

Towards Process-Aware Personalised Feedback in Microlearning

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Abstract

Microlearning environments offer flexible, focused learning experiences; however, providing timely, personalised feedback remains a key challenge, particularly in short, self-paced learning activities. This paper introduces a process-aware educational analytics framework that integrates Process Mining, predictive modelling, and local Large Language Models (LLMs) to provide personalised feedback from students' interaction traces. Students' interactions with a web-based tutorial comprising ten microlearning lessons are transformed into event logs and analysed to derive a process model enriched with behavioural indicators. These indicators, together with the predicted learning outcome obtained through predictive process monitoring, provide a dynamic representation of each learner's progress and are used to select one of three high-level feedback intents: Encouragement, Review, or Warning. The selected intent guides a local LLM in generating coherent, personalised, and actionable feedback aligned with the learner's observed behaviour, while avoiding reliance on external cloud services. A case study of a real microlearning environment demonstrates the framework's feasibility, highlighting its potential to transform process analytics into adaptive educational support through personalised feedback generation. Although the initial results provide proof of concept for the technical feasibility of the end-to-end approach, a systematic evaluation with students remains necessary to assess students' perceptions, acceptance, and the educational effectiveness of the generated feedback.

Keywords

Microlearning Systems, Personalised Feedback, Process Mining, Large Language Models

1. Introduction

Feedback is central to effective learning support. When it is timely, understandable, and actionable, feedback can help learners recognise gaps in their understanding, regulate their learning strategies, and decide how to proceed [1, 2]. This role becomes particularly relevant in microlearning environments, where learning activities are short, focused, and often self-paced [3, 4]. In such settings, students may complete the learning experience within a limited time frame, leaving only a narrow window to detect difficulties and provide useful guidance.

Digital microlearning platforms enable the collection of fine-grained traces of students' interactions, such as page visits, navigation actions, clicks, and quiz submissions. These traces can be transformed into event logs and analysed using Process Mining (PM) to reconstruct how learners navigate the learning material [5]. In addition, Predictive Process Monitoring (PPM) can leverage partial traces to estimate future outcomes while the learning session is still underway [6]. Previous work has shown the potential of PM and PPM for analysing students' behaviour in short-term tutorials and microlearning

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settings [7, 8]. However, translating behavioural and predictive signals into meaningful student feedback remains challenging.

Large Language Models (LLMs) offer new opportunities to generate natural-language feedback and support personalised learning in educational contexts [9, 10]. Recent educational applications have explored LLMs for personalised learning experiences and guided student interaction [11, 12]. However, their use requires appropriate control mechanisms. In particular, feedback should remain grounded in available evidence, avoid unsupported interpretations, and align with the learner's current situation. Moreover, in educational settings, privacy concerns may discourage the use of external cloud-based services [13]. For this reason, locally deployed LLMs represent a promising option for generating personalised feedback while keeping students' interaction data within the local infrastructure [14].

Feedback effectiveness also depends on human-centred factors such as tone, length, and level of detail, which may affect acceptance, perceived usefulness, and educational effectiveness. In fact, learning environments should minimise students' cognitive workload and avoid diverting their attention from the learning material [15]. Additionally, learning is widely understood as a situated and relational process; consequently, it must be investigated within the social, cultural, and institutional contexts in which it unfolds [16, 17]. From this perspective, ethnography, through systematic observation of naturally occurring practices and interactions, provides a valuable methodological approach for exploring the dynamics of educational processes. A holistic combination of these different perspectives remains largely unexplored, representing an important research gap.

Building on these premises, the proposed approach explores the feasibility of a process-aware framework for personalised feedback in microlearning. In particular, we present a proof of concept (PoC) that integrates PM, predictive process monitoring (PPM), feedback-intent selection, and local LLM-based text generation. We transform students' interaction traces into event logs, analyse them to derive behavioural indicators, and combine these with predicted learning outcomes to generate personalised feedback. Beyond the technical pipeline, prior HCI evidence provides context, while we plan micro-ethnographic observation for future learner-side evaluation.

The contribution of this paper is threefold: (i) a process-aware framework for generating personalised feedback from students' interaction traces; (ii) a feedback strategy that combines behavioural indicators and predicted learning outcomes to derive high-level feedback intents; and (iii) a controlled LLM-based generation component that produces coherent, personalised, and actionable feedback. The proposed framework is implemented in a web-based Python tutorial and illustrated through a preliminary case study based on real interaction traces. HCI and future micro-ethnographic evaluation complement the process-based perspective with learner-side evidence.

The remainder of this paper is organised as follows. Section 2 reviews related work. Section 3 presents the proposed feedback pipeline. Section 4 describes the microlearning case study. Section 5 reports the preliminary results. Section 6 discusses the main findings and limitations, while Section 7 concludes the paper and outlines future work.

2. Related work

AI-based educational feedback. Recent work has investigated how AI and LLMs can support assessment and feedback practices in educational contexts. In [10], LLMs are discussed as a means to support sustainable assessment and feedback in higher education, with particular attention to the analysis of student work and the provision of feedback based on predefined criteria. In [18], teacher-AI interaction is investigated in the correction of student assessments and in the selection of target texts requiring further evaluation. Unlike these works, our approach focuses on feedback generated from students' interaction traces during a microlearning session, rather than on assessing submitted textual answers.

User-centred feedback systems. Adaptive learning systems exploit personalised feedback implementations to improve instruction and learning. In their pioneering contribution, Vasilyeva et al. [19] classified learning systems based on 1) the feedback features that were adapted, and 2) students' features

to which feedback was adapted. In their systematic literature review, Maier and Klotz [20] found that most previous studies adapted feedback based on students' current knowledge or learning-related behavioural data, ignoring aspects such as students' preferences, emotions or personality. Similarly, our approach uses behavioural data captured in event logs to generate personalised feedback, but we acknowledge the relevance of personal characteristics in decision-making [21] and plan to account for them in future work.

Learning analytics and predictive modelling for tutoring. Learning analytics and predictive models have also been used to identify learning difficulties and support data-based tutoring actions. In [22], an analysis model for LMS data is proposed to identify potential critical issues in learning processes and support targeted tutoring interventions. In [23], EasyDKT is presented as a Deep Knowledge Tracing framework that models students' progress over time and predicts future performance. Related work has also explored LLM-based outcome prediction from narrative representations derived from event logs [24]. Our work is aligned with this predictive perspective but uses the predicted learning outcome as one component of a feedback strategy that guides the generation of personalised feedback.

Process Mining in education. PM provides a process-centric framework for discovering, monitoring, and analysing processes from event logs [5]. In educational contexts, Educational Process Mining has been used to analyse learning traces collected from digital environments and to make students' learning processes more explicit [25, 26, 27]. Previous studies on microlearning settings applied PM to students' web learning traces, first combining behavioural analysis with ethnographic observations [28], and then investigating short-term tutorial interactions and behavioural patterns associated with learning effectiveness [7]. PM has also been applied to large-scale MOOC data to identify theory-based patterns of self-regulated learning from learners' interaction sequences [29]. Subsequently, the authors proposed a domain-driven event abstraction framework to transform fine-grained MOOC interactions into seven predefined high-level learning dynamics [30]. The extended study further applied the framework to an introductory programming MOOC and combined process analysis with clustering to identify recurring behavioural patterns and distinct learning-session types [31]. Beyond education, PM has also been combined with automated event-log enrichment in public procurement [32, 33] and with narrative-based outcome prediction in healthcare [24, 34]. Building on this line of work, the present paper moves from retrospective behavioural analysis to using PM-derived indicators as input for live, process-aware feedback generation.

LLMs for personalised learning. LLMs are increasingly being explored as components of personalised learning environments. In [11], the proposed platform is presented as a web-based educational tool that uses LLMs to support personalised learning experiences and controlled student interaction with AI. In [12], LLMs are fine-tuned to support Socratic interactions, guiding students towards discovering answers rather than directly providing them. While these works emphasise conversational interaction and personalised support, our approach uses a local LLM as the final component of a process-aware pipeline, in which the generated feedback is constrained by behavioural indicators, the predicted outcome, and a predefined feedback intent.

Micro-Ethnography. Micro-ethnography, originally developed within the tradition of educational anthropology [16, 35], provides a qualitative approach for the fine-grained analysis of naturally occurring classroom interactions. More recently, researchers have revisited and extended its methodological foundations within the framework of Microethnographic Discourse Analysis [17], confirming its relevance for investigating how educational practices are collaboratively accomplished through situated interaction.

The novelty lies in operationalising these components as a single process-aware pipeline, where PM-derived evidence and outcome prediction determine the feedback intent and constrain LLM generation.

3. Proposed Approach

The framework centres on the quantitative analysis of digital traces, complemented by prior HCI evidence and planned micro-ethnographic evaluation.

The feedback-generation approach adopted in this study is an end-to-end PoC pipeline that operationalises feedback generation from recorded learning interactions, rather than a fully validated tutoring system. As shown in Figure 1, it integrates PM, learning outcome prediction, a feedback strategy, and local LLM-based text generation to produce feedback tailored to students’ observed behaviour.

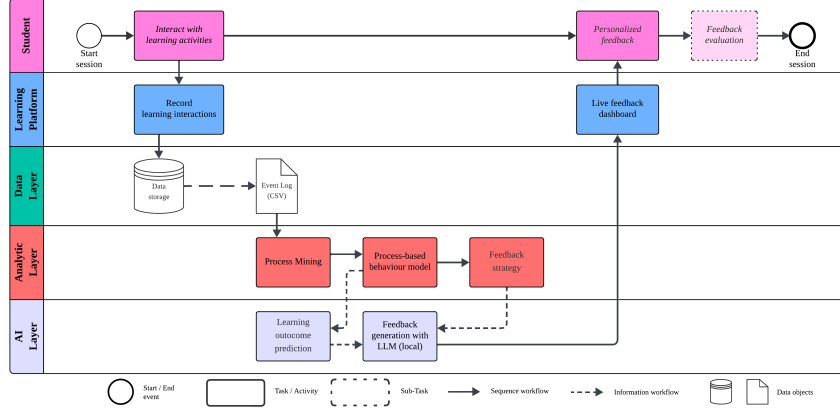


Figure 1: Overview of the proposed process-aware feedback pipeline. Student interactions are recorded as event logs, analysed through PM, combined with outcome prediction and feedback-intent selection, and used to generate personalised feedback through a local LLM.

Learning Platform. The pipeline is built on a web-based microlearning platform that delivers short programming lessons interspersed with multiple-choice quizzes (see Section 4) and automatically records students’ interactions during the learning session. Each navigation event (e.g., page transitions, mouse interactions, quiz submissions, and other navigation actions) is logged and stored for subsequent analysis.

Data Layer. Students’ interactions are stored in a relational database and subsequently transformed into an *event log*, the standard data representation adopted in PM [5]. Each *trace* of the event log is associated with a *case identifier* (the student session ID), an *activity*, a *timestamp*, and additional contextual attributes. The resulting event log serves as the input for the subsequent PM analysis. Further details on the database schema and event log construction are available in [7].

Analytic Layer. The Analytic Layer transforms the event log into meaningful educational information through the following four steps.

Process Mining. The event log is analysed through PM techniques to discover a process-centric representation of students’ navigation paths in the form of a Directly-Follows Graph (DFG) [5]. The model is then used to extract behavioural indicators that describe navigation patterns and learning dynamics. A detailed description of the adopted PM pipeline is available in [7].

Process-based behaviour model. The discovered process is enriched with behavioural indicators, including Cyclomatic Complexity (CC) and Coefficient of Variation (CV) [36], backwards jumps, clicks, and double clicks. Students’ performance is further represented through related metrics, e.g. the quiz rate, defined as the ratio of correctly answered quizzes and classified into three levels: *Low* (<0.5), *Medium* (0.5–0.8), and *High* (>0.8). These indicators support both learning outcome prediction [7, 8] and the generation of personalised feedback.

Feedback Strategy. Based on the process-based behaviour model and the predicted learning outcome, the system determines the feedback type before invoking the LLM. Specifically, the learner is assigned to one of three intervention categories: (i) *Encouragement*, (ii) *Review*, or (iii) *Warning*, based on observed evidence and the predicted learning outcome. The selected intent, along with the behavioural context and predicted outcome, is then incorporated into the prompt to guide the generation of coherent, personalised feedback. Table 1 illustrates how behavioural evidence and predicted outcomes are mapped to the three feedback intents. We implemented the feedback-intent strategy via an external JSON configuration file that defines the mapping between predicted outcomes, behavioural evidence, and feedback intents. An excerpt of this configuration is reported in Appendix A.

Table 1
Feedback intents adopted by the proposed approach

Feedback intent	Behavioural evidence	Predicted outcome	Purpose
<i>Encouragement</i>	Strong engagement and effective learning behaviour, e.g., high quiz rate, adequate time spent on activities, and reflective navigation through backward jumps.	High	Reinforce positive learning behaviour and motivate the learner to continue.
<i>Review</i>	Mixed behavioural patterns suggesting partial understanding, e.g., medium quiz rate, irregular time spent on activities, and moderate process complexity.	Medium	Recommend revisiting selected learning materials before progressing.
<i>Warning</i>	Behaviour indicating potential learning difficulties, e.g., low quiz rate, very short time spent on activities, and frequent forward/backward jumps.	Low	Alert the learner to potential learning difficulties and encourage corrective actions.

Feedback usefulness rating. To collect an immediate learner-side signal, the interface includes a lightweight usefulness rating. Students can rate the perceived usefulness of the generated message on a five-point scale, from 1 = *Not useful* to 5 = *Very useful*. This rating is not intended to measure learning effectiveness but to provide preliminary evidence on the acceptability and perceived value of the generated feedback.

AI Layer. The AI Layer combines predictive modelling and LLM-based generation to transform process-based behavioural evidence into personalised feedback through two successive steps.

Learning outcome prediction. To support live feedback generation, the proposed approach incorporates an outcome prediction step based on students' partial learning traces. In line with PPM [37], each ongoing tutorial session is progressively transformed into a set of *prefixes*, i.e., incomplete traces containing only the events observed up to a given point in the learning process. These prefixes represent the student's early behaviour and are used to estimate the expected learning outcome before the session is completed. The prediction relies on the *encoded* prefix together with the behavioural indicators described above. The prefixes are converted into feature vectors through standard encoding strategies, including *Index Encoding*, *Boolean Encoding*, and *Frequency Encoding* [6]. Since eXtreme Gradient Boosting (XGB) achieved the best predictive performance among the models evaluated in our previous experiments on early-stage learning outcome prediction in short-term tutorials [7], we adopt it in the proposed framework as the learning outcome prediction component. The resulting prediction is not presented directly to the student; instead, we combine it with process-based behavioural indicators to select the most appropriate feedback intent.

Feedback Generation. The selected feedback intent (Table 1), together with the behavioural evidence and the predicted learning outcome, is incorporated into a structured prompt submitted to a local LLM through Ollama¹, an open-source framework that enables the local execution of different LLMs without relying on external cloud services, preserving data privacy. The prompt combines the selected feedback intent, the student's behavioural context, and the predicted learning outcome to generate coherent, personalised, and actionable feedback. The complete prompt template and the main generation parameters are reported in Appendix B. This design operationalises feedback as a formative support mechanism, in line with the view that effective feedback should provide learners with timely, understandable, and actionable information to guide subsequent learning actions [2].

Micro-ethnographic analysis. Future micro-ethnographic evaluation will complement system logs by capturing situated verbal and non-verbal behaviours not inferable from digital traces.

Implementation details. We implemented the feedback dashboard in Python 3.11 and exposed it as a web-based interface using Flask². Students' interaction data are retrieved from a *MySQL 8.4* relational

¹Ollama is available for Linux, macOS and Windows at <https://ollama.com>

²Flask available at <https://flask.palletsprojects.com/en/stable>

database using the *SQLAlchemy*³ library to extract the data and construct the event log. *PM4Py* [38] is used for event log handling and DFG discovery, while *scikit-learn* and *XGBoost* libraries support the predictive component. Finally, personalised feedback is generated locally using *Ollama 0.31* and its Python client, avoiding reliance on external AI services; *Llama 3.2-3B*⁴ was selected as a practical trade-off between feedback quality and local hardware requirements. All the data underlying this study are openly available in the following repository: <https://github.com/roberto-nai/AILEAP-2026>.

4. Case Study

Learning Platform. The case study uses a web-based microlearning platform introduced in [28]. The platform delivers a Python programming tutorial⁵ comprising ten self-contained microlearning lessons. Each lesson is followed by a multiple-choice quiz targeting the corresponding learning topic. The tutorial covers the following lessons: (1) Introduction, (2) First program, (3) Variables, (4) Data Types, (5) Type Conversion, (6) If-Else Statements, (7) For and While loops, (8) Lists, (9) Dictionaries, and (10) Functions. We defined and reviewed the tutorial content, learning sequence, and quiz questions with a domain expert in computer science education, as described in detail in [28]. Figure 2 provides an overview of the tutorial sequence.

The tutorial is designed as a freely navigable learning environment: students can move through lessons and quizzes, and the platform automatically records their interactions. The collected data include page visits, navigation events, clicks, double-clicks, and quiz submissions, and form the basis of the event log analysed by the proposed approach. A detailed description of the platform architecture, web-tracking infrastructure, and event log construction is available in [7].

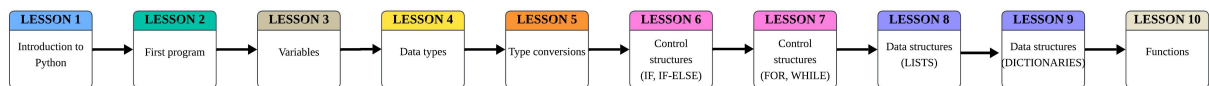


Figure 2: Overview of the Python programming tutorial, consisting of ten microlearning lessons, each followed by a multiple-choice quiz.

Application Scenario. The case study relies on an existing administration of the Python microlearning tutorial, previously conducted without live personalised feedback. The tutorial was administered to seven second-year university class groups from non-computer-science degree courses, namely Economics (ECO), School of Administration and Management (SAA), and Sports Sciences (SMCN and SMTO groups). In fact, more than 80% of students self-assessed their initial programming experience as either “little” or “fairly”. After filtering incomplete or inconsistent sessions, the resulting event log included 332 student sessions, distributed across the class groups and degree areas reported in Table 2.

The same administration was previously analysed from an HCI perspective [8]; here, these findings provide only contextual information, while the analysis focuses on interaction traces. Each student session is treated as one case in the event log. The recorded interactions are used to reconstruct the learning path, compute behavioural indicators, estimate the expected learning outcome, and generate personalised feedback. The pipeline is therefore applied to real traces collected from the microlearning platform to reproduce the feedback-generation workflow (notice that the feedback was not delivered to students during the original tutorial administration).

5. Preliminary Results

This section describes the implementation of the proposed approach in the microlearning case study, focusing on the event log representation, the feedback dashboard, the intent selection step, and examples of generated feedback.

³SQLAlchemy available at <https://www.sqlalchemy.org>

⁴Llama 3.2 model available at <https://ollama.com/library/llama3.2>

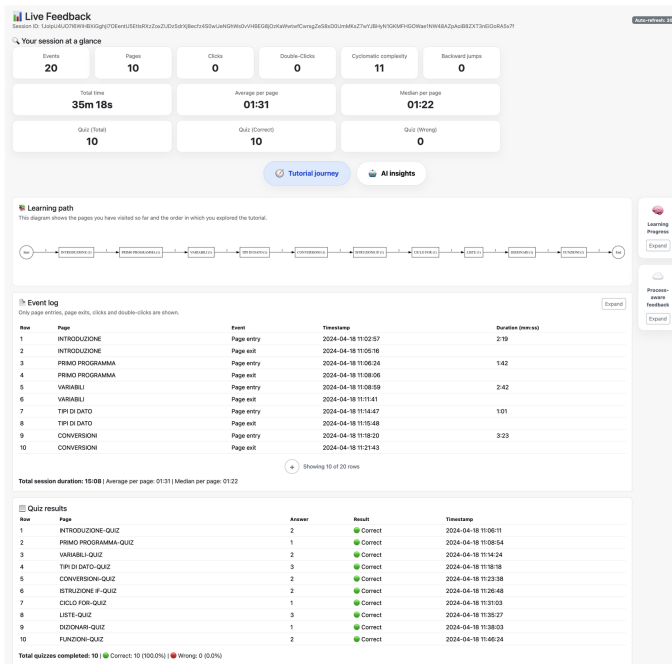
⁵Python tutorial available at <http://webtutorial.altervista.org/python>

Table 2
Distribution of student sessions by class group and degree area

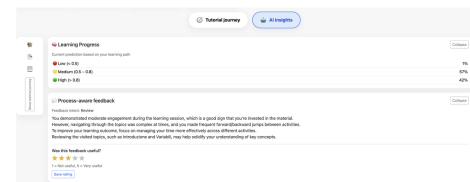
Class group	Degree area	Cases
ECO	Economics	125
SAA	School of Administration and Management	97
SMCN1	Sports Sciences	17
SMCN2	Sports Sciences	26
SMT01	Sports Sciences	27
SMT02	Sports Sciences	22
SMT03	Sports Sciences	18
Total	–	332

Event log and behavioural indicators. In practice, the proposed pipeline can transform raw interaction data into a process-based representation for each learning session. For each student, the system reconstructs the learning path, computes behavioural indicators, and visualises the corresponding DFG. This representation provides an interpretable overview of how the student navigated the tutorial, including visited topics, repeated transitions, backward movements, and quiz-related events.

Live dashboard. Figure 3(a) shows the prototype dashboard. The interface keeps a compact session summary visible at the top, reporting indicators such as event count, visited pages, quiz results, clicks, backward jumps, process complexity, and total time. The detailed information is organised into expandable views: the *Tutorial journey* view shows the reconstructed learning path in DFG, event log information, and quiz results, while the *AI insights* view presents the predicted learning progress, the selected feedback intent, the personalised feedback generated by the local LLM, and the usefulness rating.



(a)



(b)

Figure 3: (a) Feedback dashboard showing session-level indicators, the reconstructed tutorial journey, event log information, and quiz results; (b) example of the AI insights view, showing the learner-oriented progress prediction, the selected feedback intent, the personalised feedback generated by the local LLM, and the usefulness rating.

Outcome prediction and feedback intent. As shown in Figure 3(b), the predicted learning outcome is presented in the *Learning progress* panel in a learner-oriented form, rather than as a raw technical

output. The prediction is combined with the behavioural indicators to select the appropriate feedback intent, as shown in the *Process-aware feedback* panel, thereby guiding the generation of the personalised message. This design enables the system to translate predictive information into formative support, focusing on actionable learning suggestions.

Manual assessment confirmed consistency with the selected intent and behavioural evidence, but did not evaluate educational effectiveness. Table 3 reports representative examples of generated feedback for the three feedback intents considered in this study, showing how different behavioural profiles are translated into personalised messages. In particular, the LLM produced concise, actionable messages without exposing technical information such as PM metrics, predictive models, or internal system decisions. Future “in-the-wild” studies [39] will aim to complement this preliminary assessment with students’ perspectives, captured using both quantitative measurement instruments, such as the lightweight usefulness rating described in Section 3, and micro-ethnographic analysis to shed light on situated learning processes.

Table 3

Examples of generated feedback according to the selected feedback intent

Feedback intent	Behavioural evidence	Generated feedback
<i>Encouragement</i>	The student completed all 10 quizzes with an overall quiz correctness ratio of 1.0. The learning path follows the expected tutorial sequence, with few forward or backward jumps.	You are progressing very well through the tutorial. Your quiz answers show a strong understanding of the topics covered so far, and your learning path is consistent and complete. Keep following this approach; it supports effective learning.
<i>Review</i>	The student achieved an overall quiz correctness ratio of 0.5, with 5 correct answers across 6 completed quizzes. The path is mostly regular, but some quiz activities are wrong in the first part of the tutorial, suggesting that not all topics were consolidated through assessment.	You are showing a reasonable level of understanding, but some parts of the tutorial may benefit from further consolidation. Before moving on, it may be useful to review the topics not followed by a quiz attempt and check whether the key concepts are clear.
<i>Warning</i>	The student completed 10 quizzes but obtained only 1 correct answer out of 10, with an overall quiz correctness ratio of 0.1. Although the path includes all main tutorial topics, several activities are completed very quickly, especially in the second half of the tutorial, suggesting limited engagement with the learning material.	Your quiz results suggest that several concepts may still be unclear. Try slowing down and revisiting the lessons before answering the quizzes, especially the topics completed very quickly. Review the examples and try the questions again to strengthen your understanding.

6. Discussion

The case study illustrates the proposed approach’s potential to connect low-level interaction traces with student-facing feedback. In particular, process-based behavioural indicators and outcome prediction are not presented to learners as technical outputs, but can be translated into a feedback intent that guides the generation of personalised messages through a local LLM.

A relevant aspect of the proposed approach is that the LLM is not used as an unconstrained feedback generator, but as the final component of a structured pipeline. The feedback intent, behavioural indicators, predicted outcome, and prompt constraints define the context for message generation. This design grounds LLM generation in observable evidence, following a principle also adopted in retrieval-augmented decision-support systems [40], to reduce generic or unsupported suggestions. Expert validation could further assess the reliability of these constraints, as explored in other domain-sensitive LLM pipelines [41]. At the same time, using a local LLM facilitates privacy-preserving deployment, which is particularly relevant when students’ interaction traces are used to personalise feedback [42]. However, local inference introduces latency, hardware, and scalability trade-offs, particularly with concurrent learners.

The usefulness rating in the interface provides a lightweight way to collect learner-side feedback on generated messages. However, this rating captures perceived usefulness and acceptability, not the feedback’s actual educational effectiveness. A systematic evaluation with students is still required to

assess the clarity, perceived value, and educational impact of the generated feedback.

Beyond its technical feasibility, the proposed framework also raises broader educational questions concerning the role of AI-mediated feedback in supporting learners' critical agency. Personalised feedback should not merely optimise learning efficiency or predict performance, but also foster learners' capacity to reflect on their own learning processes, critically interpret AI-generated suggestions, and make autonomous educational decisions. From this perspective, process-aware feedback may contribute to educational environments in which AI functions not simply as an adaptive technology but as a pedagogical mediator that supports reflective judgement rather than replacing it. This broader perspective aligns with recent pedagogical approaches that emphasise the need to educate learners to develop a critical, creative, and responsible relationship with artificial intelligence, viewing AI systems as socio-technical artefacts whose educational value depends on how they shape human agency, deliberation, and responsibility [43, 44].

7. Conclusions and future work

This paper presented a process-aware personalised feedback pipeline for microlearning. The proposed pipeline can be instantiated in a web-based Python tutorial using real interaction traces. Overall, the initial results suggest that PM-derived behavioural indicators and predicted learning outcomes can be operationally combined with a structured feedback strategy and a controlled text-generation component to generate student-facing feedback.

Future work will focus on an “in-the-wild” [39] evaluation with students, since both the users' experience with and the educational value of LLM-generated feedback need to be assessed empirically in interaction with learners [45]. This evaluation will consider the perceived usefulness, clarity, and educational impact of the generated feedback, and may distinguish between learners' perceptions of different feedback intents, such as Encouragement, Review, and Warning. Future work will also investigate conformance between observed and recommended learning paths, using process-based measures to quantify meaningful deviations [27, 46]. An equally important direction will investigate whether the feedback strategy should adapt to different microlearning domains, levels of prior knowledge, or personal characteristics such as preferences, emotional state, and personality traits [21, 20]. In parallel, we will systematically vary feedback features, including length, level of support, style, and tone of voice. In addition, future experiments will compare different locally deployable LLMs on feedback quality, consistency, latency, hardware requirements, and scalability.

Finally, we plan to investigate not only the accuracy and usefulness of AI-generated feedback, but also its potential impact on learners' critical thinking, self-regulation, and ethical decision-making.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly and ChatGPT in order to: grammar and spelling checks. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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A. Feedback Intents

Table 1 summarises the adopted feedback intents, implemented through an external JSON configuration. Listing 1 shows a shortened excerpt, where each intent defines the predicted outcome, quiz-rate level, behavioural thresholds, and purpose.

```

1 {
2   "feedback_intents":

```

```

3  {
4    "Encouragement":
5    {
6      "predicted_outcome": "High",
7      "quiz_rate_level":
8      {
9        "label": "High",
10       "min": 0.8,
11       "...": ...
12     },
13     "behaviour_thresholds":
14     {
15       "...": "...",
16       "...": "..."
17     },
18     "...": "...",
19     "purpose": "Reinforce positive learning behaviour and motivate the learner to continue."
20   },
21   "Review": { "...": "..." },
22   "Warning": { "...": "..." }
23 }
24 }

```

Listing 1: Shortened excerpt of the JSON configuration used to encode feedback intents

B. LLM Prompt and Generation Configuration

Listing 2 reports the prompt template used to generate personalised feedback, while Listing 3 provides the corresponding LLM model and generation configuration.

```

1  System prompt:
2  You are an educational feedback generator.
3  Generate personalised feedback exclusively from the information provided.
4  The feedback intent has already been selected by the system and must not be changed.
5  Do not invent information or mention technical concepts, process mining metrics, prediction models, or AI technologies. Write concise, supportive, and
   ↪ actionable feedback for the student.
6  Start directly with the feedback content: do not use lead-ins such as "Here is your personalised feedback" or similar introductory phrases.
7  User prompt template: Generate personalised feedback for the current learning session.
8  Feedback intent: {feedback_intent}
9  Behaviour summary:
10 - Engagement level: {engagement_level}
11 - Quiz performance: {quiz_rate}
12 - Navigation behaviour: {navigation_behaviour}
13 - Time management: {time_management}
14 Predicted learning outcome: {predicted_outcome}
15 Visited topics: {visited_pages}
16 Write 3-5 sentences.
17 Follow the selected feedback intent, refer only to the provided information, and suggest concrete next actions when appropriate.

```

Listing 2: Prompt template used by the local LLM to generate personalised feedback. Elements enclosed in curly brackets represent runtime input variables

```

1  {
2    "model": "llama3.2:3b",
3    "common_generation_parameters":
4    {
5      "temperature": 0.1,
6      "top_p": 0.8,
7      "max_output_tokens": 256
8    },
9    "ollama_options":
10   {
11     "seed": 42,
12     "num_ctx": 4096,
13     "repeat_penalty": 1.1
14   }
15 }

```

Listing 3: Generation configuration used for personalised feedback. The common parameters are model-independent, while the remaining options refer to the Ollama runtime