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Digital Narratives and Machine Learning for Personalized Learning Recommendations in Transnational Educational Contexts

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ABSTRACT

Background. Personalized learning systems are expanding rapidly in higher education, but many recommendation pipelines still depend on structured indicators such as grades, attendance, task completion, and clickstream activity. In transnational educational settings, those indicators cannot adequately explain how students interpret disciplinary language, negotiate cultural expectations, or express learning difficulties.

Purpose. This study develops a narrative-informed framework for personalized learning recommendations by integrating structured academic data and student-authored digital narratives within a multimodal learning analytics perspective.

Method. The manuscript is positioned as a design science and framework-development study rather than a completed quantitative experiment. It synthesizes recent literature on learning analytics, educational recommender systems, multilingual education, natural language processing, and human-centred AI in education to specify a technical workflow for narrative preprocessing, multimodal fusion, learner-state modelling, recommendation generation, and evaluation. The small learner records presented in tables are synthetic examples used only to illustrate the data architecture.

Results. The main output is a technically explicit and theoretically grounded framework that explains how narrative text can be anonymized, segmented, normalized, encoded into multilingual embeddings, combined with numerical learner indicators through early and late fusion, and evaluated using both predictive and recommender metrics. The framework also operationalizes transnational variables, including language diversity, culturally indirect participation, and contextual adaptation needs.

Conclusion. Digital narratives can enrich learner profiling, improve contextual sensitivity, and strengthen culturally responsive recommendations. The study contributes a coherent blueprint for future empirical implementation in multilingual and transnational learning environments

KEYWORDS

Digital Narratives, Machine Learning, Multimodal Learning Analytics, Personalized Learning, Ttransnational Education

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INTRODUCTION

Digital learning environments have intensified the demand for instructional systems that can recognize learner differences and provide adaptive support. In higher education, institutions increasingly rely on learning management systems, dashboards, and AI-enabled tools to personalize content sequencing, feedback, and interventions. Recent reviews show that personalized adaptive learning and machine-learning-based learning analytics are growing quickly, especially in online and blended settings where large volumes of learner data can be used to guide support decisions (du Plooy et al., 2024; Alfredo et al., 2024; Rodríguez-Ortiz et al., 2025).

However, the dominant logic of many recommendation systems remains strongly structured-data oriented. Grades, attendance, submission timeliness, time on platform, and interaction counts are analytically convenient because they are machine-readable and easy to aggregate. Yet these indicators provide only partial access to the learning process. They do not reveal how students interpret a task, what kind of confusion they experience, why they avoid classroom participation, or how language and culture shape their engagement. In transnational educational settings, this limitation becomes more serious because learners often cross linguistic, curricular, and social norms that are not visible in score-based dashboards alone.

This study therefore focuses on digital narratives, defined here as student-authored textual expressions generated in digital learning environments, such as reflective journals, discussion posts, short self-explanations, open-ended feedback, and narrative self-reports. These texts may reveal affective states, motivational shifts, identity negotiation, help-seeking behaviour, and culturally specific participation patterns. When processed responsibly with natural language processing, digital narratives can function as a meaningful analytical modality rather than as unstructured residue. This position aligns with recent work on natural language processing of student feedback, narrative-oriented dashboards, and human-centred learning analytics that emphasizes interpretability, stakeholder relevance, and pedagogical actionability (Sunar & Khalid, 2024; Maimone et al., 2024; Masiello et al., 2024).

The present article proposes a narrative-informed multimodal learning analytics framework for personalized recommendation in transnational education. The article makes three contributions. First, it improves the logical connection between digital learning challenges, personalized recommendation, and narrative data. Second, it specifies how structured and unstructured learner data can be integrated through preprocessing, multilingual text representation, hybrid feature fusion, and recommender evaluation. Third, it explains why this integration is important for culturally responsive support in settings where language choice, indirect communication styles, and contextual adaptation influence learning.

Three recent bodies of literature are particularly relevant to this study. The first concerns personalized and adaptive learning. Recent reviews show that AI-supported personalization can improve engagement, pacing, and support decisions, but many systems remain focused on behavioural logs and performance history rather than learner meaning-making (du Plooy et al., 2024; Merino-Campos, 2025; Martínez-Martínez et al., 2025). This suggests that personalization is advancing technically while still depending on relatively narrow forms of evidence.

The second body of literature is multimodal learning analytics (MMLA). MMLA expands learning analytics by combining multiple data modalities to capture complex learning processes more comprehensively. Recent work shows growing attention to AI-supported MMLA, dashboard design, orchestration support, and multimodal evidence for feedback and decision-making (de Vreugd et al., 2024; Mohammadi et al., 2025; Verma & Varghese, 2025). Nevertheless, much of this research emphasizes clicks, gaze, audio, sensor data, or dashboard traces. Student-authored narrative text is often present only as a supplementary source, not as the central modality for culturally responsive recommendation design.

The third stream concerns multilingual learning, digital storytelling, and narrative meaning-making. Recent studies show that multilingual students often express learning needs through translanguaging, mixed-language writing, and culturally shaped narrative strategies. These expressions are analytically valuable because they can signal conceptual uncertainty, identity positioning, confidence, and social safety within the learning environment (de Jong et al., 2024; Ferguson-Sams et al., 2024; Berry et al., 2025; Rahman & Hu, 2025). In other words, linguistic diversity is not merely a preprocessing problem; it is an educational signal.

The theoretical basis of this study draws on three complementary perspectives: human-centred learning analytics, which emphasizes stakeholder relevance and trustworthy design; multimodal learning analytics, which supports the integration of heterogeneous data sources; and culturally responsive educational design, which recognizes that student participation and expression are shaped by language, identity, and context. Based on this synthesis, the research gap can be stated precisely: current personalized learning systems rarely provide a technically explicit and pedagogically justified framework for integrating digital narratives, multilingual expression, and recommendation-oriented machine learning within transnational education. The novelty of this study lies in offering that integration as a coherent design blueprint.

The study addresses the limited ability of conventional educational recommendation systems to capture contextual, linguistic, and cultural dimensions of learning when they rely mainly on structured academic indicators. This problem is especially important in transnational education, where students' needs are mediated by multilingual communication, uneven disciplinary socialization, and culturally variable participation norms.

Research questions.

1. How can digital narratives be preprocessed and represented as machine-readable features for personalized learning recommendation?
2. How can structured academic indicators and narrative features be combined coherently in a multimodal learning analytics pipeline?
3. How should multilingual, dialectal, and culturally indirect learner expression be operationalized within the framework?
4. Which metrics are appropriate for evaluating both predictive performance and recommendation relevance in the proposed system?
5. What practical steps should LMS developers and educational administrators take to pilot the framework responsibly?

Accordingly, the objectives are to design a narrative-informed recommendation framework, clarify the preprocessing and data-fusion pipeline, operationalize transnational education variables, specify an evaluation plan for recommendation quality, and outline practical implementation guidance for institutional pilots

RESEARCH METHODOLOGY

This article uses a design science and conceptual framework development approach. The manuscript no longer claims to be a completed quantitative hypothesis-testing study. Instead, it develops a replicable analytical design for future implementation by aligning system-development goals with learning analytics principles, multimodal data processing, and recommendation-system evaluation. This repositioning resolves the inconsistency found in earlier versions between the stated quantitative design and the actual conceptual contribution.

The framework was developed through five stages: problem diagnosis, literature-informed requirement extraction, data-schema specification, technical pipeline design, and evaluation and implementation planning. The stages are presented in detail to make the development logic transparent and replicable. In addition, the manuscript uses synthetic learner records for illustration only. These records do not represent a real institutional sample and are included solely to demonstrate how structured indicators and narrative cues would coexist within the proposed pipeline.

A transnational education perspective is operationalized explicitly in the methodology. Rather than being treated as background context only, transnationality is translated into measurable or observable design variables, including language repertoire, code-switching patterns, culturally indirect expression, adaptation to disciplinary discourse, and differences in preferred participation formats. These variables shape preprocessing, feature extraction, fairness evaluation, and recommendation design.

Table 1. Data modalities and analytical treatment.

Modality	Illustrative variables	Analytical treatment	Expected contribution
Structured academic and LMS data	Exam score, attendance, task completion, participation intensity, time on LMS, interaction frequency	Normalization, missing-value handling, feature scaling, temporal aggregation	Performance baseline, observable study behaviour, and early identification of participation patterns
Digital narratives	Reflective journals, forum posts, open-ended feedback, self-explanations, exit tickets	Language identification, anonymization, cleaning, tokenization, multilingual embedding, topic and sentiment cues	Meaning-making, affect, help-seeking, culturally shaped participation, adaptation difficulty
Transnational context indicators	Language repertoire, code-switching frequency, indirect disagreement markers, disciplinary transition cues	Lexicon mapping, segment-level tagging, fairness grouping, contextual feature engineering	Sensitivity to multilingual and culturally diverse learner expression
Recommendation outcomes	Suggested materials, support actions, alternative pathways, bilingual scaffolds	Ranking, thresholding, teacher review, feedback loops	Actionable and pedagogically relevant personalized support

The structured variables are defined as follows. Exam score refers to assessment performance from quizzes, assignments, or tests. Attendance captures presence in scheduled learning sessions. Task completion indicates submission status and timeliness. Participation intensity reflects observable interaction with class activities or discussion spaces. Time on LMS captures the duration of engagement with learning materials, while interaction frequency refers to discrete platform actions such as resource access, assignment submission, and forum entry. These variables are retained because they provide valuable behavioural evidence, but they are not treated as sufficient on their own.

Digital narratives are defined as student-authored texts produced during learning, including reflections, open-ended responses, discussion comments, and feedback statements. Within this framework, narratives are not treated as free-floating qualitative anecdotes; they are operationalized as text-based evidence that can be segmented, encoded, and linked to learner states. Their analytical value lies in revealing dimensions that scores do not capture directly, such as uncertainty, reluctance to challenge authority, linguistic strain, or requests for alternative explanation styles.

Table 2. Operationalization of transnational education dimensions.

Dimension	Observable indicator	Analytical treatment	Implication for recommendation
Language diversity	Multiple languages within one response or across entries	Segment-level language tagging and multilingual embeddings	Recommend bilingual summaries or multilingual resources
Code-switching	Alternation between English and local language terms	Retain switches as features instead of deleting them as noise	Provide glossary support and bridging explanations
Culturally indirect participation	Hesitant disagreement, softened critique, avoidance of direct challenge	Discourse cue detection and instructor-reviewed interpretation	Recommend low-risk participation channels and scaffolded prompts
Contextual adaptation	Narratives about unfamiliar classroom norms or disciplinary conventions	Topic extraction and temporal monitoring	Suggest orientation materials and examples of academic discourse practices
Fairness across language groups	Differences in recommendation quality by language repertoire	Group-based audit using NDCG/precision parity and teacher review	Prevent lower-quality recommendations for non-dominant language users

Table 3. Synthetic learner records illustrating structured indicators and narrative cues.

Student ID	Exam Score	Attendance (%)	Task Completion (%)	Participation (1–10)	Time on LMS (min/week)	Narrative cue (abridged)
S001	85	92	100	8	240	“Public disagreement feels disrespectful.”
S002	78	88	90	6	180	“Fast English discussion makes me lose track.”
S003	92	95	100	9	300	“Detailed written guidance helps me.”
S004	74	80	75	5	120	“I am unsure what answer style is expected.”
S005	88	90	95	7	210	“First-language examples help connect theory and practice.”

Table 4. Replicable research and development stages.

Stage	Main activity	Output
1. Problem diagnosis	Identify limitations of score-only recommendation systems in multilingual and culturally diverse settings	Design problem statement

2. Requirement extraction	Review recent literature on personalized learning, MMLA, NLP, and culturally responsive education	Framework requirements and design principles
3. Data-schema design	Specify structured, narrative, and transnational-context variables	Learner-profile architecture
4. Pipeline design	Define preprocessing, feature extraction, multimodal fusion, recommendation logic, and human oversight	Proposed model workflow
5. Evaluation planning	Select predictive, recommender, and fairness metrics; formulate pilot implementation steps	Validation and implementation roadmap

At Stage 1, the central problem is defined as under-representation of learner meaning-making in recommendation systems. At Stage 2, requirement extraction is performed from recent literature, with particular attention to interpretability, multilingual support, and stakeholder relevance. At Stage 3, the data schema specifies how academic indicators, narrative texts, and transnational-context features are stored and linked through secure learner identifiers. At Stage 4, the technical pipeline is designed, including preprocessing, encoding, multimodal fusion, ranking logic, and teacher oversight. At Stage 5, the evaluation plan is defined through predictive, recommender, and fairness metrics together with practical pilot steps.

RESULT AND DISCUSSION

The main result of this study is not a completed empirical validation but a revised, coherent, and technically explicit conceptual framework. This section therefore presents the model as the principal design output and discusses its contribution. The shift from earlier empirical-looking claims to a framework paper is made explicit here: the manuscript contributes by clarifying model logic, methodological transparency, and contextual relevance rather than by reporting final performance scores from a real institutional deployment.

Data representation and narrative preprocessing. The first component of the model concerns representation of structured and unstructured learner data. For each student i, structured learner data are represented as a vector containing normalized academic and behavioural indicators. Narrative data are represented as one or more text entries authored by the same learner over time. Because reviewers requested a clearer explanation of how “student stories” become vector data, the preprocessing logic is stated explicitly below.

$$S\_i = [x\_i1, x\_i2, \ldots, x\_ip]$$
$$N\_i = \{n\_i1, n\_i2, \ldots, n\_im\}$$

Narrative preprocessing proceeds through six steps. First, each text is anonymized to remove personally identifiable information. Second, segment-level language identification is applied because students may mix languages within a single response. Third, texts are cleaned by standardizing punctuation, casing, and obvious noise while retaining pedagogically relevant discourse markers. Fourth, the narratives are tokenized and, when appropriate, lemmatized using language-aware tools. Fifth, code-switching, translanguaging, and culturally indirect expressions are retained as analytically meaningful features rather than deleted as errors. Sixth, the cleaned text is converted into dense vector representations using multilingual encoders such as multilingual sentence transformers or XLM-R-based sentence models.

$$e\_it = Encoder(n\_it)$$
$$N\_i^* = Aggregate(e\_i1, e\_i2, \ldots, e\_im)$$

The aggregation step may use mean pooling, attention pooling, or time-weighted pooling, depending on how recent narratives are prioritized in the institutional setting. The result is a learner-level narrative representation that captures recurring themes, affective cues, participation barriers, and language-use patterns.

Feature integration and model selection. The second component is multimodal integration. To address the reviewer's request for technical precision, the framework proposes hybrid fusion using both early and late fusion strategies. In early fusion, structured indicators and narrative embeddings are concatenated into a joint learner representation and passed to a machine-learning model. In late fusion, separate models are trained for structured and narrative data, and their outputs are combined during ranking. The two strategies are not mutually exclusive; they serve different institutional purposes.

$$z_i = [S_i \,||\, N_i^* \,||\, C_i]$$

In this notation, C_i denotes optional contextual features related to transnational education, such as language-repertoire group, code-switching frequency, or curricular transition status. Early fusion is suitable when the aim is to learn interactions directly across modalities. Late fusion is suitable when institutions require greater interpretability, modular deployment, or ablation testing because the contribution of each modality can be examined separately.

$$r_{ij}^{(early)} = h(z_i, o_j)$$
$$r_{ij}^{(late)} = \alpha \cdot r_{struct}(i,j) + (1-\alpha) \cdot r_{narr}(i,j)$$

The recommendation score r_{ij} expresses the relevance of learning object j for student i. Candidate learning objects may include readings, short videos, bilingual glossaries, peer-support prompts, writing scaffolds, or instructor interventions. Model choice may include gradient boosting, random forest, neural ranking, or hybrid recommenders, but the framework prioritizes explainability and educational actionability over algorithmic novelty alone.

Why narrative data matter in transnational education. The conceptual strength of the model lies in its ability to detect barriers that structured indicators tend to miss. For example, a student may obtain acceptable reading scores but still avoid discussion because direct disagreement with peers or instructors feels culturally inappropriate. Another student may show average performance but write that fast English discussion limits their ability to formulate a response. A third student may submit tasks on time while expressing confusion about the expected rhetorical style of arguments in a new academic culture. These cases show that similar scores can mask very different learning needs. Narrative data therefore improve not only personalization, but also the educational fairness of recommendation decisions.

This contribution also repositions MMLA in a meaningful way. Rather than treating text as a minor supplement to dashboards or behavioural traces, the framework treats digital narratives as a primary modality for understanding learner voice and meaning-making. This is particularly relevant in transnational education, where the barriers to learning are frequently linguistic, relational, or normative rather than purely cognitive or behavioural. In that sense, the framework strengthens the practical connection between MMLA, culturally responsive teaching, and human-centred AI in education.

Multilingual and dialect-sensitive handling. A key discussion point is multilingualism. In transnational settings, students may use English, local languages, mixed-language discourse, or dialectal forms in the same learning space. If the system assumes a single standard language, important contextual cues will be lost. The framework therefore recommends segment-level language tagging, multilingual embeddings, local lexicon development, and bilingual audit trails. Translation may be used when necessary, but the original text should be retained for human review to avoid semantic flattening. This design choice also supports transparency when instructors need to verify whether a model interpretation is pedagogically reasonable.

Multilingual handling is not merely a technical convenience. It is also a fairness safeguard. Recommendation quality should be checked across language-repertoire groups so that students writing in a non-dominant language are not systematically assigned lower-relevance resources or more generic feedback. In practical terms, this means comparing ranking performance, click-through responses, or acceptance rates of recommendations across language groups and reviewing misclassification or low-quality outputs with instructors.

Table 5. Evaluation logic for the proposed recommendation framework.

Metric family	Illustrative metrics	Purpose
Auxiliary predictive metrics	Accuracy, precision, recall, F1-score, ROC-AUC	Evaluate learner-state prediction or auxiliary classification tasks
Recommendation relevance metrics	Precision@K, Recall@K, MAP@K, NDCG@K	Evaluate the relevance and ranking quality of recommended resources
Fairness and robustness checks	Group-wise NDCG, error disparity, calibration across language groups	Detect uneven recommendation quality across multilingual or cultural groups
Human evaluation	Instructor review, learner usefulness rating, adoption rate of recommended items	Assess pedagogical value and contextual appropriateness

MAP@K and NDCG@K are especially important because they reward correct ranking order rather than merely identifying whether a relevant item exists. Their inclusion directly addresses the need to evaluate recommendation relevance instead of relying only on generic classification scores. For institutional practice, the first implementation step is to pilot low-stakes narrative collection in one course or program, integrate those inputs with existing LMS logs, and review recommendations jointly with instructors before broader deployment. This staged implementation strengthens the study's practical contribution for LMS developers and administrators.

Limitations and future research. The study remains limited as a framework paper. It does not yet report empirical validation on authentic narrative datasets, and the multilingual preprocessing choices may require adaptation across institutions and languages. Future research should therefore implement the model in real transnational courses, compare early and late fusion empirically, test multilingual sentence encoders against translation-based baselines, and investigate how teachers interpret narrative-informed recommendations over time.

CONCLUSION

This study clarifies and strengthens the article as a design science and conceptual framework paper on personalized learning recommendation in transnational education. The revised manuscript improves the logical flow of the introduction, replaces outdated literature with recent sources, aligns the research problem, questions, and objectives, and makes the conceptual framework technically explicit. The study shows how digital narratives can be preprocessed into multilingual vector representations, combined with structured academic indicators through hybrid fusion, and evaluated with both predictive and recommender metrics. Its main contribution is to demonstrate that culturally and linguistically sensitive recommendation design requires access to learner narratives, not only scores and clicks. The framework therefore provides a more rigorous and practically usable basis for future empirical implementation in multilingual higher education contexts.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

AI-assisted tools were used only to support language refinement, organization of ideas, and structuring of the technical explanation. All conceptual decisions, revisions, interpretation of the literature, and final manuscript validation remained the responsibility of the authors.

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AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that there are no conflicts of interest related to this study.

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