JOFIET

(Journal of Financial Intelligence And Emerging Technologies)

Volume 1, Number 1 | June 2026

Machine Learning Techniques for Predicting User Behavior in Digital Platforms: A Systematic Review

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Article Info

Article history:

Received May 12, 2026
Revised June 18, 2026
Accepted June 26, 2026
Published June 30, 2026

Keywords:

Machine Learning
Deep Learning
User Behavior Prediction

ABSTRACT

This systematic review examines some machine learning techniques by which prediction can be made for user behavior on a digital platform, alongside the evaluation of deep learning architectures, collaborative filtering, and other natural language processing approaches. Based on the PRISMA guidelines, we conducted a search of the literature using Google Scholar, followed by retrieving all papers from the SciSpace robust databases (n = 500) and filtering to only high-quality Q1/Q2 journal publications (n = 15). We show that session-based recommendation systems with graph neural networks (GNNs) combined with sequential models outperform conventional recurrent architectures. LSTM- and transformer-based deep learning methods exhibit superior performance over purchase behavior prediction and user engagement forecasting in many cases. The main findings provide evidence that integrating aspects of temporal dynamics, temporal positional encoding, and self-supervised learning into hybrid approaches significantly improves the prediction performance. Graph-based methods improve collaborative signals and high-order user-item interactions, whereas attention mechanisms are used to improve interpretability. However, challenges remain, including data sparsity, cold-start problems, and selection bias. Future Work: Causal Inference frameworks, Multi-Criteria Recommendation Systems, Domain-Specific Adaptations, among others. This review offers researchers and practitioners developing prediction models for digital platform use behavior extensive details across the pipeline of reconstructing predictive models of how users interact on digital platforms.

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1. INTRODUCTION

With mankind moving towards digital platforms and content, products, or services interactions, trillions of behavior records are produced. Click-through rates, purchase decisions, engagement patterns, and who is likely to churn are all important user-centric features that must be accurately predicted for the platform to recommend intelligent content or services. Advances in machine learning models have rendered traditional statistical methods and rule-based systems obsolete; through advanced ML techniques, complex nonlinear patterns in user interactions can be effectively captured (Raza & Ding, 2021).

Over the last few years, deep learning has transformed user behavior prediction, where architectures such as RNNs, LSTMs, Transformers and GNNs have all dramatically improved performance. These models perform well in capturing temporal dependencies, sequential patterns, and collaborative signals that already exist in user behavior data. Deep neural architectures of collaborative filtering techniques are still the main components in recommendation systems, while methods from natural language processing (NLP) have become useful for sentiment analysis as well as content-based predictions (Chen et al., 2019).
While much progress has been made, work remains to be completed. Model performance is limited by data sparsity, especially in cold starts, where users have not established a history. Spurious correlations or suboptimal recommendations can arise due to selection bias in observational studies. Because user preferences change over time, modeling approaches must be both adaptive and able to differentiate short-term behavior from long-term behavior (Yi & Sun, 2025).
This systematic literature review answers four key research questions: (1) Which machine learning techniques have been proven to be the best at predicting user movement across digital platforms? (2) How do deep learning architectures compare with traditional methods in predicting engagement and retention? (3) How are collaborative filtering and reinforcement learning used in recommendation systems (4) Which NLP methods lead to predicting behavior? We concentrate on deep learning approaches such as GNNs, RNNs, LSTMs, and Transformers when it comes to their applications to sequential recommendation, purchase prediction, churn forecasting, and engagement modeling

2. METHOD

The clarity and transparency of this systematic literature review process were ensured by applying the PRISMA guidelines for systematic reviews and meta-analyses. The review process comprised four stages: identification, screening, eligibility, and inclusion.
Search Strategy: We performed a systematic search in two leading databases (Google Scholar and SciSpace). The search strategy used Boolean operators and keywords with words of precision in the study was the use of machine learning techniques for predicting user behavior. The main search terms were: ("machine learning" OR "deep learning" OR "reinforcement learning" OR "Collaborative Filtering" OR "neural network") AND ("user behavior" OR "click through" rate OR "CTR prediction" OR "churn prediction" OR "user engagement" OR "recommendation system") AND ("digital platform" OR "online platform" OR "web platform"). More search filtered by architecture: ("CNN" OR "RNN" OR "LSTM" OR "Transformer" OR "GNN" OR "graph neural network") AND ("user retention" OR "engagement prediction" OR "behavioral prediction" OR "session-based recommendation")
Identification Phase: According to the criteria above, the first search in the Google Scholar and SciSpace databases yielded 500 papers published between 2019 and 202[29]. This wide search incorporated newer advances in machine learning for predicting human behavior while maintaining adequate coverage of state-of-the-art deep learning architectures.
Screening Phase: All 500 papers were screened for relevance to the research questions based on their titles and abstracts. The inclusion criteria stipulated that papers must: (1) be concerned with either machine learning or deep learning techniques, (2) predict user behavior on digital platforms, (3) contain empirical results or new methodologies, and (4) be published in a peer-reviewed venue. We removed studies that were theoretical only (without any empirical validation), non-English studies, and those that were not set in the digital platform context.
Eligibility Assessment: After abstract screening, full-text articles were evaluated for their methodology and publication quality. We used a quality filter, stipulating that papers needed to be published in Q1 or Q2 journals (as ranked by Scimago Journal Rankings (SJR), that is, top journals with high peer-review quality). Papers were assessed in terms of the clarity of the methods used, validity of the experimental design, and contribution to the field.
Final Inclusion: After filtering, 15 papers were included (Fig.1). The resultsA: The grades represent top-H quality research published in leading journals, including Information Sciences, Expert Systems with Applications, ACM Transactions on Information Systems, ACM Transactions on Recommender Systems, IEEE Transactions on Knowledge and Data Engineering, Software: Practice and Experience, Applied Soft Computing, Decision Support Systems, Artificial Intelligence Review, ACM Computing Surveys, Electronic Commerce Research and Applications, and IEEE Access. This review synthesizes evidence from the highest-quality sources, as all 15 papers are Q1 publications.
Data Extraction: We extracted the following data from each included paper: (1) machine learning techniques used, (2) application domain and prediction task, (3) datasets and evaluation metrics, (4)

major findings and performance results, and (5) limitations and future directions. Structured data capture facilitates systematic comparisons among studies and trend identification in the field.

3. FINDINGS

3.1 Sequential and Session-Based Recommendation

Sequential and session-oriented recommendation systems are used to predict what users will do next based on their past interaction sequences. This is a difficult task because the sessions are short, users are anonymous, and short- and long-term patterns need to be captured. Recent studies have focused on three different architectures of graph neural networks and transformer-based approaches as the best approaches in this domain.

Graph Neural Network Approaches: GNNs have been shown in multiple studies to learn to aggregate collaborative signals through higher-order connectivity in user-item interactions. Wu et al. (2023), The Graph-Coupled Time Interval Network (GCTN), which further models sequential patterns using graph neural networks combined with Transformers. To solve performance degradation problems in long-tail distribution scenarios, the GCTN introduces a category-aware graph propagation module to learn better user and item embeddings using item category information. The model contains a time-aware self-attention mechanism that explicitly models the temporal distance between events, considering that recent events are more relevant for prediction. The proposed personalized gating strategy combines the advantages of graph-based and attention-based components, demonstrating state-of-the-art performance on four real-world datasets (Wu et al., 2023).

EAT-SGNN: a self-supervised local-global enhanced attention for session-based recommendation developed by Zhang and Du (2023). This method solves data sparsity by self-supervised learning, which creates supervised signals from raw data and boosts session representation mutual information. When the improved attention module contains knowledge from global- and session-level graphs, a transformer architecture is employed to enhance session intent representation. They showed state-of-the-art performance on the Tmall, Nowplaying, and Diginetica datasets, validating the benefits of harnessing self-supervised learning within the context of graph-based representation learning (Zhang & Du, 2023).

The integration of dynamic graph structures is a study on dynamic graph neural networks for sequential recommendation that connects two different user sequences using a dynamic graph structure and investigates the interactive behavior with time and order information. They transform the next-item prediction into a link prediction task between the nodes of the user and item, while the dynamic graph retains the collaborative signals that sequential models miss. The Dynamic Graph Recommendation Network abstracts user preferences from this growing graph structure and outperforms state-of-the-art methods on four public benchmarks (Anonymous, 2022a).

Disentangling Long-Term and Short-Term Interests: A Self-Supervised GNN-based Sequential Recommendation Model that Tackles Noisy User Behavior and Long-Tail Interaction Distributions Yi and Sun (2025) solved a similar problem of noisy user behavior and long-tail distributions of interactions. We built two standalone encoders to separately represent users long-term and short-term interests in LS4SRec, which recognizes the different timescales at which they operate and that they each require their own modeling approach. With the WITG that has a person behavior sequence globally, the model delivers extra collaborative signals, designing a way to ease data sparsity. Modeling WITG with contrastive learning reduces noise and enables better-quality sequence representations. Sequence readers, interest allocation matrices, and sequence models track interest evolution patterns, whereas sequence graph data augmentation and pseudo-label construction techniques provide unsupervised training signals. The model has been confirmed through multiple experiments based on real-world data with the ability to disentangling temporal interest dynamics (Yi & Sun, 2025)

Position- and Time-Aware Modeling: Recognizing that existing methods revolve heavily around user-centric dynamics and that item dynamics over time have been somewhat overlooked, a position-enhanced and time-aware graph convolutional network (PTGCN) was proposed for sequential recommendation. PTGCN [13] models the interaction between users and items as a bipartite graph structure and proposes position-enhanced and time-aware graph convolutional operations. A self-attention aggregator learns dynamic representations of both users and items simultaneously while using multi-layer graph convolutions to capture high-order connectivity. The PTGCN obtains consistently superior performance with its computational efficiency and is thus applicable to online session-based recommendation settings (Anonymous, 2023).

Frequent Sub-Sequence Modeling: Huang et al. Append (2022) introduced the Frequent Sub-Sequence Modeling (FSM) method, which aggregates frequent sub-sequences that occur in more than one session. This increasingly viable approach assumes that sequences of items are important signals of user preferences when considering long-term items. The FSM builds a local session graph from the current session and a global session graph from frequent subsequences. This gated layer controls the contribution of these two graphs such that the model can learn both session-level item embedding as well as global-level item embeddings. Performance on four benchmark datasets demonstrates the benefit of using cross-session patterns (Huang et al., 2022) over state-of-the-art approaches consistently.

Comprehensive Survey Insights: Li et al. (2024) provided a thorough review of graph and sequence neural networks and their key terms and differences at a high level before analyzing the SR task and comparing the similarities and differences of SR against other recommendation problems. It classifies the existing methods as sequence neural network-based and GNN-based approaches and analyzes their frameworks and technical details. The main takeaway of this systematic overview is that, while sequential models can capture the temporal dependencies well, GNN-based methods overall outperform pure sequential models (Li et al., 2024) by capturing collaborative signals and item-item relationships.

3.2 Purchase Behavior Prediction

Predicting purchase behavior on e-commerce platforms is a role of sieving as an indiscriminate business activity, and the relationships between the two influences (platform engagement and customer characteristics) are complicated. In this field, deep learning-based approaches have exhibited numerous advantages over traditional machine-learning algorithms.

Chaudhuri et al. Using a million unique web sessions from a large web dataset of 50k unique web sessions per unique user, the authors tracked their movement on the web over this time to build a longitudinal study of customer buying behavior based on deep learning (2021), which used two groups of variables: one (the level of engagement on the platform (session length, page views, bounce rate) level, and the other group of variables describes customer attributes (demographics, device type, traffic source). Machine learning algorithms, such as decision trees, random forests, support vector machines (SVM), and Artificial Neural Networks, were compared with deep learning methods. Regardless of the machine learning technique used, a similar analysis of the improvement brought by deep learning was performed on all techniques as well as on the same dataset. The researchers said that trends on actual purchase behavior, not expedited purchase intent, signal value to players in the online marketplace. This is useful because these insights tell platform designers how engaging features are useful and because they also contribute to academic knowledge on the mechanisms of how purchases can be predicted (Chaudhuri et al., 2021).

Liu and Li (2023) classified and addressed two major data quality issues in predicting consumer preferences, missing values and class imbalance. Using this methodology, this study proposed a general pipeline to select the best combinations of these components according to performance metrics. From three consumer behavioral datasets from the UCI Machine Learning Repository, we observed large interaction effects (these terms account for 51% of significant interaction effects, respectively, between the amputation mechanisms and the imputation algorithms; 38.2% of significant interactions between imputation and imbalance treatments; and 27% of interaction effects as quantified by the IEP model, between imbalance treatments and the classification algorithms). While Random Forest delivered the most optimal predictive prowess over datasets, the imbalance problem severely attenuated the predictive advantage of the most widely applied classification technique (Logistic Regression) on practical datasets. Overall, Metacost stacked within the top imbalance treatment reproducibly across all imputation techniques and missing value mechanisms. This has practical implications for practitioners on how to handle imperfect real-world consumer data (Liu & Li, 2023).

3.3 News Recommendation Systems

These two natures of the news pose the challenge of news recommendation, which are: short life cycle of news content, fast change of user interest; online recommendation of news. Raza and Ding (2021) surveyed the state of the art in news recommender systems by focusing on challenges and solutions in general. This review focused on analyzing recommendation solutions, datasets, evaluation metrics other than accuracy, and news recommendation system platforms. The model class contains the most basic collaborative filtering and content-based filtering with impressive performances, along with a newly introduced model class and implementations using deep neural networks to learn the latent representation of item content, user preferences, and other properties semantically. In a novel approach, they also examined the impact of news recommendations on people's filter bubbles and echo chambers, potential interventions to minimize any adverse effects, and why deep neural networks, especially Natural Language Processing (NLP), to analyze the content, and Recurrent Neural Networks (RNNs), to represent temporal reading patterns hold promise as one of the ways to fight against news recommendation problems. Surveys continue to receive novel updates and open new avenues of research in this dynamic field (Raza & Ding, 2021)..

3.4 Graph Neural Networks for User Behavior Modeling

Graph neural networks (GNNs) are a promising paradigm for user behavior modeling because they capture sophisticated relational structures and collaborative signals. In addition to session-based recommendations, GNNs allow the natural modeling of complex user-item interactions, multi-criteria preferences, and heterogeneous demand shocks.

Causal Inference and Multi-Criteria Modeling: Guo et al. (2025) addressed selection bias and multi-criteria preferences through the Multi-Criteria Causal Recommendation (MCCR) framework. Conventional single-criteria approaches, where the overall rating is primarily accounted for without considering users multi-dimensional behavior characteristics (for example, environ, location, and service as in rating hotels as separate dimensions). MCCR utilizes structural causal models to represent causal relationships among variables and to address selection bias using backdoor adjustment. The framework builds on a graph representation learning method for multi-criteria ratings that aims to capture higher-order information and infer the heterogeneity of users' preferences across criteria. However, existing methods either ignore the multi-criteria nature of preferences or draw unwarranted conclusions because they do not account for the causal structure underlying user behavior (Guo et al., 2025). Experimental results on six real datasets show that MCCR compares favorably with existing baselines by simultaneously incorporating both factors.

Heterogeneous Demand Effects: Heterogeneous demand effects of recommendation strategies in mobile applications: Analysis of the effectiveness of recommendation approaches on consumer utility and demand. Recommendation Strategies The differences in effectiveness were significant across recommendation strategies, with recommendations where social proofs are directly embedded in suggested alternatives being the most effective. The effects in mobile channels were even stronger, as recommendation strategies that combine social proofs with higher induced awareness of temporal diversity showed. Heterogeneous research across items, users, and contextual settings is verified through information and persuasion mechanisms. We developed novel econometric instruments that use deep learning models of user-generated reviews to estimate causal effects in the presence of endogeneity. This explains the conflicting previous results and has important business implications for mobile recommendation design (Anonymous, 2022b).

Cross-Domain Applications: Chen et al. (2019) educated deep learning usability in predetermining user behavior in the transportation field from social media text and traffic information detection. Using continuous bag-of-words models, this study learned word embeddings from three billion microblogs and then clustered them to visualize semantic similarity. We used three machine learning models (CNN, LSTM, and LSTM-CNN) on the microblogs to extract those that are relevant to traffic. Deep learning approaches were more effective than classic SVM models based on bag-of-n-grams or word vectors and multilayer perceptron models. This cross-domain application demonstrated the generalization of deep learning models for predicting user behaviors not only in e-commerce and entertainment but also in a specialized domain (Chen et al., 2019).

Educational Platform Engagement: Abdulkader et al. (2025) conducted a systematic literature review Using Deep-Learning to predict academic performance and engagement of students in Massive Open Online Courses: a systematic literature review (2025) Though the extended abstract we have access to provides limited detail about specific findings, this work exemplifies the application of user behavior prediction methods to educational platforms to predict engagement and, thereby, guide proactive interventions to improve learning and prevent drop out (Abdulkader et al., 2025).

Hardware Acceleration Considerations: Silvano et al. (2025) conducted a survey of deep-learning hardware accelerators for heterogeneous HPC platforms, including GPU, TPU, FPGA, and ASIC-based accelerators, along with newer technologies such as 3D-stacked Processor-In-Memory and

Neuromorphic Processing Units. Although not directly related to user behavior prediction, this survey highlights the infrastructure for the online deployment of deep learning architectures for the real-time prediction of user behavior at scale in production systems. Dedicated hardware accelerators have enabled GNN and generalized transformer-based models to implement sophisticated models for real-time recommendations and predictions (Silvano et al., 2025)..

4. DISCUSSION

Many trends and insights into machine learning for predicting user behavior on digital platforms are highlighted in this systematic review. The ongoing convergence towards graph neural networks in combination with sequential models articulates a fundamental shift from RNN-dominated models in the past. The capacity of GNNs to capture collaborative signals and high-order connectivity uncovers core deficits in user-sequence models that neglect to consider the interdependencies between users.

Architectural Innovations: The successful approaches incorporate various modeling paradigms. Three key trends can be observed in the literature: hybrid architectures pairing GNNs with Transformers (Wu et al., 2023), self-supervised learning with graph pour-building (Zhang & Du, 2023), and within practical implementations, identity background and position-aware graph convolutions (Anonymous, 2023) consistently outperform single-paradigm methods. This implies that modeling user behavior relies on multiple aspects, as sequential models capture temporal dynamics, collaborative signals are percolated in a graph structure, and semantic relations are captured through attention. The explicit modelling of time intervals and positional information is essential because the temporal context has a strong influence on the accuracy of the prediction.

Addressing Data Challenges: Data sparsity and quality issues remain problematic. In particular, self-supervised learning approaches (Yi & Sun, 2025; Zhang & Du, 2023) can create more training signals from unlabeled data, thus alleviating the sparsity problems. Specifically, the disentanglement of long- and short-term interests (Yi & Sun, 2025) solves the problem of noisy user behavior by modeling long- and short-term interests at different temporal scales. Although random forests exhibit robustness over data quality scenarios and can handle missing values and class imbalances effectively (Liu & Li, 2023), appropriate processing of missing values and class imbalances plays a significant role in the performance of models in purchase behavior prediction.

Causal Inference and Bias Mitigation: The introduction of causal inference frameworks (Guo et al., 2025) is an important methodological breakthrough in this field. Conventional data-driven methods are susceptible to learning aliases from biased observational data. The third addresses the strength of the prediction by signal detection in structural causal models. Back-door adjustment-type strategies make confounding factors and selection bias explicit. This is of particular importance in recommendation systems, where user exposure to items is non-random, and the observed interactions reflect user preferences and system biases.

Domain-Specific Considerations: Application domains have different behavioral characteristics and require different approaches. In e-commerce, session-based recommendations greatly improve the modeling of frequent subsequences and collaborative signals (Huang et al., 2022). In news recommendation, it is necessary to adapt to the fast-evolving content and temporal nature of reading patterns (Raza & Ding, 2021). Predicting purchase behavior stresses engagement measures on the platform and the personal attributes of customers (Chaudhuri et al., 2021). These domain-dependent requirements imply that while general architectural principles (GNNs, attention mechanisms, temporal modeling) can transfer across domains, optimal design requires design as per domain.

Evaluation and Interpretability: Most studies are evaluated using standard metrics (precision, recall, NDCG, MRR) on offline datasets. However, a recent heterogeneous demand effects study (Anonymous, 2022b) makes it clear that causal mechanisms and heterogeneity across users and contexts matter. The interpretability of attention mechanisms and graph structures reveals which items, features, or time periods create predictions; however, further work needs to be done to create transparent and trustworthy high-stakes deep learning models.

Limitations and Gaps: Draw your attention to Several limitations are highlighted. Most studies are guided by accuracy metrics, and the trade–offs between fairness, diversity, and long-term user satisfaction receive insufficient attention. Furthermore, despite some advances in transfer and meta-learning, the cold-start problem for new users or items continues to be a challenge. Third, in large-scale systems, computational efficiency sometimes takes the back seat to better accuracy, yet real-time prediction demands exact optimization. Fourth, privacy issues are given scant focus, although user behavior is extremely privacy-sensitive. What makes matters worse is that most of the research is evaluated offline on historical datasets, which may differ in performance from online where model predictions directly affect user behavior, creating feedback loops.

Practical Implications: This review offers several practical insights for practitioners. Whether applications utilizing rich relational structures and collaborative signals should be preferred over graph neural networks. GNN only hybrid architectures with Transformers or RNN for better performance at the cost of high computational power. Self-supervised learning can help us take advantage of unlabeled data to improve performance in data-sparse situations. Proper data preprocessing, such as outlier handling and dealing with missing values or class imbalances, is fundamental for real use cases. Selection bias is one of the scenarios in which one should tread into the territory of causal inference frameworks. Finally, although deep learning can automatically learn to represent data, domain-specific adaptations and feature engineering remain essential.

5. DISCUSSION

We conduct a systematic literature review of machine learning methods to predict user behavior on digital platforms, analyzing 15 of the best rated Q1 ranked publications. The experiments show that, especially when combined with a sequential model such as recurrent neural networks (RNNs) or attention mechanisms, graph neural networks currently lead the user behavior prediction literature. For applications ranging from session-based recommendation, purchase behavior prediction, news recommendation, and engagement forecasting, deep learning approaches consistently outperform traditional machine learning methods in tangible use cases.Recent research advances in recommendation systems include: (1) the combination of Global Graph Networks (GNNs) and transformers, integrating collaborative signals with temporal dynamics; (2) self-supervised learning methods that overcome data sparsity by generating training signals from unlabeled data; (3) learning to model time intervals and positional information for more accurate prediction; (4) disentangled long-term and short-term user interests to tackle noisy behavior patterns; (5) causal inference frameworks to reduce selection bias and spurious correlations; And lastly, multi-criteria modelling approaches that capture heterogeneous user preferences.

Although we have achieved particular milestones, there are still many obstacles. There is still a data sparsity effect and cold-start, and it is difficult to achieve good performance without an adequate user-item interaction history for new users or items. While observational data alone are insufficient to provide good predictions, selection bias will lead to worse predicted instances if we do not consider it when establishing causal models. This computational efficiency continues to be an issue for deploying complex models in large-scale systems in real time. As predicting user behavior becomes more prevalent, so too do privacy considerations and fairness issues also arise.

Future research opportunities include more advanced causal inference frameworks that allow for time-varying confounders and feedback loops; unified models that can perform many prediction tasks (e.g., recommendation, churn, and engagement) within a single model; transfer learning and meta-learning, where cold-start problems for new items or users can be solved faster; optimization with fairness constraints or diversity objectives; privacy-preserving techniques allowing accurate prediction without leaking sensitive user data; online experiments validating previous offline findings about prediction systems while tracking their long-term effects on user behavior.

This review provides a good foundation for existing researchers and practitioners studying user behavior prediction on digital platforms. The movement toward graph and hybrid architectures, coupled with breakthroughs in self-supervised learning and causal inference, provides a path forward for building more accurate, robust, and trustworthy prediction systems. With digital platforms constantly changing and user behavior growing ever more sophisticated, moving forward will require the integration of many modeling paradigms with rigorous standards for modeling in all respects, including data reliability and bias on the domain-expertise level.

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