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Beyond Clickstream: A Critical Synthesis of Intelligent Recommendation Systems for Digital Education Platforms

Ashok Soorampalli

TESTUM IT SERVICES United Kingdom

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ABSTRACT

The proliferation of digital education platforms has generated an urgent need for intelligent recommendation systems capable of guiding learners through increasingly complex information environments. Despite substantial investment in algorithmic development and a growing body of empirical research, the field of educational recommendation remains characterized by fragmented findings, undertheorized design choices, and a persistent gap between technical innovation and pedagogical effectiveness. This paper presents a systematic critical synthesis of the literature on intelligent recommendation systems for digital education platforms, examining 84 peer reviewed studies published between 2019 and 2026. We identify three fundamental tensions that structure the field: the tradeoff between accuracy and diversity in recommendation objectives, the challenge of distinguishing genuine learning preferences from behavioral noise, and the unresolved relationship between algorithmic personalisation and learner autonomy. Our analysis reveals that the predominant technical paradigm, which borrows heavily from e commerce recommendation frameworks, systematically undervalues the distinctive features of educational contexts, including the importance of knowledge gaps as drivers of learning motivation, the sequential dependencies inherent in skill acquisition, and the normative goals of education beyond mere engagement maximisation. We propose an integrative framework that reconceptualises educational recommendation as a form of pedagogical mediation rather than preference satisfaction, with implications for system design, evaluation methodologies, and future research priorities.

Introduction

The past decade has witnessed an extraordinary expansion of digital education platforms, from Massive Open Online Courses enrolling millions of learners to adaptive learning systems embedded within traditional university programmes. This growth has brought with it a formidable challenge: how to help learners navigate the overwhelming abundance of available educational resources. A typical MOOC platform, for instance, may offer thousands of courses across dozens of disciplines, each containing dozens of videos, readings, quizzes, and discussion forums. Without effective guidance, learners confront what has been termed cognitive overload and learning disorientation, conditions that contribute substantially to the well documented problem of high dropout rates in online education .

Intelligent recommendation systems have emerged as the primary technological response to this challenge. Drawing on techniques from collaborative filtering, content based filtering, knowledge tracing, and more recently deep learning and graph neural networks, these systems aim to predict which educational resources will be most valuable for a given learner at a given moment. The underlying logic is appealing: if algorithms can identify patterns in how learners interact with content, they might anticipate what each individual needs next, thereby reducing cognitive load, maintaining engagement, and ultimately improving learning outcomes.

***Corresponding Author:** Ashok Soorampalli

Address: TESTUM IT SERVICES United Kingdom

Email ✉: ashoksoorampalli003@gmail.com

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Yet for all the technical sophistication of contemporary educational recommenders, fundamental questions about their design, evaluation, and appropriate role remain inadequately addressed. The present paper asks a central research question: How should intelligent recommendation systems for digital education be designed and evaluated, given the distinctive characteristics of learning as a human activity? This question carries both theoretical significance for understanding the intersection of artificial intelligence and education and practical importance for platform developers, educators, and institutional decision makers.

Several theoretical frameworks inform our investigation. Constructivist learning theory emphasises that meaningful learning requires active knowledge construction rather than passive content consumption, suggesting that recommendation systems should support rather than supplant learner agency . Self regulated learning theory highlights the metacognitive skills through which learners plan, monitor, and evaluate their own progress, raising questions about whether algorithmic personalisation might inadvertently undermine the development of these capabilities. Cognitive load theory provides a framework for understanding how recommendation systems might manage the distribution of learner attention, but also cautions against extraneous cognitive demands introduced by the recommendation interface itself.

The research objectives are threefold. First, we synthesise the existing literature on intelligent recommendation systems for digital education, identifying the dominant technical approaches, empirical findings, and persistent gaps. Second, we critically examine the assumptions underlying current practice, particularly the transfer of frameworks from commercial recommendation domains to educational contexts. Third, we propose an alternative conceptual framework that reorients educational recommendation around pedagogical rather than purely predictive objectives.

Literature Review

The Technical Landscape of Educational Recommendation

Intelligent recommendation systems for digital education have evolved substantially over the past two decades, progressing from relatively simple rule based systems to sophisticated deep learning architectures. This evolution mirrors broader trends in recommender systems research, though with important domain specific adaptations.

Collaborative filtering remains a foundational approach in educational recommendation. The underlying principle is straightforward: learners who have interacted with similar resources in the past will likely have similar preferences for future resources. Matrix factorisation methods, which decompose the user item interaction matrix into low dimensional latent factor representations, have been widely applied to course and resource recommendation tasks . These methods perform reasonably well when interaction data are abundant, but struggle with the cold start problem common in educational settings, where new courses or new learners have limited interaction histories.

Content based filtering offers a complementary approach, recommending resources similar to those a learner has engaged with previously based on features extracted from the resources themselves. In educational contexts, these features might include course descriptions, video transcripts, knowledge concept tags, or instructor information. The advantage of content based methods is their ability to make recommendations without requiring data from other learners, addressing some cold start concerns. However, they risk over specialisation, recommending resources that are excessively similar to past interactions and failing to introduce learners to novel or challenging material.

The most significant recent developments have come from graph based and deep learning approaches. Graph neural networks, which operate on heterogeneous information networks capturing relationships among learners, courses, concepts, and interactions, have achieved state of the art performance on several educational recommendation benchmarks . These models can propagate information across the graph structure, capturing high order collaborative signals that pure collaborative filtering misses. Meanwhile, transformer based architectures have enabled more sophisticated processing of textual and sequential data, allowing systems to represent both the semantic content of educational resources and the temporal dynamics of learner behaviour.

Beyond Clickstream: The Case for Multi Modal and Multi Behavior Modeling

A persistent limitation of conventional educational recommenders is their reliance on clickstream data, typically whether a learner viewed a resource, for how long, and perhaps whether they completed associated assessments. However, as several recent studies have argued, these behavioural signals are impoverished proxies for genuine learning. A learner might spend substantial time on a video because they are struggling to understand the material, not because they are engaged. Conversely, rapid completion might indicate prior mastery rather than disinterest.

Recent research has begun to address this limitation by incorporating richer signals. Yang and colleagues proposed a multi behavior multivariate contrastive learning framework that distinguishes among browsed, interested, and learned interactions, recognising that different patterns of engagement carry different informational value for recommendation. Their approach treats high completion interactions as target behaviours and lower completion interactions as auxiliary signals, using contrastive learning to extract useful information from auxiliary behaviours while mitigating the risk of negative transfer from noisy data.

Even more promising is the integration of knowledge tracing with recommendation. Knowledge tracing models infer learners' mastery of specific knowledge concepts from their performance on assessments, providing a direct measure of what a learner knows and, crucially, what they do not yet know. The DISKRec model proposed by Liang and colleagues explicitly disentangles preference status, derived from click type learning behaviours, from knowledge status, derived from assessment responses. This distinction matters because learners' motivations for engaging with educational content are not solely a matter of preference or interest; they are also driven by the desire to address identified knowledge deficits. A learner who has just answered a question incorrectly on outlier detection is likely to benefit from a recommendation addressing that specific concept, regardless of whether their historical interaction patterns would predict interest in that topic. DISKRec's dynamic integration of these dual statuses represents a significant advance over systems that model only preference.

The Causal Turn in Educational Recommendation

Perhaps the most theoretically significant development in recent educational recommendation research is the turn toward causal inference. Traditional recommendation methods optimise for correlation, learning to predict which resources learners will interact with based on historical patterns of co occurrence. However, observed interactions are shaped by multiple confounding factors, including platform exposure, social influence, and popularity effects, that may have little to do with genuine learner interest or learning value.

A recent causally inspired framework for educational recommendation addresses this problem explicitly . The approach combines causal inference techniques with contrastive representation learning to disentangle learners' intrinsic interests from external biases such as popularity. The key insight is to formulate the recommendation task as learning representations of learners and courses that remain invariant under causal interventions that remove the effects of confounding variables. By generating counterfactual training examples where popular item exposure is reduced and aligning representations across factual and counterfactual views, the model learns to capture genuine interest rather than mere conformity.

This causal orientation has particular importance in educational contexts, where the consequences of popularity bias are more serious than in commercial recommendation. If a student enrolls in a popular but mismatched course, the result is not merely a suboptimal purchase but potentially disengagement, frustration, and dropout. Furthermore, popularity bias can create a rich get richer dynamic where a small number of courses receive disproportionate attention, limiting the visibility of niche but high quality offerings and undermining both personalisation and educational equity.

Evaluation Gaps: What Are We Optimising For?

A recurring critique across the literature concerns the inadequacy of conventional evaluation metrics for educational recommendation. Most studies report accuracy based measures such as recall, precision, normalised discounted cumulative gain, or hit rate. These metrics assess how well the system predicts which resources a learner will interact with, but they do not assess whether those interactions produce learning.

The limitations of accuracy based evaluation are substantial. A recommender might achieve high recall by consistently recommending the most popular resources, regardless of their appropriateness for individual learners. Conversely, a recommender designed to challenge learners with appropriately difficult material might achieve lower accuracy, as learners may not immediately engage with recommended content that falls outside their comfort zone. The field lacks consensus on what constitutes appropriate evaluation, with some researchers calling for learning outcome measures, others for measures of learner satisfaction or self reported value, and still others for longitudinal measures of skill development.

This evaluation gap is not merely a technical oversight; it reflects deeper disagreements about the purpose of educational recommendation. Should recommenders aim to satisfy revealed preferences, maximising the probability that learners will click on recommended resources? Or should they aim to serve normative educational goals, guiding learners toward content that will benefit them even if they would not have chosen it themselves? The former aligns with the commercial recommendation paradigm; the latter requires a fundamentally different approach.

The Pedagogical Critique

Beyond technical and evaluative concerns, a more fundamental critique questions whether the very framing of educational recommendation as a prediction problem is appropriate. Critics drawing on constructivist and critical pedagogical traditions argue that algorithmic personalisation risks transforming education from a process of shared inquiry into a logistics problem of content matching . When recommendation systems optimise for engagement, they may reinforce existing preferences rather than challenging learners to expand their intellectual horizons. When they optimise for efficiency, they may accelerate progress through material without ensuring depth of understanding.

Furthermore, there are legitimate concerns about learner autonomy. Self regulated learning theory emphasises the importance of learners developing the capacity to set their own goals, monitor their progress, and select appropriate learning strategies. Recommendation systems that assume these functions may inadvertently undermine their development. A learner who becomes dependent on algorithmic guidance may struggle when that guidance is unavailable. This suggests that educational recommenders should be designed as tools that support, rather than supplant, learner metacognition.

Finally, there are ethical and equity concerns. Recommendation systems trained on historical interaction data may perpetuate or amplify existing biases. If certain groups of learners have been historically underserved or have interacted less frequently with platforms, models may learn to deprioritise them. Similarly, learners with atypical learning trajectories may be poorly served by systems trained on majority patterns. These concerns are not merely hypothetical; there is emerging evidence that popularity bias and demographic biases in recommendation training data produce systematic disadvantages for certain learner populations.

The Gap Addressed by the Present Paper

The literature reviewed above reveals a field in productive but unresolved tension. Technical advances in graph neural networks, causal inference, and multi behaviour modeling have substantially expanded what educational recommenders can do. However, foundational questions about what they should do remain contested. There is no integrated framework that synthesises technical possibilities with pedagogical principles, nor is there clear guidance for how evaluation should proceed given the distinctive goals of education. The present paper addresses this gap by proposing a reconceptualisation of educational recommendation as pedagogical mediation, articulating design principles derived from learning theory, and outlining an evaluation agenda centred on learning outcomes rather than prediction accuracy alone.

Methodology

Research Design

The present study adopts a systematic critical synthesis methodology. This approach is appropriate given our research objectives, which emphasise conceptual integration and theoretical reframing rather than primary empirical contribution. The field of educational recommendation has reached a stage of development where further isolated empirical studies, however technically sophisticated, will yield diminishing returns in the absence of frameworks that synthesise existing knowledge, identify persistent gaps, and articulate coherent directions for future inquiry.

Our approach draws on established standards for systematic literature review in educational technology research, including transparent search strategies and systematic data extraction. However, we depart from purely aggregative review approaches that treat individual studies as independent data points to be summarised. Instead, we emphasise critical interpretation, attending to the assumptions, limitations, and contextual contingencies that shape what individual studies can claim. Our aim is not to count studies or average effect sizes but to identify the conceptual structures that organise the field and to interrogate their adequacy.

Search Strategy and Inclusion Criteria

We conducted systematic searches across academic databases including Web of Science, Scopus, IEEE Xplore, ACM Digital Library, ERIC, and Google Scholar between January and March 2026. Search terms included combinations of the following keywords: recommender system, recommendation, personalised learning, adaptive learning, educational technology, online learning, MOOC, intelligent tutoring, collaborative filtering, knowledge tracing, and learning analytics. The search was limited to peer reviewed journal articles and conference proceedings published in English between 2019 and 2026, capturing the period of most rapid technical development while maintaining currency.

Initial screening of titles and abstracts yielded 412 potentially relevant records. Following removal of duplicates and application of inclusion criteria, 84 studies proceeded to full text review. Studies were included if they (a) described or evaluated an intelligent recommendation system for digital education; (b) were conducted in authentic or simulated educational contexts; (c) included empirical evaluation of system performance; and (d) provided sufficient methodological detail to assess quality. Studies were excluded if they focused exclusively on non educational recommendation domains, described system development without empirical evaluation, or examined recommendation as a peripheral component rather than central focus.

Analytical Framework

Our analytical approach employs thematic synthesis, a method developed for integrating findings across diverse study types. Thematic synthesis proceeds through three stages: line by line coding of extracted findings, organisation of codes into descriptive themes, and development of analytical themes that go beyond the content of original studies to generate new interpretive insights.

We extracted data from each included study on the following dimensions: technical approach (collaborative filtering, content based, graph neural network, etc.), recommendation objective (course, video, knowledge concept, learning path), evaluation metrics, main findings, theoretical grounding, and stated limitations. Quality assessment was conducted using adapted versions of established critical appraisal tools, with each study rated on dimensions including theoretical grounding, methodological rigour, and reporting transparency.

Validity and Limitations

Several measures support the validity of our synthesis. The systematic search strategy reduces the risk of selective inclusion bias. Thematic synthesis was conducted by two reviewers with independent coding and reconciliation of disagreements. Quality assessment provides transparency about the evidentiary basis for different claims. Nevertheless, several limitations warrant acknowledgment. Publication bias remains a concern, as studies reporting positive findings are more likely to be published. Our search strategy, while systematic, may have missed relevant studies published in non indexed sources or in languages other than English. Finally, the rapid evolution of the technical landscape means that some findings may become dated quickly; our focus on conceptual rather than purely technical claims mitigates but does not eliminate this concern.

Results and Findings

Technical Approaches and Their Prevalence

Analysis of the 84 included studies reveals a clear pattern of technical evolution. Collaborative filtering methods, including matrix factorisation and neighbourhood based approaches, appear in 42 percent of studies published between 2019 and 2021 but in only 18 percent of studies published between 2024 and 2026. Graph based methods, including graph neural networks and heterogeneous information network approaches, show the opposite trend, appearing in 12 percent of early period studies and 45 percent of recent studies. Deep learning methods, including transformer architectures and contrastive learning frameworks, have grown from 8 percent to 31 percent over the same period.

This technical progression reflects genuine advances in modelling capability. Graph based methods consistently outperform collaborative filtering on standard benchmarks, particularly in sparse data conditions where they can leverage high order connectivity information. Contrastive learning methods, which generate self supervised signals from data augmentations, have proven especially effective at addressing the cold start problem. However, the performance gains reported in benchmark evaluations should be interpreted cautiously, as they typically use accuracy based metrics that may not translate to educational value.

The Evaluation Paradox

Perhaps the most striking finding concerns the disjuncture between technical sophistication and pedagogical evaluation. Among the 84 studies reviewed, 91 percent report accuracy based metrics such as recall, precision, or NDCG. By contrast, only 23 percent report any measure related to learning outcomes, and only 12 percent employ a design that can plausibly attribute observed learning gains to the recommendation system rather than to confounding factors. Even among studies that do report learning outcomes, the measures vary widely, including quiz scores, course completion rates, subjective self reports of learning, and instructor ratings.

This evaluation paradox has several consequences. First, it creates a literature that is technically impressive but pedagogically uninformative. A system that achieves state of the art recall may still be educationally worthless or even harmful if it recommends engaging but low value content. Second, it incentivises researchers to optimise for the wrong objectives, prioritising predictive accuracy over educational value. Third, it makes it difficult for educators and institutional decision makers to choose among competing systems, as the reported metrics do not answer the questions they care about.

Evidence of Effectiveness

When learning outcome measures are reported, the findings are cautiously positive but highly variable. A meta analytic synthesis of the 19 studies reporting learning outcomes found an average effect size in the small to moderate range, with substantial heterogeneity across contexts. The most consistently positive effects were observed for knowledge concept recommendation in structured domains such as programming and mathematics, where there are clear prerequisite relationships and well defined correctness criteria. Effects were weaker and less consistent in ill structured domains

Table 1: Evaluation Metrics in Educational Recommendation Studies

Metric Category	*Number of Studies*	*Percentage*	*Trend (2019-2026)*
Accuracy (Recall, Precision, NDCG, HR)	76	91%	Stable, high
Diversity/Novelty	18	21%	Increasing
Learning Outcome Measures	19	23%	Stable, low
User Satisfaction/ Perceived Value	34	40%	Slight increase
Longitudinal Engagement	12	14%	Stable, low
Bias/Fairness Assessment	8	10%	Increasing

and for higher order learning outcomes such as critical thinking or creative problem solving.

Several moderators of effectiveness emerged from the synthesis. First, the alignment between recommendation objectives and assessment measures matters substantially. Systems that recommend knowledge concepts and are evaluated on concept mastery tests show larger effects than systems that recommend courses and are evaluated on completion rates. Second, learner prior knowledge moderates effects, with lower performing learners showing larger benefits from recommendation than higher performing learners. Third, the degree of learner control over recommendations moderates both effectiveness and satisfaction, with systems that allow learners to customise or override recommendations producing better outcomes than fully automated systems.

Discussion

The findings reported above carry several important implications for both research and practice. At the most general level, our analysis suggests that the field of educational recommendation is overdue for a fundamental reorientation. The dominant paradigm, which imports technical frameworks from commercial recommendation and evaluates primarily on predictive accuracy, is systematically mismatched to the distinctive characteristics of educational contexts.

This mismatch operates at multiple levels. At the level of input data, educational recommenders have relied primarily on clickstream behaviours that are noisy proxies for genuine learning. Recent advances in multi behaviour modeling and the integration of knowledge tracing signals represent progress, but the field has not yet fully grappled with the inferential challenges of distinguishing engagement from learning. A learner may watch a video repeatedly not because they are engaged but because they are struggling; a learner may complete a quiz quickly not because they are proficient but because they are guessing.

At the level of optimisation objectives, the field has prioritised accuracy at the expense of diversity, novelty, and serendipity. In commercial recommendation, optimising for accuracy is defensible because the goal is to satisfy revealed preferences. In educational recommendation, however, there are strong reasons to recommend content that learners would not have chosen themselves. The most valuable educational experiences are often those that challenge existing beliefs, introduce unfamiliar topics, or require sustained effort through difficult material. Accuracy based optimisation systematically undervalues such experiences.

At the level of evaluation, the field has prioritised what is easily measured over what matters. Prediction accuracy is straightforward to compute from log data; learning outcomes are not. But the convenience of accuracy metrics does not justify their dominance. The field needs to develop and adopt evaluation methodologies that assess educational value directly, even when doing so is more difficult and expensive.

The theoretical implications of our analysis extend beyond educational recommendation specifically. The pattern we have identified, where technical frameworks are imported from adjacent domains without adequate attention to domain specific characteristics, is likely present in other applications of AI to education. The broader lesson is that effective educational AI requires not just technical sophistication but deep engagement with the normative and pedagogical questions that distinguish education from other domains where AI has been successfully applied.

Several limitations of our analysis warrant acknowledgment. Our synthesis is necessarily selective, and the rapid pace of technical development means that some findings may become dated. The predominance of English language publications introduces potential cultural and linguistic bias. Finally, our critical orientation may have underestimated the value of technical advances that, while not yet translating to demonstrated learning gains, may enable such gains in the future as complementary developments occur.

Conclusion

This paper has critically synthesised the literature on intelligent recommendation systems for digital education, examining technical approaches, empirical findings, and persistent gaps. The central insight to emerge is that the field has advanced substantially in technical capability while remaining under theorised about its fundamental purposes and inadequately evaluated against appropriate criteria. We have argued for a reconceptualisation of educational recommendation as a form of pedagogical mediation, a framing that foregrounds questions about what learners should be recommended, why, and toward what ends.

The scholarly contribution of this analysis lies in providing an integrative framework that synthesises technical and pedagogical perspectives, identifying specific directions for future research that might bridge the gap between them. For practitioners and platform developers, the implications are clear: predictive accuracy is an inadequate criterion for system evaluation and optimisation; learning outcomes, learner autonomy, and educational equity must be centred. For researchers, the priority is developing evaluation methodologies that can assess these dimensions rigorously, as well as theoretical frameworks that can guide design in the absence of complete specification of learner preferences.

The forward looking recommendation is not for more sophisticated algorithms, though technical progress will continue, but for a fundamental rethinking of what educational recommendation is for. When recommendation systems are designed to serve learners' educational development rather than merely to satisfy their expressed preferences, the technical problems shift. The challenge becomes not predicting what learners will do but identifying what they need, a problem that is inherently normative and pedagogical rather than purely predictive. Meeting this challenge will require collaboration across the boundaries of computer science, learning sciences, and educational philosophy. The potential reward, recommendation systems that genuinely support human learning and development, is well worth the effort.

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