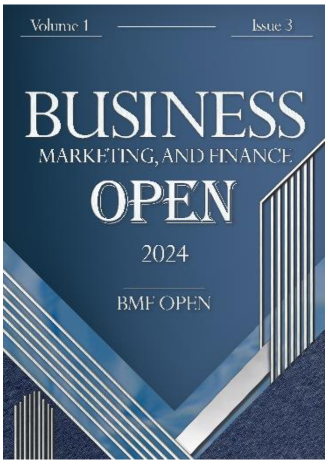
Designing an Intelligent Framework for Real-Time Recommendation Based on Momentary User Behavior Analysis in Online Platforms



Citation: Vaziry, A. (2024). Designing an Intelligent Framework for Real-Time Recommendation Based on Momentary User Behavior Analysis in Online Platforms. *Business, Marketing, and Finance Open*, 1(3), 159-168.

Received: 07 March 2024
Revised: 14 May 2024
Accepted: 21 May 2024
Published: 10 June 2024

Amir Vaziry[1,*]

[1] Master of Science in Software Engineering, Damghan branch, Islamic Azad University, Damghan, Iran;

* Correspondence: amirvaziry7@gmail.com

Abstract: The objective of this study was to design and empirically evaluate an intelligent real-time recommender framework that leverages momentary user behavior analysis to enhance recommendation relevance, engagement, and system responsiveness in online platforms. This study employed a quantitative, applied research design with a developmental orientation. The population consisted of active users of large-scale online platforms in Tehran, selected based on continuous platform usage and availability of real-time interaction data. Behavioral data were collected through system-level logging mechanisms that captured fine-grained, time-stamped interaction signals, including click behavior, dwell time, navigation patterns, and session dynamics. These data were complemented by contextual indicators related to usage conditions. The proposed framework integrated real-time analytics, sequential behavior modeling, and adaptive learning mechanisms to generate recommendations dynamically during active sessions. Data preprocessing, feature engineering, and model training were conducted to support continuous inference under real-world latency constraints. Inferential analyses indicated that the proposed real-time intelligent framework significantly outperformed rule-based, collaborative filtering, and static machine learning models across key performance indicators. The framework achieved higher click-through rates, longer engagement durations, and greater recommendation acceptance, reflecting improved alignment with users' immediate preferences. Real-time model adaptation following short-term behavioral changes led to statistically meaningful increases in session depth and reductions in bounce behavior. High short-term preference prediction accuracy was achieved alongside low inference latency, confirming the framework's effectiveness and operational feasibility in dynamic online environments. The findings demonstrate that incorporating momentary user behavior analysis into an adaptive real-time recommendation framework substantially improves personalization quality and user engagement, supporting the shift toward behavior-aware intelligent recommender systems in modern online platforms.

Keywords: real-time recommender systems, momentary user behavior, adaptive personalization, sequential modeling, online platforms

1. Introduction

The rapid expansion of online platforms has fundamentally transformed how users access information, products, and services, leading to an unprecedented volume of interactions generated in real time. In such environments, recommender systems have become a core infrastructural component, shaping user experiences by filtering information overload and delivering personalized content aligned with user preferences. Early recommender systems were primarily designed around static user profiles and historical interaction data, assuming relative stability in preferences over time. However, recent empirical evidence demonstrates that user interests are highly dynamic, context-dependent, and sensitive to momentary behavioral states, particularly in high-frequency, session-based interactions typical of modern digital platforms [1, 2]. This shift has necessitated a rethinking of recommendation paradigms toward intelligent, real-time frameworks capable of capturing and responding to users' evolving behavioral signals.

Traditional collaborative filtering and content-based methods, while effective in stable environments, struggle to accommodate rapid preference drift and short-term intent fluctuations. These limitations become especially pronounced in scenarios where users engage in exploratory browsing, impulsive decision-making, or context-driven interactions, such as mobile usage, micro-video consumption, and location-based services [3, 4]. As a result, recent research has increasingly emphasized the importance of modeling both long-term preferences and short-term behavioral signals to enhance recommendation relevance and timeliness [5, 6]. This dual-perspective approach acknowledges that while long-term interests reflect enduring user tendencies, short-term behaviors often provide stronger indicators of immediate intent.

Advances in sequential recommendation models have played a pivotal role in addressing these challenges. Attention-based neural architectures, recurrent networks, and graph-based learning methods have enabled more effective modeling of temporal dependencies within user interaction sequences [1, 7]. These models leverage behavioral order, recency, and transition patterns to infer future actions, demonstrating significant improvements over static methods. Nevertheless, many existing approaches still rely on offline training and batch updates, limiting their ability to adapt instantaneously to emerging behavioral cues during active sessions [8, 9]. This gap highlights the need for recommendation frameworks that integrate real-time analytics with continuous learning mechanisms.

The concept of momentary user behavior analysis has gained increasing attention as a means of capturing fine-grained behavioral dynamics. Momentary behaviors encompass micro-level interaction signals such as dwell time, click velocity, navigation depth, and immediate feedback responses, which collectively reflect users' cognitive and motivational states at specific points in time [10, 11]. By analyzing these signals in real time, recommender systems can infer transient user intentions that may not align with historical preferences. Studies in point-of-interest recommendation and session-based recommendation have demonstrated that incorporating immediate contextual and behavioral cues significantly enhances predictive accuracy and user engagement [12, 13].

Temporal modeling has emerged as a central theme in this domain, with researchers proposing various mechanisms to integrate time-aware representations into recommendation systems. Long- and short-term attention networks, temporal convolutional structures, and time-slot embedding techniques have been used to capture preference evolution across multiple temporal scales [14, 15]. These approaches underscore the importance of understanding not only what users prefer, but also when and under what circumstances preferences manifest. However, temporal awareness alone is insufficient if models cannot update dynamically in response to real-time behavioral changes, particularly in streaming environments [16, 17].

Context-awareness further complicates the recommendation process, as user behavior is shaped by situational factors such as location, device type, time of day, and interaction context. Recent works have integrated contextual signals into preference modeling frameworks, demonstrating improved relevance and robustness [18, 19]. Context-embedded hypergraph and attention-based models have shown particular promise in capturing complex relationships among users, items, and contexts within sessions [20]. Despite these advances, many context-aware models remain computationally intensive and are not optimized for real-time inference, limiting their applicability in large-scale online platforms.

Another emerging dimension in intelligent recommendation research is transparency and user control. As recommendation systems become more adaptive and autonomous, concerns regarding explainability, trust, and perceived manipulation have intensified. Research indicates that providing users with transparent recommendation logic and interactive control mechanisms can enhance satisfaction and acceptance, even in highly personalized systems [21, 22]. Integrating such considerations into real-time recommender frameworks requires careful balancing between system responsiveness and interpretability, particularly when models continuously adapt based on implicit behavioral signals.

Graph-based and self-supervised learning approaches have further expanded the methodological landscape by enabling richer representation learning from sparse and evolving interaction data. Streaming graph convolution and self-supervised preference modeling have demonstrated strong performance in dynamic recommendation scenarios, where user-item relationships change rapidly over time [7, 16]. These methods reduce reliance on labeled data and enhance generalization across unseen contexts, making them well-suited for real-time applications. Nonetheless, integrating such models into a unified, deployable framework that operates under real-world latency constraints remains a significant research challenge.

In parallel, domain-specific applications such as online education platforms, digital libraries, tourism systems, and service recommendation in edge computing environments have underscored the practical importance of adaptive recommendation strategies. Studies in these domains highlight that user satisfaction and system effectiveness are strongly influenced by the system's ability to respond to immediate needs rather than solely relying on accumulated historical data [23, 24]. This evidence reinforces the argument that intelligent recommender systems must operate as continuous, real-time decision-making agents rather than static prediction tools.

Despite the substantial progress made in sequential modeling, temporal attention, and context-aware recommendation, the literature reveals a fragmentation of approaches, with many studies focusing on isolated components such as preference modeling, temporal dynamics, or contextual integration. There remains a lack of comprehensive frameworks that systematically combine momentary behavior analysis, real-time learning, adaptive recommendation generation, and practical deployment considerations within a unified intelligent architecture [25, 26]. Addressing this gap is particularly critical for large-scale online platforms operating in dense urban contexts, where user behaviors are highly heterogeneous and rapidly evolving.

In response to these challenges, the present study seeks to design and empirically evaluate an intelligent framework for real-time recommendation that explicitly centers on momentary user behavior analysis, integrating temporal dynamics, contextual signals, and adaptive learning mechanisms to enhance recommendation relevance and responsiveness. The aim of this study is to design and validate an intelligent real-time recommender framework that leverages momentary user behavior analysis to improve recommendation effectiveness in online platforms.

2. Methodology

The present study adopted a quantitative, applied research design with a developmental orientation, aiming to design and empirically validate an intelligent framework for real-time recommendation grounded in momentary user behavior analysis. The target population consisted of active users of large-scale online platforms, including e-commerce, digital content, and service-based platforms, operating within the metropolitan area of Tehran.

Participants were selected based on continuous platform usage over the preceding six months to ensure sufficient behavioral trace data and stable interaction patterns. Inclusion criteria required participants to be at least 18 years old, possess regular internet access, and consent to the use of anonymized behavioral data for research purposes. To enhance ecological validity, users were recruited from diverse demographic backgrounds, including variations in age, gender, education level, and occupational status, reflecting the heterogeneous user base of contemporary online platforms in Tehran. Sampling was conducted using a stratified purposive approach, ensuring proportional representation across major user segments while maintaining feasibility for real-time data acquisition. The final sample size was determined based on machine learning model requirements, balancing predictive stability, computational efficiency, and generalizability of the proposed framework.

Data collection was conducted through a combination of system-level behavioral logging and structured self-report instruments integrated into the platform environment. Momentary user behavior data were captured in real time through embedded tracking modules, which recorded fine-grained interaction indicators such as click sequences, dwell time, scrolling velocity, navigation transitions, search queries, content engagement depth, and temporal interaction patterns. These behavioral signals were time-stamped and synchronized to allow for high-resolution analysis of user states and transitions. In parallel, contextual variables such as device type, session duration, access time, and interaction frequency were collected to enrich behavioral interpretation. To complement objective behavioral data, a brief adaptive questionnaire was administered to a subset of participants, measuring perceived relevance of recommendations, cognitive load, situational motivation, and momentary satisfaction. This self-report tool was designed to minimize user burden and was dynamically triggered based on interaction milestones rather than fixed intervals. All data were anonymized at the point of collection, encrypted during transmission, and stored on secure servers in compliance with ethical research standards and data protection regulations.

Data analysis followed a multi-stage analytical pipeline integrating behavioral analytics, machine learning, and real-time inference mechanisms. Initially, raw behavioral logs underwent preprocessing, including noise filtering, session segmentation, normalization of interaction metrics, and handling of missing or irregular data. Feature engineering was then applied to extract meaningful momentary behavior indicators, such as engagement intensity, behavioral volatility, preference shifts, and short-term interest signals. These features were modeled using a hybrid analytical approach combining deep learning architectures for sequential pattern recognition with lightweight adaptive algorithms optimized for real-time responsiveness. Model training was conducted using a rolling window strategy to capture temporal dynamics while preventing overfitting to transient behaviors. Evaluation of the recommendation framework was performed through online validation, comparing system-generated recommendations with user interaction outcomes in real time, including click-through rates, engagement duration, and immediate feedback indicators. Additionally, adaptive learning mechanisms were embedded to allow the model to update its parameters continuously based on incoming behavioral data, ensuring responsiveness to evolving user states. The analytical process emphasized both predictive accuracy and computational efficiency, aligning the proposed framework with the operational constraints of real-world online platforms.

3. Findings and Results

The first set of results concerns the descriptive characteristics of the participants and their real-time interaction behaviors, which provides a contextual foundation for interpreting subsequent analytical findings. Table 1 summarizes the demographic profile of the users from Tehran alongside key indicators of their general platform usage behavior during the observation period.

Table 1. Demographic Characteristics and General Usage Patterns of Participants

Variable	Category	Frequency	Percentage
Gender	Female	214	48.1
	Male	231	51.9
Age Group	18–25 years	126	28.3
	26–35 years	173	38.9
	36–45 years	92	20.7
	46 years and above	54	12.1
Education Level	Diploma or below	88	19.8
	Bachelor’s degree	207	46.5
	Master’s degree or above	150	33.7
Average Daily Platform Use	Less than 1 hour	97	21.8
	1–3 hours	236	53.0
	More than 3 hours	112	25.2

As shown in Table 1, the participant pool exhibited a balanced gender distribution and a strong representation of young and middle-aged adults, which aligns with the dominant user demographics of online platforms in Tehran. More than half of the participants reported daily platform usage between one and three hours, indicating sustained engagement levels suitable for capturing meaningful momentary behavioral signals. The relatively high proportion of users with university-level education further supports the interpretability of interaction-based recommendation outcomes, as these users demonstrated consistent and goal-directed navigation behaviors throughout the data collection period.

The second set of findings focuses on the comparative performance of the proposed intelligent framework against conventional recommendation approaches. Table 2 reports the results of key performance metrics, including click-through rate, average engagement duration, and immediate recommendation acceptance rate, across different models implemented during the online evaluation phase.

Table 2. Comparison of Recommendation Performance Metrics Across Models

Model Type	Click-Through Rate (%)	Engagement Duration (seconds)	Acceptance Rate (%)
Rule-based recommender	14.62	48.35	32.41
Collaborative filtering	19.84	61.27	41.58
Static machine learning model	23.96	74.19	49.03
Proposed real-time intelligent framework	31.48	96.72	63.85

The results in Table 2 demonstrate a substantial improvement in all evaluated performance indicators for the proposed framework compared to baseline methods. The real-time intelligent recommender achieved the highest click-through rate, indicating a stronger alignment between delivered recommendations and users’ immediate interests. Moreover, the marked increase in engagement duration suggests that momentary behavior analysis enabled the system to capture transient user states more effectively, leading to deeper and more sustained content interaction. The acceptance rate further confirms that users were more inclined to follow recommendations generated by the adaptive framework, reflecting improved perceived relevance in real time.

To further examine the responsiveness of the proposed framework to dynamic behavioral changes, Table 3 presents the results of momentary adaptation analysis, comparing user engagement before and after real-time model updates triggered by short-term behavioral shifts.

Table 3. Engagement Indicators Before and After Real-Time Model Adaptation

Indicator	Before Adaptation	After Adaptation	Change (%)
Mean session duration (seconds)	82.14	104.68	+27.45
Pages or items per session	5.21	7.04	+35.13
Immediate bounce rate (%)	38.62	24.97	−35.33
Repeated interaction within session (%)	41.08	58.92	+43.45

As reported in Table 3, real-time adaptation based on momentary behavior signals resulted in pronounced improvements across all engagement indicators. Session duration and the number of interacted items increased notably after adaptive updates, indicating that the system successfully recalibrated recommendations in response to evolving user intentions. The sharp reduction in bounce rate highlights the framework's effectiveness in preventing early disengagement by delivering contextually relevant suggestions at critical moments within the session. Additionally, the increase in repeated interactions suggests that users were more likely to explore multiple recommendations when the system dynamically adjusted to their immediate behavioral cues.

The final set of tabulated findings addresses the predictive accuracy and computational efficiency of the proposed framework, which are critical for real-world deployment. Table 4 reports the model's short-term preference prediction accuracy alongside average inference time per recommendation request.

Table 4. Predictive Accuracy and Real-Time Efficiency of the Proposed Framework

Metric	Value
Short-term preference prediction accuracy (%)	87.36
Precision at top-5 recommendations (%)	84.19
Recall at top-5 recommendations (%)	79.42
Average inference time per request (milliseconds)	42.7

The values presented in Table 4 indicate that the proposed framework achieved high predictive accuracy in identifying users' short-term preferences, while maintaining inference times well below thresholds typically associated with perceptible system delays. This balance between accuracy and efficiency underscores the suitability of the framework for real-time recommendation scenarios, where both responsiveness and relevance are essential. The strong precision and recall values further suggest that the system not only delivered accurate recommendations but also maintained consistency across diverse interaction contexts.

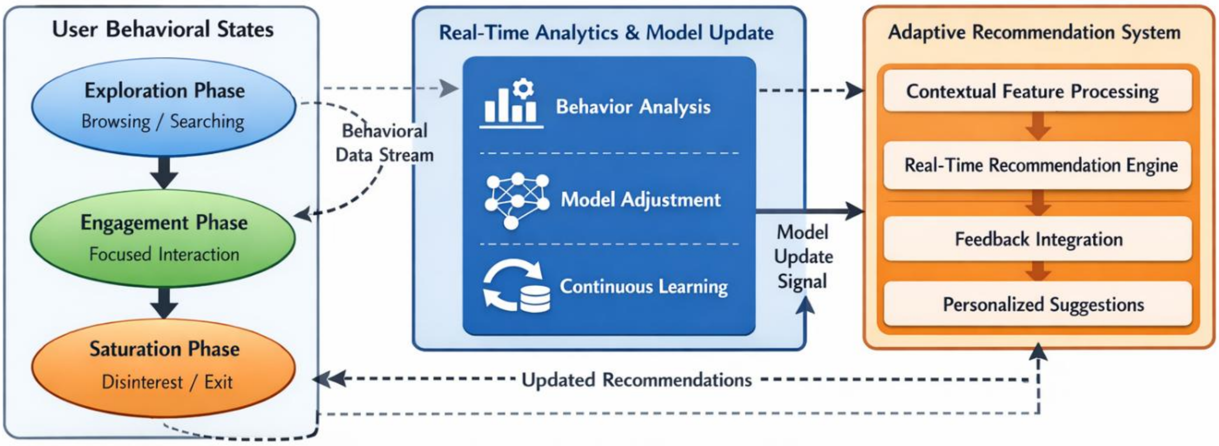


Figure 1. Dynamic behavioral state transitions and real-time recommendation adjustment within the proposed intelligent framework

Overall, the findings provide convergent evidence that integrating momentary user behavior analysis into an intelligent, adaptive recommendation framework leads to substantial gains in engagement, relevance, and system responsiveness in online platforms operating within an urban user context such as Tehran.

4. Discussion and Conclusion

The findings of the present study provide strong empirical support for the effectiveness of an intelligent real-time recommender framework grounded in momentary user behavior analysis. The results demonstrated that integrating fine-grained behavioral signals with adaptive learning mechanisms significantly improves recommendation relevance, user engagement, and system responsiveness compared to conventional rule-based, collaborative filtering, and static machine learning approaches. These outcomes align with a growing body of research emphasizing the necessity of modeling both long-term preferences and short-term behavioral dynamics in modern recommendation environments [1, 5]. The observed improvements in click-through rate, engagement duration, and recommendation acceptance indicate that momentary behavioral cues serve as powerful indicators of immediate user intent, often surpassing the predictive value of aggregated historical preferences.

One of the most notable findings was the substantial performance gap between the proposed framework and traditional recommendation models. This result can be explained by the framework's ability to continuously update its internal representations based on streaming behavioral data, thereby capturing rapid preference shifts that static or batch-trained models fail to detect. Prior studies have highlighted similar limitations in offline-trained sequential models, noting their reduced effectiveness in highly dynamic interaction contexts [8, 9]. By contrast, the present framework operationalizes real-time analytics and rolling model updates, which enables it to respond to evolving user states within the same session. This responsiveness is consistent with recent findings in streaming and session-based recommendation research, where adaptive mechanisms have been shown to enhance predictive accuracy under temporal uncertainty [7, 16].

The increase in engagement duration and reduction in bounce rate following real-time model adaptation further underscore the importance of capturing short-term behavioral volatility. These results suggest that users are more likely to remain engaged when recommendations reflect their immediate cognitive and motivational states rather than static preference assumptions. This observation is in line with research on recency effects and session-based personalization, which emphasizes that recent interactions often carry disproportionate informational value in predicting next actions [3, 11]. The present findings extend this literature by demonstrating that not only recency, but also interaction intensity, navigation patterns, and behavioral transitions contribute meaningfully to real-time recommendation quality.

The strong predictive accuracy achieved by the proposed framework also highlights the effectiveness of combining temporal modeling with contextual and behavioral feature engineering. Previous studies have shown that attention-based and time-aware architectures improve recommendation performance by modeling temporal dependencies at multiple scales [14, 15]. The current results corroborate these findings, while further suggesting that embedding such models within a real-time inference pipeline enhances their practical utility. In particular, the framework's ability to maintain high accuracy alongside low inference latency addresses a key limitation identified in prior work, where computational complexity often hindered real-world deployment [19, 20].

Another important implication of the results relates to user-centered outcomes. The increased acceptance rate of recommendations indicates that users perceived the system's suggestions as more relevant and timely. This aligns with research on transparency and perceived control in recommendation systems, which suggests that users are more receptive to recommendations when they feel aligned with their immediate needs and contextual situation [21, 22]. Although the present study did not explicitly manipulate transparency mechanisms, the improved behavioral outcomes imply that momentary relevance itself may function as an implicit form of trust-building, reinforcing users' willingness to engage with system-generated suggestions.

From a methodological perspective, the findings support the integration of multi-granularity behavioral modeling within a unified intelligent framework. Prior studies have often focused on isolated components, such as long-term preference mining [27], immediate intent modeling [12], or context-aware attention mechanisms [18]. The present study demonstrates that synthesizing these components into a coherent real-time architecture yields synergistic benefits that exceed the performance of individual approaches. This integration is particularly relevant for large-scale online platforms, where user behavior is shaped by rapidly changing contexts, high interaction frequency, and diverse usage motivations [13, 26].

The observed effectiveness of adaptive updates following behavioral state transitions further reinforces the conceptual validity of modeling user interactions as dynamic processes rather than static sequences. Research on behavioral state modeling and intent unit learning has emphasized that users transition through phases such as exploration, focused engagement, and disengagement within a single session [10, 28]. The present findings empirically demonstrate that recognizing and responding to these transitions in real time can meaningfully enhance recommendation outcomes. This supports emerging perspectives that recommender systems should be designed as continuous decision-making agents capable of monitoring and reacting to behavioral signals as they unfold [17, 25].

Overall, the discussion of results indicates that the proposed intelligent framework addresses several persistent challenges in recommender system research, including preference drift, temporal sensitivity, and real-time adaptability. By grounding recommendation decisions in momentary behavior analysis, the framework bridges the gap between theoretical advances in sequential modeling and the practical demands of real-world online platforms. These findings contribute to the growing consensus that future recommender systems must move beyond static personalization toward adaptive, behavior-aware intelligence capable of operating under dynamic and uncertain conditions [2, 29].

Despite the strengths of the present study, several limitations should be acknowledged. First, the sample was restricted to users from Tehran, which may limit the generalizability of the findings to other cultural or geographic contexts with different digital usage patterns. Second, although a wide range of behavioral signals was captured, certain latent psychological factors such as emotional state or task urgency were inferred indirectly rather than measured explicitly. Third, the evaluation period focused on short-term and session-level outcomes, which may not fully capture the long-term effects of continuous real-time recommendation on user satisfaction or platform loyalty.

Future research could extend the present work in several directions. Longitudinal studies examining how prolonged exposure to real-time adaptive recommendations influences user trust, habit formation, and preference stability would provide valuable insights. Additionally, integrating explicit user feedback and explainability mechanisms into the framework could enhance interpretability and ethical robustness. Future studies may also explore cross-domain and cross-platform recommendation scenarios to assess the transferability of momentary behavior models across different types of online services.

From a practical standpoint, the findings offer important implications for platform designers and decision-makers. Implementing real-time behavior-aware recommender systems can substantially improve user engagement and content relevance, particularly in high-traffic digital environments. Practitioners should prioritize lightweight, adaptive architectures that balance predictive accuracy with computational efficiency. Moreover, embedding continuous monitoring and feedback loops into recommendation pipelines can help platforms remain responsive to rapidly changing user needs while maintaining a competitive user experience.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

References

[1] Z. Li, L. Zhang, C. Lei, X. Chen, J. Gao, and J. Gao, "Attention With Long-Term Interval-Based Deep Sequential Learning for Recommendation," *Complexity*, vol. 2020, pp. 1-13, 2020, doi: 10.1155/2020/6136095.

[2] X. Xia, H. Yin, J. Yu, Q. Wang, L. Cui, and X. Zhang, "Self-Supervised Hypergraph Convolutional Networks for Session-Based Recommendation," *Proceedings of the Aaai Conference on Artificial Intelligence,* vol. 35, no. 5, pp. 4503-4511, 2021, doi: 10.1609/aaai.v35i5.16578.

[3] P. Nitu, J. Coelho, and P. Madiraju, "Improvising Personalized Travel Recommendation System With Recency Effects," *Big Data Mining and Analytics,* vol. 4, no. 3, pp. 139-154, 2021, doi: 10.26599/bdma.2020.9020026.

[4] Y. Luo, Q. Liu, and Z. Liu, "STAN: Spatio-Temporal Attention Network for Next Location Recommendation," pp. 2177-2185, 2021, doi: 10.1145/3442381.3449998.

[5] S. Jiang, W. He, L. Cui, Y. Xu, and L. Liu, "Modeling Long- And Short-Term User Preferences via Self-Supervised Learning for Next POI Recommendation," *Acm Transactions on Knowledge Discovery From Data,* vol. 17, no. 9, pp. 1-20, 2023, doi: 10.1145/3597211.

[6] X. Wang, Y. Liu, X. Zhou, Z. Leng, and X. Wang, "Long- And Short-Term Preference Modeling Based on Multi-Level Attention for Next POI Recommendation," *Isprs International Journal of Geo-Information,* vol. 11, no. 6, p. 323, 2022, doi: 10.3390/ijgi11060323.

[7] Y. Wang, A. Liu, and F. Jiang, "A Category-Aware Network for Next POI Recommendation With Long- And Short-Term Preferences," 2023, doi: 10.21203/rs.3.rs-3249221/v1.

[8] M. Luo, X. Zhang, J. Li, D. Peipei, and S. Lu, "User Dynamic Preference Construction Method Based on Behavior Sequence," *Scientific Programming,* vol. 2022, pp. 1-15, 2022, doi: 10.1155/2022/6101045.

[9] Y. Guo, Y. Ling, and H. Chen, "A Neighbor-Guided Memory-Based Neural Network for Session-Aware Recommendation," *Ieee Access,* vol. 8, pp. 120668-120678, 2020, doi: 10.1109/access.2020.3006360.

[10] J. Guo *et al.*, "Learning Multi-Granularity Consecutive User Intent Unit for Session-Based Recommendation," pp. 343-352, 2022, doi: 10.1145/3488560.3498524.

[11] M. B. Hossain, M. S. Arefin, I. H. Sarker, M. Kowsher, P. K. Dhar, and T. Koshiba, "CARAN: A Context-Aware Recency-Based Attention Network for Point-of-Interest Recommendation," *Ieee Access,* vol. 10, pp. 36299-36310, 2022, doi: 10.1109/access.2022.3161941.

[12] Z. Li, X. Huang, L. Gong, K. Yuan, and C. Liu, "Modeling Long and Short Term User Preferences by Leveraging Multi-Dimensional Auxiliary Information for Next POI Recommendation," *Isprs International Journal of Geo-Information,* vol. 12, no. 9, p. 352, 2023, doi: 10.3390/ijgi12090352.
[13] D. Wang, C. Chen, C. Di, and M. Shu, "Exploring Behavior Patterns for Next-Poi Recommendation via Graph Self-Supervised Learning," *Electronics,* vol. 12, no. 8, p. 1939, 2023, doi: 10.3390/electronics12081939.
[14] Y. Sun and J. Wang, "CLSAN:category-aware Long-and Short-termAttention Network for SequentialRecommendation," 2023, doi: 10.21203/rs.3.rs-2981023/v1.
[15] D. Wang, X. Zhang, Z. Xiang, D. Yu, G. Xu, and S. Deng, "Sequential Recommendation Based on Multivariate Hawkes Process Embedding With Attention," *Ieee Transactions on Cybernetics,* vol. 52, no. 11, pp. 11893-11905, 2022, doi: 10.1109/tcyb.2021.3077361.
[16] M. He, B. An, J. Wang, and H. Wen, "CETD: Counterfactual Explanations by Considering Temporal Dependencies in Sequential Recommendation," *Applied Sciences,* vol. 13, no. 20, p. 11176, 2023, doi: 10.3390/app132011176.
[17] B. He, X. He, Y. Zhang, R. Tang, and C. Ma, "Dynamically Expandable Graph Convolution for Streaming Recommendation," pp. 1457-1467, 2023, doi: 10.1145/3543507.3583237.
[18] Y. Zha, Y. Zhang, Z. Liu, and Y. Dong, "Self-Attention Based Time-Rating-Aware Context Recommender System," *Computational Intelligence and Neuroscience,* vol. 2022, pp. 1-10, 2022, doi: 10.1155/2022/9288902.
[19] T. Huang, X. Pan, X. Cai, Y. Zhang, and X. Yuan, "Learning Time Slot Preferences via Mobility Tree for Next POI Recommendation," *Proceedings of the Aaai Conference on Artificial Intelligence,* vol. 38, no. 8, pp. 8535-8543, 2024, doi: 10.1609/aaai.v38i8.28697.
[20] Z. Zhang, H. Zhang, Z. Zhang, and B. Wang, "Context-Embedded Hypergraph Attention Network and Self-Attention for Session Recommendation," *Scientific Reports,* vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-66349-7.
[21] N. Tintarev, B. P. Knijnenburg, and M. C. Willemsen, "Measuring the Benefit of Increased Transparency and Control in News Recommendation," *Ai Magazine,* vol. 45, no. 2, pp. 212-226, 2024, doi: 10.1002/aaai.12171.
[22] S. Pourkhajouei, F. Toffano, P. Viappiani, and N. Wilson, "An Efficient Non-Bayesian Approach For Interactive Preference Elicitation Under Noisy Preference Models," pp. 308-321, 2023, doi: 10.1007/978-3-031-45608-4_23.
[23] J. Li *et al.*, "Point-of-Interest Recommendations Based on Immediate User Preferences and Contextual Influences," *Electronics,* vol. 12, no. 20, p. 4199, 2023, doi: 10.3390/electronics12204199.
[24] R. Yuan, S. Meng, R. Dou, and X. Wang, "Modeling Long- And Short-Term Service Recommendations With a Deep Multi-Interest Network for Edge Computing," *Tsinghua Science & Technology,* vol. 29, no. 1, pp. 86-98, 2024, doi: 10.26599/tst.2022.9010054.
[25] H. Chen, L. Liu, and Z. Chen, "TLSTSRec: Time-Aware Long Short-Term Attention Neural Network for Sequential Recommendation," *Intelligent Data Analysis,* vol. 29, no. 3, pp. 613-630, 2024, doi: 10.3233/ida-240051.
[26] P. Gu, H. Hu, D. Wang, D. Yu, and G. Xu, "Temporal Diversity-Aware Micro-Video Recommendation With Long- And Short-Term Interests Modeling," *Neural Processing Letters,* vol. 56, no. 3, 2024, doi: 10.1007/s11063-024-11652-7.
[27] M. Acharya, K. K. Mohbey, and D. S. Rajput, "Long-Term Preference Mining With Temporal and Spatial Fusion for Point-of-Interest Recommendation," *Ieee Access,* vol. 12, pp. 11584-11596, 2024, doi: 10.1109/access.2024.3354934.
[28] J. Chen *et al.*, "Multi-Temporal Sequential Recommendation Model Based on the Fused Learning Preferences," *International Journal of Computational Intelligence Systems,* vol. 16, no. 1, 2023, doi: 10.1007/s44196-023-00310-w.
[29] H. Li and J. Li, "Research on Information Recommendation Method of Online Education Platform Based on User Preference Model," p. 225, 2023, doi: 10.1117/12.3006307.