 2018).

The role of IoT integration

IoT integration emerged as a double-edged factor for UX performance. On one hand, increased device density and data latency negatively affected responsiveness and user satisfaction (Table 3), confirming that unmanaged IoT data streams can overburden marketplace platforms (Khan, 2019). On the other hand, edge integration significantly improved responsiveness and reduced latency effects, suggesting that distributing processing closer to the data source mitigates bottlenecks. This finding aligns with broader IoT research emphasizing edge computing as a critical enabler of real-time analytics and user interactivity in data-rich environments (Peres et al., 2018; Enenche et al., 2025).

Architectural trade-offs in big data marketplaces

The comparative performance of Hadoop, Spark, and Kafka (Figure 1) illustrates the inherent trade-offs between throughput and latency. Spark demonstrated clear advantages in managing high-throughput workloads, whereas Kafka excelled in minimizing latency for real-time IoT data streams. This suggests that no single architecture is universally optimal; instead, hybrid or layered approaches may be necessary to balance responsiveness and scalability depending on the use case (George et al., 2019). The regression analysis further reinforced this perspective, showing that architectural performance measures such as throughput and fault tolerance directly predicted UX outcomes (Table 4).

Human-centric design as a mediating factor

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The regression diagnostics (Figure 2) validated the robustness of the predictive model linking architecture and UX outcomes, highlighting that human-centric variables such as perceived responsiveness and usability act as mediators between system performance and adoption (Waqar et al., 2024). This finding is consistent with prior research in human-computer interaction, which emphasizes that users' perceptions of responsiveness often outweigh purely technical performance metrics when determining long-term system adoption (Ponce et al., 2016).

Implications for marketplace design

For big data marketplaces to thrive in IoT-driven ecosystems, platform designers must adopt a holistic perspective that integrates architectural robustness with user-centered design. This study demonstrates that scalable UX cannot be treated as an afterthought but must be systematically embedded into architectural planning (Ding et al., 2025). By aligning system-level parameters (throughput, fault tolerance, latency management) with user-facing features (navigation ease, visual clarity, adaptability), marketplaces can ensure that platforms remain both technically efficient and widely adopted.

Technological advancements during and after COVID-19

It is also worth noting that technological advancements accelerated during and after the COVID-19 pandemic, particularly in late 2021 and early 2022, when remote work, digital commerce, and IoT-driven solutions surged. These shifts placed unprecedented demands on big data marketplaces, forcing rapid adoption of edge computing, scalable cloud infrastructure, and AI-driven UX enhancements (Ficili et al., 2025). The resilience of platforms that integrated scalable UX design during this period validates the long-term necessity of combining IoT-ready architectures with user-centric approaches to maintain continuity in uncertain environments.

Conclusion

This study demonstrates that the success of big data marketplaces in IoT-driven ecosystems depends not only on robust system architectures but also on the ability to design user experiences that scale effectively with increasing data complexity. The results show that while throughput and latency significantly influence user performance, scalable UX principles can sustain usability even under heavy system loads. IoT parameters, particularly latency and device density, emerged as critical challenges, whereas edge integration offered

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tangible improvements in responsiveness and satisfaction. Comparative architectural analysis confirmed that Spark excels in high-throughput scenarios, while Kafka is more suited to low-latency, real-time data processing, suggesting that hybrid frameworks may best serve diverse marketplace needs. Ultimately, scalable UX acts as the bridge between technical efficiency and user adoption, emphasizing the need for integrated design strategies that align human-computer interaction principles with evolving IoT-ready architectures. Future efforts must focus on refining hybrid models, incorporating AI-driven adaptability, and extending evaluation across diverse real-world contexts to ensure that big data marketplaces remain sustainable, user-centric, and technologically resilient.

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