A User-Intent Context-Aware Recommendation Approach for Low-Resource Online Learning Environments (Mauritanian Context)

Massra Sabeima
Department of Computer Science, University of Nouakchott, Nouakchott, Mauritania

***Abstract*—User experience in distance learning is often conceptualized through interactions between the learner and the system's interface. These interactions can be understood as the dynamic interplay between user behavior and system behavior, each initiated or guided by distinct mechanisms. User behavior, inherently autonomous, cannot be directly dictated, whereas system behavior can be designed to guide or constrain user actions. In human-guided systems, the process primarily responds to user input, offering limited control over the learning experience. Conversely, system-guided interactions selectively present content and collect targeted information, shaping the learner's engagement and, in some cases, eliciting responses that the user may not consciously provide. This duality of guidance highlights the critical role of system design in influencing both overt and latent aspects of learner behavior, emphasizing the importance of adaptive mechanisms to optimize user experience in distance learning environments.**

***Keywords*—User intent modeling; context-aware recommendation; low-resource online environments**

I. Introduction

The global health crisis of recent years accelerated the worldwide adoption of distance and online learning, intensifying research interest in how learners interact with digital learning environments. User experience in distance learning is increasingly conceptualized as the outcome of interactions between learner behavior, which remains autonomous, and system behavior, which can be deliberately designed to guide, constrain, and adapt the learning process. Adaptive recommender systems offer a promising means of shaping this interplay, as they model learner profiles and interactions to personalize content delivery [1]. Their effectiveness has already been demonstrated in student-facing platforms, where machine learning-based recommenders have been shown to measurably improve learners' experience [2].

In the Mauritanian context, however, distance learning platforms remain underutilized and insufficiently adapted to local constraints. Existing solutions often fail to adequately reflect learners' needs, infrastructural limitations, and national educational priorities. Persistent challenges such as unstable internet connectivity, limited access to computing devices, and heterogeneous levels of digital literacy significantly influence how learners interact with online platforms in Mauritania. In such low-resource environments, contextual constraints strongly shape user behavior, limiting the effectiveness of conventional learning systems and calling for adaptive approaches capable of leveraging limited interaction data while actively guiding learners toward relevant educational resources.

Among established recommendation techniques, Content-Based Filtering (CBF) and Collaborative Filtering (CF) remain the two most widely adopted approaches in online learning environments. CBF recommends resources by matching item attributes, such as subject domain or language, with a learner's interaction history, offering transparency and remaining effective when interaction data are scarce, although it often produces narrowly focused recommendations [3]. CF instead generates recommendations by identifying similarities among learners or learning resources, leveraging collective interaction patterns to support personalization at scale [4]; its performance, however, deteriorates in contexts marked by limited or uneven user engagement. To balance individual learner profiles with group-level interaction patterns, several studies combine both techniques into Hybrid Recommender Systems, which improve robustness and stability across diverse learning contexts [5].

More recent research explores Context-Aware Recommender Systems (CARS), which extend adaptive learning by incorporating situational information, such as time, location, and access conditions, into the recommendation process [6]. Recent surveys have further mapped this evolving landscape, from classical filtering techniques to modern hybrid and context-aware pipelines [7]. By accounting for contextual constraints, CARS allow platforms to dynamically adapt system behavior to learners' circumstances, which is particularly relevant in regions such as Mauritania, where connectivity and access conditions vary widely, although the integration of contextual data also raises concerns related to privacy, data governance, and ethical use.

Despite their demonstrated effectiveness, these techniques face notable limitations in low-adoption and resource-constrained settings. Data sparsity and cold-start problems are exacerbated by limited learner interaction data, and scalability remains a concern for platforms serving heterogeneous learner populations [8]. Insufficient explainability can further undermine user trust and reduce system acceptance, particularly when deep learning methods are used to capture complex and latent behavioral patterns, since such methods also introduce challenges related to interpretability, computational cost, and deployment complexity [9]. CBF-based approaches that focus on individual learner profiles remain useful in this regard precisely because interaction data are often scarce in e-learning settings [10], while neural architectures, including sequence-aware networks, have demonstrated improved performance in modeling temporal learning behaviors when sufficient data are available [11], [12]. In educational settings specifically, context-aware mechanisms driven by real-time learning analytics have been shown to improve the relevance of recommended learning paths [13]. Fairness concerns may also arise in linguistically and culturally diverse environments, underscoring the need for transparent, explainable, and adaptive system design [14].

Building on these observations, this study proposes a recommendation approach centered on learner profiles and user-system interactions, integrating hybrid, context-aware, and deep learning techniques to support distance learning in the Mauritanian context. The contribution of this work lies not in the development of new algorithms, but in the adaptation and validation of state-of-the-art recommendation mechanisms for environments characterized by limited infrastructure, scarce data, and the need for equitable and transparent system guidance. The proposed approach aims to enhance user experience by balancing learner autonomy with system-guided adaptation, particularly in underprivileged regions with restricted internet access.

II. Related Work

Beyond the individual filtering and context-modeling techniques discussed above, several recent studies have proposed complete recommendation frameworks that pursue objectives closely related to those of this work, namely combining hybrid filtering strategies with contextual signals or deep learning components to improve personalization in online learning.

Sundar et al. introduced a context-aware content recommendation engine driven by hybrid reinforcement learning, which adapts instructional material to situational signals and reports measurable gains in learner engagement on general-purpose personalized learning platforms [15]. Chen et al. proposed a context-conditioned sequential framework that couples Conditional Variational Autoencoders with Transformer-based sequential modeling and IoT-derived contextual embeddings, achieving strong ranking accuracy on large MOOC datasets such as MOOCCube and edX, although its design presumes continuous access to device and session telemetry that cannot be guaranteed in low-connectivity settings [16]. A hybrid attribute-based recommender that combines knowledge-based filtering with collaborative filtering has also been proposed to mitigate the cold-start problem in personalized e-learning, and was validated through a prototype platform rather than in a resource-constrained deployment scenario [17].

Complementary systematic reviews further contextualize these efforts. Jangid and Kumar surveyed deep learning solutions to the cold-start and long-tail problems, underscoring the persistent trade-off between representational richness and computational cost in data-scarce regimes [18], while a broader systematic review of deep learning and large language model strategies for cold-start recommendation confirms that no single paradigm generalizes across all data-availability conditions [19]. A separate systematic literature review of hybrid recommender architectures highlights the general benefits of combining filtering paradigms but does not address the specific constraints of educational deployment in low-resource regions [20]. Taken together, this body of work confirms the effectiveness of hybridization, context-awareness, and deep learning for recommendation quality, but it also reveals a persistent gap: most recent frameworks are designed and evaluated under the assumption of stable connectivity, rich contextual telemetry, or abundant interaction data, none of which can be taken for granted in the Mauritanian context targeted by this study. A structured comparison against these related frameworks, together with the corresponding reported performance figures where available, is presented in Table II in the Results and Discussion section.

III. Proposed Approach

The proposed recommendation approach leverages the complementary strengths of Content-Based Filtering (CBF), Collaborative Filtering (CF), Deep Learning, and Context-Aware Recommender Systems (CARS) to adapt learning resources to the specific needs of Mauritanian learners [4], [6], [21]. Each technique addresses distinct challenges inherent to online learning in resource-constrained environments. CBF provides interpretability and effectively supports new or infrequently accessed items, making it particularly suitable for learners with limited interaction histories [3]. CF complements this individual-focused approach by exploiting patterns across learner groups to enhance personalization even when individual data remain sparse [10]. Deep Learning further alleviates data sparsity by modeling complex and latent learner behaviors, enabling the system to generate accurate recommendations despite limited historical data [5].

CARS extend personalization by incorporating contextual factors such as study time, geographic location, and device type, which is especially relevant in the Mauritanian context, where access conditions vary significantly [6]. This context-sensitive adaptation ensures that recommended resources remain relevant, feasible, and engaging across diverse learning situations. In addition, an explicit focus on fairness enables the system to account for linguistic and cultural diversity, mitigating potential biases and promoting equitable access to educational opportunities [14]. By integrating these techniques, the proposed system offers a unified, adaptive, and context-aware framework capable of delivering personalized, ethical, and practically deployable recommendations for Mauritania's diverse online learner population.

A. Architecture of the Proposed System

To operationalize the hybrid approach described above, the proposed architecture is structured into three main layers: the Data Layer, the Processing Layer, and the Application Layer, as illustrated in Fig. 1. This layered architecture is designed to support Mauritanian learners by integrating hybrid recommendation strategies and deep learning techniques, while addressing key challenges such as data sparsity, linguistic diversity, and technological disparities.

The proposed recommendation framework integrates a multi-layered system architecture with a human-centered interface, leveraging both learner profiles and user-intent modeling to enhance online learning. The architecture is organized around a central processing engine designed to address key

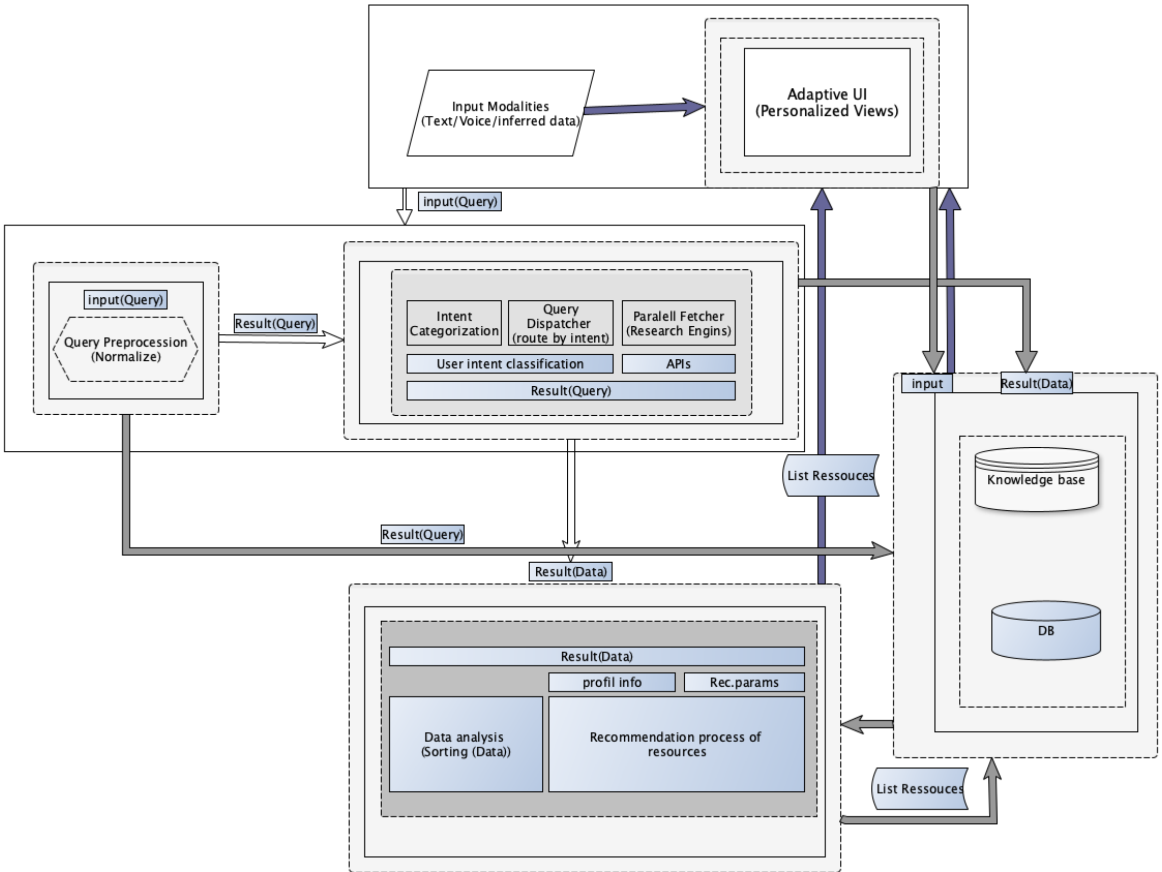

Fig. 1. Architecture of the proposed approach.

challenges, including data sparsity, contextual relevance, linguistic diversity, and fairness. In addition to standard user interaction data, the system captures contextual data describing environmental factors such as time of access, geographic location, and device type. This information is incorporated into the recommendation process to enable context-aware recommendations, allowing the system to adapt to learners' access conditions, which is particularly important for learners in rural areas or regions with limited internet connectivity.

The Recommendation Techniques Module implements CBF and CF to align learning resources with individual learner profiles and group-level interaction patterns, effectively mitigating data sparsity and addressing linguistic diversity. In parallel, the Deep Learning Module employs neural networks with embeddings to model complex relationships between learners, learning resources, and contextual features, capturing both temporal and latent behavioral patterns even when historical data are limited. Outputs from these modules are integrated within a Hybrid Fusion Unit, which applies a weighted strategy to balance their respective contributions based on learner context and data availability. For new users, the system prioritizes interpretable approaches such as CBF, while deep learning increasingly informs recommendations as user interaction data accumulate. The Recommendation Engine ranks and presents personalized learning resources, while the Feedback System collects user ratings and behavioral data to support continuous refinement of the recommendation models.

In parallel, the system incorporates user-intent modeling to further guide learning. Learners provide initial input to construct a profile and express their interests. The system classifies this information into intent categories, formulates research queries, and retrieves results from multiple search engines and databases. These results are then filtered, ranked, and structured according to learner preferences. By predicting learner intent and inferring knowledge that may not be explicitly stated, the system enhances recommendation quality and guides learners more efficiently through the platform. Synthetic data help mitigate sparsity, contextual features enable adaptation to environmental conditions, and the human-centered interface enhances engagement while generating actionable learning traces for analytics. Collectively, these components form a robust, fair, and personalized recommendation system tailored to the needs of learners in low-resource regions, particularly in Africa.

B. System Workflow

To clarify how the layers described above interact at runtime, the end-to-end workflow can be summarized in six stages. First, the Data Layer ingests learner profiles, course metadata, interaction logs, and contextual signals (time of access, approximate location, and device type), applying normalization, categorical encoding, and imputation to handle missing or sparse fields. Second, the Processing Layer routes the cleaned data to the Recommendation Techniques Module, where CBF computes item-similarity scores based on subject domain and language, and CF computes neighborhood- or factorization-based scores from the user-item interaction matrix. Third, in parallel, the Deep Learning Module encodes learners, courses, and contextual features into dense embeddings and produces a latent-space score that captures non-linear interactions the linear CBF and CF components cannot represent. Fourth, the Hybrid Fusion Unit combines these three scores through a context- and data-availability-dependent weighting scheme: weights favor CBF when a learner has little or no interaction history, gradually shift toward CF as peer-group data accumulate, and increasingly incorporate the Deep Learning score as the volume of individual and collective interaction data grows. Fifth, the fused score is combined with the outputs of the predictive component described in Section IV-A, namely the expected rating and completion-likelihood estimates, to produce a single ranked list of recommended resources. Sixth, the Application Layer renders this list through the human-centered interface, while the Feedback System logs explicit ratings and implicit behavioral signals (dwell time, revisits, completions) that are periodically used to retrain the Recommendation Techniques Module and the Deep Learning Module, closing the adaptive loop.

This staged design has two practical consequences for low-resource deployment. First, because the Hybrid Fusion Unit degrades gracefully to CBF-dominant behavior when data are scarce, the system remains usable from the very first learner session, which is essential in a context where public usage logs are not yet available. Second, because the Deep Learning Module is only weighted heavily once sufficient interaction data exist, its computational cost is incurred progressively rather than uniformly, which eases deployment on institutions with modest computing infrastructure.

IV. Results and Discussion

A. Evaluation

Within the proposed architecture, a predictive learning model is integrated into the central processing engine to support both personalized course recommendation and student success prediction. This model acts as an intelligent decision-support component, guiding learners toward courses that align with their preferences while estimating their likelihood of successful completion. The model operates on a structured pipeline that combines learner characteristics, course attributes, and engagement patterns. Learner-related features include demographic information, learning preferences, and subject interests, while course-related features capture domain, difficulty level, and historical feedback. Behavioral signals such as time spent on learning activities and engagement intensity are further incorporated to reflect learners' interaction dynamics. Data preprocessing ensures consistency through normalization, categorical encoding, and imputation strategies for missing values, enabling robust analysis even under sparse data conditions.

As noted in the Data Availability statement, the interaction data used to train and evaluate the predictive component were synthetically generated, given the absence of a public dataset describing Mauritanian distance learners at the time of writing. The generation procedure was designed to preserve the structural properties that make e-learning interaction data challenging to model, namely sparsity, cold-start users, and heterogeneous engagement levels, rather than to represent any specific real institution. Learner profiles were sampled to reflect plausible distributions of age range, prior digital literacy, and preferred instructional language, while course attributes were sampled across a catalog of subject domains and difficulty levels representative of common distance-learning offerings. Interaction sequences were then generated so that a substantial share of learners have short histories, a smaller share have moderately long histories, and a minority have extensive interaction records, mirroring the typically skewed engagement distribution observed in real platforms. Ratings and completion outcomes were generated with a controlled dependence on learner-course affinity and engagement intensity, so that the predictive component has a genuine, learnable signal to recover, while contextual features (time of access, device type, and connectivity proxy) were sampled independently of outcomes to avoid trivially encoding the target variables. This procedure allows the architecture to be validated end-to-end before institutional data collection is complete, while making clear that the reported metrics characterize the learning capacity of the model on data with realistic structural properties rather than the accuracy that should be expected once real Mauritanian usage logs become available; the corresponding validation on real data is identified as a priority direction in the Conclusion.

This predictive component extends the recommendation framework by jointly addressing two complementary objectives: estimating learners' potential appreciation of learning resources by predicting expected course ratings, and assessing completion likelihood, allowing the system to favor recommendations that learners are not only interested in but also likely to complete. These predictions are fed into the Hybrid Fusion Unit, where they are combined with outputs from the content-based, collaborative, and deep learning recommendation modules. By embedding success prediction into the recommendation loop, the architecture moves beyond relevance-based personalization toward outcome-aware recommendation, which is particularly valuable in contexts characterized by heterogeneous learner profiles and uneven access conditions, such as rural or connectivity-constrained environments, where early identification of disengagement risks can significantly improve learning outcomes.

The system was evaluated using precision, recall, and F1-score to assess recommendation accuracy. Table I summarizes the test results obtained over 100 training epochs, and Fig. 2 presents the corresponding training and validation curves for loss, rating error, and completion accuracy.

To contextualize the model's performance, its results were compared against several baseline recommendation methods: Content-Based Filtering, which recommends resources based solely on resource similarity; Collaborative Filtering, implemented as matrix factorization based on user-resource interactions; and a Random Recommendation baseline that serves resources without personalization. User satisfaction can further be measured through surveys focusing on engagement and perceived relevance, particularly for rural learners.

TABLE I. Test Results of the Proposed Model

Metric	Value
F1-Score (Completion)	0.9919
Test MAE (Rating)	0.0185
Precision@5 (Rating)	0.9900

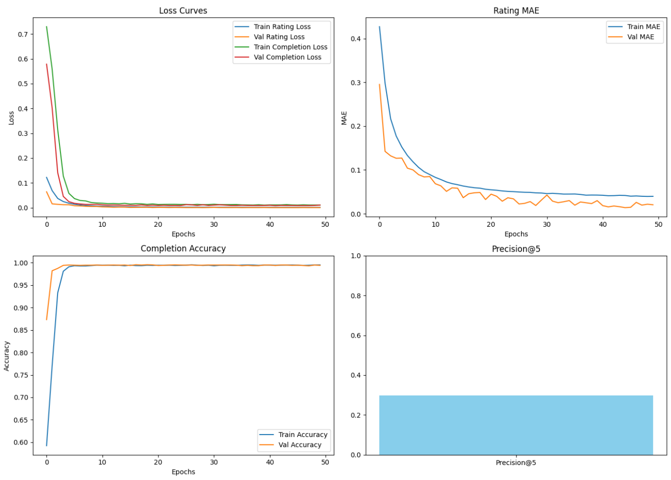

Fig. 2. Model training curves and final evaluation metrics (100 epochs).

B. Comparative Positioning with Recent Related Work

Table II positions the proposed framework relative to the recent related approaches introduced in the Related Work section, contrasting the techniques employed, the manner in which context and cold-start conditions are handled, and the deployment setting each study targets, together with the corresponding reported results where available.

As Table II illustrates, the reviewed frameworks achieve strong ranking or engagement results, but each assumes conditions, such as continuous IoT telemetry, rich device sensing, or an already-populated interaction history, that are not consistently available in the Mauritanian context. In contrast, the proposed approach is explicitly designed to remain operational when such conditions are absent: the Hybrid Fusion Unit falls back on interpretable, low-data techniques for new users, contextual features are limited to signals that are cheap to collect (coarse time, location, and device type), and the predictive component is trained to be robust to missing or imputed values. This positioning does not claim algorithmic superiority over the cited frameworks on their own evaluation benchmarks; rather, it reflects a difference in design objective, namely equitable and resilient recommendation under infrastructural scarcity rather than maximal ranking accuracy under data-rich, connectivity-rich conditions.

C. Contextual Feature Design

Because the contextual signals used by the Hybrid Fusion Unit directly shape which resources learners see, the choice of which signals to collect is itself a fairness-relevant design decision. Table III summarizes the contextual dimensions currently used by the proposed system, the information they capture, and the role each plays in shaping recommendations.

Each of these features is deliberately kept coarse-grained and inexpensive to collect, since fine-grained tracking (precise GPS coordinates, continuous sensor streams, or detailed browsing histories) would both exceed the technical capacity of many target institutions and raise proportionally greater privacy concerns for learners who may not have meaningfully consented to detailed monitoring. Consistent with the fairness considerations raised for recommender systems operating in linguistically and culturally diverse environments [14], the language-preference and geographic-region features are treated as protected dimensions that inform, rather than restrict, the resources a learner can access, so that the system broadens rather than narrows a learner's exposure to available courses.

Explainability is treated as a complementary requirement: prior work has shown that pairing recommendations with feature-level explanations, for instance via post-hoc attribution methods, can measurably increase both user trust and, in some cases, recommendation precision itself [22]. Although a full explanation interface is left for future development, the layered architecture already exposes, for each recommendation, which of CBF, CF, Deep Learning, or the predictive component contributed most to the final ranking, which provides a natural entry point for future explanation features without requiring architectural changes.

D. Limitations

Despite its promising performance, the proposed approach has several limitations that should be considered before large-scale deployment:

- Data sparsity: limited interaction history for new users may reduce recommendation accuracy.
- Infrastructure constraints: some institutions in rural areas have limited internet connectivity and computing resources.
- Scalability: the hybrid model requires efficient feature engineering and may need optimization for large-scale deployment.
- Bias: although data are anonymized, existing usage patterns may introduce biases that require ongoing monitoring.

Future deployment should consider lightweight implementations and offline training strategies to mitigate these challenges.

E. Deployment Strategy for Low-Connectivity Contexts

Translating the architecture into a system that remains usable under the connectivity and device constraints typical of Mauritanian institutions requires a small set of concrete engineering choices in addition to the model design itself. First, the client-facing application can cache a ranked shortlist of recommended resources locally, so that learners retain access to previously computed recommendations during connectivity interruptions, with synchronization and model updates deferred until a connection becomes available. Second, the heavier Deep Learning Module can be executed on institutional or regional servers rather than on end-user devices, while the lightweight CBF and rule-based fallback logic run locally, ensuring that

TABLE II. COMPARISON OF THE PROPOSED APPROACH WITH RECENT RELATED RECOMMENDATION FRAMEWORKS

Study	Approach and Context / Cold-Start Handling	Target Setting and Reported Result
Proposed Approach	Hybrid CBF + CF + Deep Learning fused via a context- and data-availability-weighted Hybrid Fusion Unit; explicit context features (time, location, device); CBF prioritized for new users, Deep Learning weight grows with interaction history	Low-connectivity, low-device-access, linguistically diverse settings (Mauritania); F1 = 0.9919 (completion), MAE = 0.0185, Precision@5 = 0.9900
Sundar et al. [15], 2025	Context-aware hybrid reinforcement-learning engine adapting content delivery via situational reward signals	General personalized e-learning platforms; reports improved engagement, not designed for connectivity-constrained deployment
Chen, Han and Liu [16], 2026	Conditional Variational Autoencoder + Transformer fused with IoT-derived context embeddings (device, session, time); prior conditioned on user profile for cold-start users	IoT-enabled MOOC platforms assuming continuous telemetry availability
Frontiers e-learning study [17], 2024	Knowledge-/attribute-based filtering combined with collaborative filtering using similarity measures on learner and material attributes	General e-learning cold-start mitigation; validated on a prototype website, without an explicit connectivity or infrastructure constraint
Jangid and Kumar [18], 2025	Systematic review and taxonomy of deep-learning solutions to cold-start and long-tail problems	Cross-domain analytical survey; identifies computational-cost and data-availability trade-offs without proposing a deployable low-resource system
Bodduluri et al. [20], 2024	Systematic literature review of hybrid recommender architectures, mostly in e-commerce	Cross-domain synthesis; confirms hybridization benefits but does not address educational or low-resource contexts specifically

TABLE III. CONTEXTUAL FEATURES USED IN THE RECOMMENDATION PROCESS

Context Dimension	Description	Role in Recommendation
Time of access	Hour of day and day of week at which the learner connects	Favors shorter, focused modules during brief connectivity windows and longer content during off-peak periods
Device type	Smartphone, shared computer lab, or basic feature phone	Determines whether text-first or multimedia-rich content is prioritized, and whether video is downscaled or substituted with text
Connectivity quality	Approximate bandwidth or connection type (2G/3G/Wi-Fi/offline)	Triggers lightweight content delivery, aggressive local caching, and deferred synchronization
Geographic region	Coarse, opt-in indicator of urban or rural setting	Weights recommendations toward resources compatible with the learner's typical infrastructure
Language preference	Learner's declared instructional language	Filters and ranks resources by linguistic accessibility, supporting Mauritania's linguistic diversity

a baseline level of personalization persists even when the connection to the central server is degraded or unavailable. Third, periodic batch retraining, rather than continuous online learning, reduces the computational and bandwidth burden on infrastructure with intermittent availability, while still allowing the Hybrid Fusion Unit to incorporate newly accumulated interaction data at regular intervals. Finally, because digital literacy and device access vary across learners, the Application Layer should support low-bandwidth interaction modes, such as text-first interfaces and compressed content previews, alongside the standard interface, so that the system degrades gracefully rather than becoming unusable on low-end devices or slow networks.

V. CONCLUSION

This work demonstrates that placing user intent and human-centered design at the core of educational technology architectures can significantly enhance the effectiveness, transparency, and relevance of learning recommendation systems. The proposed framework establishes an adaptive learning loop in which the system guides learners through a deeper understanding of their needs, infers preferences in a trust-aware manner, and generates meaningful interaction traces that reflect the authentic learning experience. These qualitative and behavioral data support more accurate analytics and reinforce learner engagement.

While existing recommendation approaches provide a solid foundation, the findings reported here highlight the necessity of contextualized and adaptive methods to recommend learning resources that are genuinely aligned with learners' profiles and environments. Ongoing research focuses on the Mauritanian context, where challenges related to data availability, infrastructure constraints, and learner diversity remain central; data collection currently represents a primary area of effort, alongside plans to conduct large-scale evaluations to further validate the robustness and generalizability of the proposed model.

Future work will include broader empirical studies, survey-based evaluations, and ablation analyses to better assess the contribution of each system component. In parallel, a user-centered online learning platform that operationalizes the proposed architecture is under development, enabling personalized learning paths tailored to diverse learner profiles. Together, these efforts aim to advance equitable, context-aware, and intent-driven learning experiences, contributing practical insights for the design of adaptive e-learning systems in resource-constrained settings.

A. Future Research Directions

Building on the comparative positioning and deployment considerations discussed above, four directions are prioritized for the continuation of this work. First, and most immediately, the synthetic evaluation reported here will be complemented with data collected from a pilot deployment among a small number of partner institutions, allowing the F1-score, MAE, and Precision@5 figures reported in Table I to be recomputed on authentic Mauritanian usage logs and directly compared against the synthetic-data baseline. Second, an ablation study analogous to those conducted in related sequential recommendation work [16] will be carried out to quantify the individual contribution of the CBF, CF, Deep Learning, and predictive components to overall recommendation quality, clarifying which elements matter most under genuine data-scarcity rather than under the controlled synthetic conditions used in this study. Third, a learner-facing explanation interface will be developed and evaluated with real users, following the evidence that feature-level explanations can improve both trust and precision in educational recommender systems [22], with particular attention to explanation formats that remain meaningful for learners with heterogeneous digital literacy. Fourth, a longitudinal evaluation is planned to assess whether context- and completion-aware recommendations measurably reduce dropout and improve course completion rates over an academic term, moving the evaluation focus from offline predictive metrics toward learning outcomes in the field. Taken together, these directions are intended to transition the proposed framework from an architecturally validated design to an empirically validated deployment.

Data Availability

The data used to train and evaluate the predictive model were synthetically generated to reflect the Mauritanian distance-learning context, given the current absence of a public dataset for this learner population. The data generation procedure and the trained model are available from the corresponding author upon reasonable request.

Acknowledgment

The authors sincerely acknowledge Mr. Ahmed Abdallahi Mohamed Lemine and Pr. Mohamedade Farouk Nanne for their valuable scientific contributions to this work, including their insightful suggestions, discussions, and constructive feedback, which greatly contributed to the quality of this research.

References

[1] K. Verbert, N. Manouselis, X. Ochoa, M. Wolpers, H. Drachsler, I. Bosnic, and E. Duval, "Context-aware recommender systems for learning: A survey and future challenges," *IEEE Transactions on Learning Technologies*, vol. 5, no. 4, pp. 318–335, 2012.

[2] N. Yanes, A. M. Mostafa, M. Ezz, and S. N. Almuayqil, "A machine learning-based recommender system for improving students' learning experiences," *IEEE Access*, vol. 8, pp. 201218–201235, 2020.

[3] A. Esteban, A. Zafra, and C. Romero, "Helping university students to choose elective courses by using a hybrid multi-criteria recommendation system with genetic optimization," *Knowledge-Based Systems*, vol. 194, p. 105385, 2020.

[4] H. Ko, S. Lee, Y. Park, and A. Choi, "A survey of recommendation systems: Recommendation models, techniques, and application fields," *Electronics*, vol. 11, no. 1, p. 141, 2022.

[5] Q. Li and J. Kim, "A deep learning-based course recommender system for sustainable development in education," *Applied Sciences*, vol. 11, no. 19, p. 8993, 2021.

[6] Q. Zhang *et al.*, "Context-Aware Recommender Systems: Advances and Challenges," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 5, pp. 123–145, 2023.

[7] Y. Li *et al.*, "Recent Developments in Recommender Systems: A Survey," *arXiv preprint arXiv:2306.12680*, 2023.

[8] I. Saifudin and T. Widiyaningtyas, "Systematic Literature Review on Recommender System: Approach, Problem, Evaluation Techniques, Datasets," *IEEE Access*, 2024.

[9] A. Da'u and N. Salim, "Recommendation system based on deep learning methods: a systematic review and new directions," *Artificial Intelligence Review*, vol. 53, no. 4, pp. 2709–2748, 2020.

[10] Q. Zhang, J. Lu, and G. Zhang, "Recommender systems in e-learning," *Journal of Smart Environments and Green Computing*, vol. 1, no. 2, pp. 76–88, 2021.

[11] Q. Zhang, J. Lu, and Y. Jin, "Artificial intelligence in recommender systems," *Complex & Intelligent Systems*, vol. 7, pp. 439–457, 2021.

[12] Y. Tay, M. Dehghani, D. Bahri, and D. Metzler, "Efficient transformers: A survey," *ACM Computing Surveys*, vol. 55, no. 2, pp. 1–37, 2022.

[13] N. S. Raj and V. G. Renumol, "An improved adaptive learning path recommendation model driven by real-time learning analytics," *Journal of Computers in Education*, vol. 11, pp. 121–148, 2024.

[14] D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," *Journal of Big Data*, vol. 9, no. 1, p. 59, 2022.

[15] R. Sundar, M. Ganesan, M. A. Anju, M. I. Niranjana, and T. Surya, "A context-aware content recommendation engine for personalized learning using hybrid reinforcement learning technique," *International Journal of Computational and Experimental Science and Engineering*, vol. 11, no. 1, 2025.

[16] G. Chen, G. Han, and S. Liu, "Context-aware sequential course recommendation via conditional variational autoencoders and transformer architectures in IoT-enabled e-learning systems," *Scientific Reports*, vol. 16, art. 15370, 2026.

[17] "Hybrid attribute-based recommender system for personalized e-learning with emphasis on cold start problem," *Frontiers in Computer Science*, vol. 6, 2024.

[18] M. Jangid and R. Kumar, "Deep learning approaches to address cold start and long tail challenges in recommendation systems: a systematic review," *Multimedia Tools and Applications*, vol. 84, pp. 2293–2325, 2025.

[19] Z. Liu *et al.*, "A review of deep learning and large language models for cold start problem in recommender systems," *WIREs Data Mining and Knowledge Discovery*, 2026.

[20] K. C. Bodduluri, F. Palma, A. Kurti, I. Jusufi, and H. Lowenadler, "Exploring the landscape of hybrid recommendation systems in e-commerce: a systematic literature review," *IEEE Access*, vol. 12, pp. 28273–28296, 2024.

[21] H. Wang, N. Wang, and D.-Y. Yeung, "Collaborative deep learning for recommender systems," in *Proc. 21st ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining (KDD)*, 2015, pp. 1235–1244.

[22] J. Govea, R. Gutierrez, and W. Villegas-Ch, "Transparency and precision in the age of AI: evaluation of explainability-enhanced recommendation systems," *Frontiers in Artificial Intelligence*, vol. 7, art. 1410790, 2024.