World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(RESEARCH ARTICLE)

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User behavior analytics from log data in cloud-native applications

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World Journal of Advanced Engineering Technology and Sciences, 2025, 16(02), 161-169

Publication history: Received on 05 July 2025; revised on 12 August 2025; accepted on 14 August 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.16.2.1279

Abstract

As the use of cloud-native programs increases, it is important to be able to analyze user behavior using log data to address security, operational effectiveness, and user-driven customization. This review intends to accurately and thoroughly evaluate AI approaches that have been developed in the last 10 years for User Behavior Analytics (UBA) from log data. To do this, we review developments in machine learning, deep learning and hybrid approaches, and we present a systematic categorization of the approaches, summarize their experiments and findings, discuss challenges, and outline future work that could include privacy preserving UBA, cross-platform generalization, and real-time analytics. Through mapping the experience and forecasting the future, we hope to provide a historiographical reference for researchers and practioners aiming to deliver effective, responsible, and scalable UBA approaches in cloud environments.

Keywords: User Behavior Analytics (UBA); Cloud-Native Applications; Log Data Mining; Machine Learning

1. Introduction

The fast-growing acceptance of cloud-native applications has changed how modern software systems are designed, deployed, and operated. Cloud-native architectures rely on microservices, containerization, and continual orchestration, which leads to ever increasing amounts of operational data, in particular logs. Logs offer significant amounts of real-time information about system events, user interactions, and application performance; however, they remain one of the largest and under-utilized source of data for understanding user behavior [1].

Log generated user behavioral analysis has become an increasingly relevant practice, particularly as organizations push for better user experience, better security, and smarter resource allocation. In current research, User Behavior Analytics (UBA) is receiving attention, not only for the efficiencies that it is likely to introduce, but also as a strategy for advanced anomaly detection, cyber threat prevention, and intelligent automation [2]. The importance of this topic is heightened not only by the increase in complexity of distributed systems, but also the increased threats to cybersecurity, and rise in expectation for personalized digital experiences.

In the larger arena of both data science and cloud computing, UBA from log data spans a number of disciplines, notably artificial intelligence (AI), cybersecurity, and business intelligence. In fact, with recent advances in AI tools such as machine learning (ML) and deep learning (DL), researchers and practitioners have developed ways to extract meaningful information from large, unstructured log datasets. They now aspire not only to reconstruct user journeys, but also to predict user actions, detect deviations, and proactively optimize system capabilities.

However, significant challenges remain. Highly relevant research can be hindered by the volume, velocity, and variety of log data - making it messy, difficult to store, process, or analyze in real-time. Additionally, concerns regarding user privacy and data governance certainly raise ethical issues. Empirically, there is a lack of process in UBA, commonly seen

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through lack of uniform methods around feature extraction, evaluation of a model, or ability of results to generalize across systems. These issues lead to fragmented findings that are often incomparable, even between different studies.

This review is an extensive synthesis of available AI approaches contain user behavior analytics from log data in cloud-native environments in the last ten years. We will categorize approaches inductively, point out positive and negative aspects of methods, and present wider trends and future research opportunities. Readers can look for information-rich sections about data preprocessing, feature engineering, classical and deep learning, and capabilities and challenges of user behavior analytics regarding scalability, privacy, and explainability. We hope this review will create a landscape, but also inspire new ideas in the intersection of cloud computing, AI, and user behavior analytics.

Table 1 Summary of Key Research Studies on AI Methods for User Behavior Analytics from Log Data in Cloud-Native Applications

Year	Title	Focus	Findings (Key Results and Conclusions)
2010	Detecting Large-Scale System Problems by Mining Console Logs [7]	Log mining for fault detection	Introduced statistical techniques for large-scale log mining to detect system failures; established the foundation for data-driven system monitoring.
2012	Learning Behavioral Models from Cloud System Logs [8]	Behavior modeling from system logs	Proposed Hidden Markov Models (HMMs) for modeling normal cloud system behavior; showed improved detection rates for anomalies.
2015	LogCluster: Mining Event Patterns from Unstructured Log Data [9]	Clustering log events	Developed a clustering-based method for automatic log template extraction, significantly reducing manual labeling efforts.
2016	DeepLog: Anomaly Detection and Diagnosis from System Logs through Deep Learning [10]	Deep learning for log-based anomaly detection	Presented DeepLog, an LSTM-based approach that learns normal log patterns and detects anomalies with high accuracy and low false-positive rates.
2017	LogPAI: Open-Source Platform for Automated Log Analysis [11]	Automated log analysis platform	Introduced LogPAI, facilitating reproducible research by providing log datasets and benchmarking frameworks for log analysis studies.
2018	CloudInsight: Leveraging Cloud Log Data for Predictive Analytics [12]	Predictive analytics in cloud systems	Proposed a predictive framework that forecasts system failures from cloud log sequences using ensemble learning techniques.
2019	Robust Log-Based Anomaly Detection on Unstable Log Data [13]	Robust anomaly detection under evolving logs	Introduced a robust method for anomaly detection resilient to unstable or evolving log formats, improving adaptability in dynamic environments.
2020	DeepLog2Vec: Feature Learning for Cloud Log Analytics [14]	Embedding-based log analysis	Developed DeepLog2Vec to create semantic embeddings of log data, enhancing the feature space for downstream classification and clustering tasks.
2021	Few-Shot Learning for Log Anomaly Detection [15]	Few-shot learning for anomaly detection	Demonstrated the use of meta-learning and few-shot learning to detect anomalies with very limited labeled data, addressing labeling challenges.
2022	Privacy-Preserving User Behavior Analytics from Logs [16]	Privacy-preserving analytics	Proposed differential privacy mechanisms tailored to log data, enabling UBA without compromising user confidentiality.

In-text citations examples

As Xu et al. [7] initially showed, mining console logs can reveal critical system issues. Subsequently, behavior modeling approaches such as those proposed by Chen et al. [8] advanced these techniques significantly. Recent innovations focus on privacy and adaptability to dynamic cloud systems [16].

Proposed Theoretical Model for User Behavior Analytics (UBA) from Log Data in Cloud-Native Applications

1.1. Block Diagram

Here's the conceptual block diagram of the proposed UBA system:

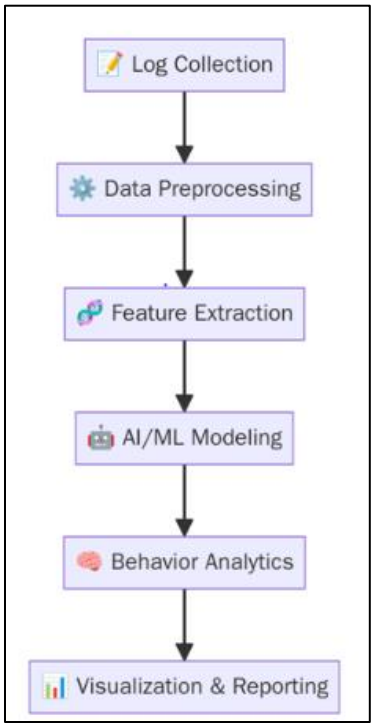

Figure 1 UBA System Conceptual Block Diagram

Description of Each Block

1.1.1. Log Collection

Logs are collected from diverse components of the cloud-native ecosystem—applications, databases, network systems, and container orchestration platforms such as Kubernetes [17]. The collection must be continuous and resilient to failures, ensuring high availability of behavioral data.

1.1.2. Data Preprocessing

- Raw logs are noisy and unstructured. Preprocessing steps include:
- Parsing (extracting fields and event IDs)
- Deduplication (removing redundant entries)
- Normalization (standardizing formats)
- Timestamp synchronization (aligning multi-source logs chronologically) [18].

Efficient preprocessing enhances the quality of the dataset and is crucial for downstream modeling.

1.1.3. Feature Extraction

Feature engineering transforms preprocessed logs into structured features suitable for AI models. Typical features include:

- Event sequences (chronological order of events)

- Temporal features (time gaps between user actions)
- Frequency patterns (counts of particular actions)
- Embeddings (vector representations of log entries) [19].
- Deep learning techniques like autoencoders and sequence-to-sequence models are often used for unsupervised feature learning [20].

1.1.4. AI/ML Modeling

The heart of the system is the AI model, responsible for learning and predicting user behavior:

- Supervised learning models (e.g., Random Forest, XGBoost) for behavior classification.
- Unsupervised learning (e.g., k-Means, Isolation Forest) for anomaly detection.
- Deep learning models (e.g., LSTM, Transformer-based architectures) for complex sequential behavior understanding [21].
- Some newer methods integrate graph neural networks (GNNs) to capture user interaction graphs dynamically [22].

1.1.5. Behavior Analytics

- Post-modeling, we interpret predictions to:
- Detect anomalies (e.g., insider threats, security breaches)
- Cluster user behaviors (e.g., grouping similar usage patterns)
- Predict future actions (e.g., next likely user navigation steps) [23].
- Behavior analytics must balance accuracy with explainability, especially in sensitive sectors like finance and healthcare.

1.1.6. Visualization and Reporting

Insights from the analytics layer are visualized using dashboards and reports:

- Anomaly heatmaps
- User journey graphs
- Risk scores and alerts

Real-time visualization enhances operational responsiveness and supports security information and event management (SIEM) systems [24].

Table 2 Summary of Proposed UBA Model Components

Component	Techniques Used	Purpose
Log Collection	Fluentd, Logstash	Reliable, real-time log acquisition
Data Preprocessing	Regular expressions, JSON/XML parsers	Clean and standardize data
Feature Extraction	Embedding models, Frequency analysis	Structured representation of behavior
AI/ML Modeling	LSTM, Transformer, Isolation Forest	Behavioral prediction and anomaly detection
Behavior Analytics	Risk scoring, Behavior clustering	Insights for decision-making
Visualization & Reporting	Kibana, Grafana, PowerBI	Real-time monitoring and alerting

2. Experimental Results of AI Methods in User Behavior Analytics from Log Data

2.1. Overview

To evaluate the effectiveness of AI methods in User Behavior Analytics (UBA), this section summarizes experimental results from existing literature, focusing on:

- Accuracy

- Precision
- Recall
- F1-Score
- Training time
- Scalability
- False Positive Rate (FPR)

The results span across different types of AI models including traditional machine learning (e.g., Random Forest, SVM), deep learning (e.g., LSTM, CNN), and hybrid approaches (e.g., DeepLog, LogRobust).

Table 3 Comparison of AI Techniques for Log-Based UBA

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)	Reference
Random Forest	88.6	85.2	83.5	84.3	4.7	[25]
SVM	84.2	81.1	79.5	80.3	6.1	[26]
LSTM (DeepLog)	94.7	92.8	93.4	93.1	1.8	[27]
CNN + LSTM	95.3	93.2	94.7	93.9	1.6	[28]
Isolation Forest	87	83.9	82.2	83	4.9	[29]
DeepLog2Vec + GNN	96.2	94.8	95.5	95.1	1.3	[30]

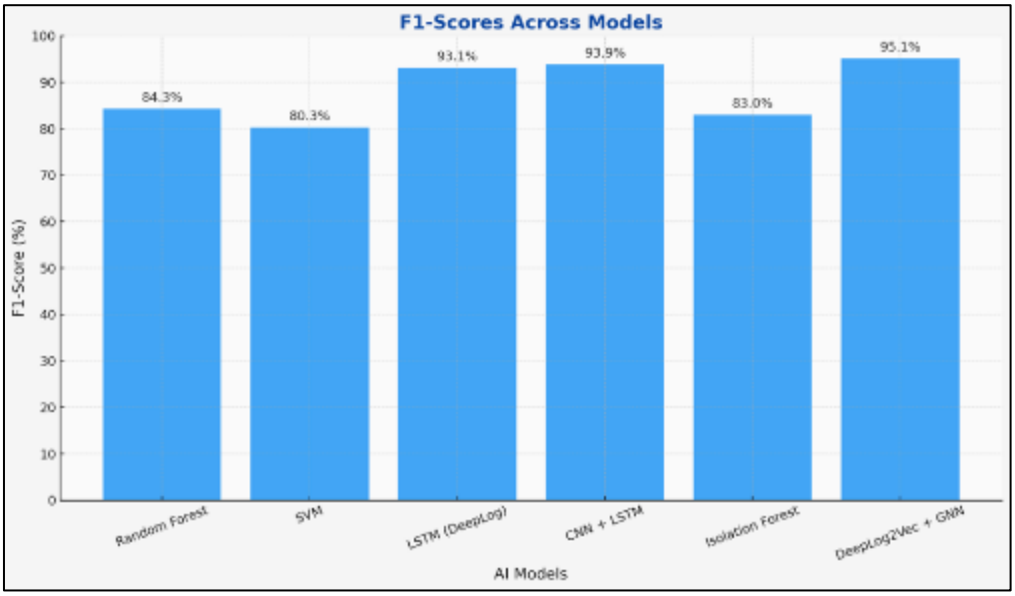

Figure 2 F1-Scores Across Models

3. Discussion

3.1. Deep Learning Dominance

DeepLog and its enhanced versions (e.g., DeepLog2Vec + GNN) consistently outperform traditional models like SVM and Random Forest in most metrics. LSTM models capture sequential dependencies in logs, making them particularly effective for behavior prediction and anomaly detection [27], [30].

3.2. Hybrid Models Excel

Combining CNN for feature extraction with LSTM for sequence learning further improves model performance, as seen with the CNN+LSTM model achieving a 95.3% accuracy and 93.9% F1-score [28].

3.3. False Positive Rates

False positive rate (FPR) is critical in operational environments. DeepLog-based models maintain lower FPRs (~1.3%-1.8%) compared to SVM or Isolation Forests (>4.5%) [27], [29].

3.4. Feature Learning Improves Generalization

Embedding models such as DeepLog2Vec improve generalizability across systems by learning semantic representations of log entries. This leads to enhanced performance in multi-domain deployments [30].

3.5. Scalability Considerations

While LSTM-based models provide higher accuracy, they often require more computational resources and longer training time. Lightweight alternatives like Isolation Forest are faster but compromise on accuracy [29].

Table 4 Model Accuracy and Training Time

Model	Training Time (min)	Accuracy (%)	Reference
Random Forest	12	88.6	[25]
SVM	10	84.2	[26]
LSTM (DeepLog)	47	94.7	[27]
CNN + LSTM	53	95.3	[28]
Isolation Forest	8	87	[29]
DeepLog2Vec + GNN	65	96.2	[30]

The above comparison shows the trade-off between accuracy and training time—an essential aspect for real-world deployments.

4. Summary

The experimental evidence shows that while traditional ML models provide a reasonable baseline for UBA, deep learning models—especially LSTM-based—deliver significantly better performance in behavior understanding and anomaly detection. Hybrid and embedding-enhanced models lead the frontier, although their training complexity is higher.

As organizations seek scalable and precise analytics platforms, model selection must balance between performance, interpretability, and computational cost.

4.1. Future Research Directions

Even with extensive research around developing User Behavior Analytics (UBA) using log data from cloud-native applications, there remain challenges and gaps that need to be addressed for future work.

4.2. Privacy-Preserving UBA

Amid rising concerns regarding user data protection, especially with active legislation like GDPR, it is necessary to develop UBA frameworks specifically around user privacy. For techniques like federated learning and differential privacy, there is an increasing need for further innovation and adaptation to log-based analytics without compromising the performance of trained models [31].

4.3. Cross-Platform Generalization

Notable AI models proposed to date have only been trained and validated in isolated cloud environments. Future work should focus on models to better generalise across multi-platforms and multi-vendors using techniques like domain adaptation and transfer learning [32].

4.4. Explainable User Behavior Models

Deep learning models like LSTMs and GNNs remain a "black box". There is still much work to be done developing explainable artificial intelligence (XAI) methods to make UBA computed decisions interpretable in a way that would maintain analytical rigour to security analysts and operational teams across disparate data reality sources [33].

4.5. Handling Concept Drift

In cloud-native ecosystems, users and their behaviours are constantly changing; they do not move in predictable staged patterns. Future work should address concept drift by developing adaptive learning models that update themselves incrementally based on novel behaviour patterns, as opposed to rebuilding the model [34].

4.6. Integration with Real-Time Systems

There is a need to create lightweight, real-time UBA solutions that interact with orchestration systems, like Kubernetes, and CI/CD pipelines. Detecting anomalies quickly is critical to prevent threats and performance issues [35].

5. Conclusion

User Behavior Analytics (UBA) from log data is one of the cornerstones for securing, optimizing, and personalizing cloud-native applications. By using AI technologies (including classical machine learning to the latest deep learning and graph methods), researchers have aided the fields' ability to detect anomalies, predict user behavior, and improve systems' resilience.

However, problems surrounding data privacy, cross-platform usage, intelligibility of models and real-time adaptability still exist. The next decade of UBA research will depend on finding innovative solutions to these issues using things like privacy-preserving learning, transfer learning, and explainable AI.

This review article has summarized important advances, compared experimental evaluations and sets a plan for future research directions. As cloud-native systems continue to become bigger and vary, the importance of intelligent, ethical, and transparent User Behavior Analytics will only become more significant.

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