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Authors	Paraskevi Topali, Alejandro Ortega-Arranz, Juan I. Asensio-Pérez, Sara L. Villagrá-Sobrino, Alejandra Martínez-Monés, Yannis Dimitriadis

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Neither of the authors have any conflicts of interest in writing this manuscript. Consent was obtained from participants who were informed about the educational nature of this study and the potential publications of the research results. Datasets have been anonymized.

BEHAVIOUR & INFORMATION TECHNOLOGIES

e-FeeD4Mi: Human-Centered Design of Personalized and Contextualized Feedback in MOOCs

Paraskevi Topali[a], Alejandro Ortega-Arranz[b], Juan I. Asensio-Pérez[c], Sara L. Villagrá-Sobrino[d], Alejandra Martínez-Monés[b] and Yannis Dimitriadis[c]

[a]NOLAI | National Education Lab AI, Behavioural Science Institute, Radboud University, The Netherlands.
[b]School of Computer Engineering, Universidad de Valladolid, Valladolid, Spain.
[c]School of Telecommunications Engineering, Universidad de Valladolid, Valladolid, Spain.
[d]Department of Pedagogy, Universidad de Valladolid, Valladolid, Spain.

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ABSTRACT
Personalized feedback in MOOCs is often prevented by the non-scalability of traditional approaches and the lack of pedagogical grounding of the current learning analytics (LA) solutions. One way to tackle such limitations is the adoption of a participatory approach through the active positioning of MOOC instructors in the design and development of LA solutions. Nonetheless, there is a scarcity of empirical proposals supporting these approaches in MOOCs. To that end, the current paper presents e-FeeD4Mi, a web-based tool, incorporating a set of catalogues, recommendations and a process, that aim to support instructors in the design of human-centered LA-informed feedback. We conducted an evaluative study with 6 MOOC instructors who employed the tool into their course designs to assess e-FeeD4Mi usefulness, usability, and associated workload. The evidence gathered permitted us to understand how e-FeeD4Mi support the design of human-centered LA-based feedback in MOOCs. Altogether, the results showed a good usability and participants' satisfaction regarding the use of the tool for shaping personalised feedback. At the same time, participants offered ideas for further tool enrichment. This study expands upon the current body of empirical research on the human-centered approaches in the design of LA-driven interventions in MOOCs.

KEYWORDS
Human-Centered Learning Analytics; Personalized Feedback, Teacher-led Interventions, MOOCs.

1. Introduction

MOOCs have shattered the barriers of traditional education by offering open learning experiences worldwide [1]. Specifically, during COVID-19 pandemic, MOOCs served as a key alternative for remote learning from primary to tertiary education levels [2, 3]. Indeed, due to the attention that MOOCs gathered, 2020 became "the Second Year of The MOOC" [4]. However, and despite their benefits (*e.g.*, accessibility, flexibility), the provision of meaningful feedback in a timely manner in MOOCs is still viewed as an important challenge, due to the high number of heterogeneous learners enrolled

Corresponding Author: Paraskevi Topali (evi.topali@ru.nl).

and their asynchronous interaction [5, 6]. MOOCs may gather more than 1000 learners coming from diverse backgrounds with different learning objectives and needs. Within this context, the provision of scalable feedback tailored to learners' needs and context is complex and often overlooked [7–9].

The use of Learning Analytics (LA) has been proposed to optimise learners' support by facilitating timely and personalized feedback interventions [10, 11]. A common example of LA in MOOCs is the representation of learners' activity (*e.g.*, time spent on a task, number of attempts of an activity, number of logins) through dashboards. Dashboards can foster instructors' awareness on behaviours that need further attention, and thus perform targeted interventions [12]. Another common application of LA in MOOCs is the use of predictive analytics to shape feedback. Researchers have applied predictive models to, among others, automatically identify struggling learners or learners at risk of dropout [13–16].

While the above LA approaches can provide support to MOOC instructors for identifying which learners may need tailored feedback, empirical research in higher education and online learning (MOOCs included) reports that LA tools often lack pedagogical foundations from learning theory and course contextualization [17–19]. This lack may result in less relevant interventions, because the course characteristics (*e.g.*, activity difficulty, course structure and connection among the resources) may affect the feedback effectiveness. For example, LA dashboards often display aggregated data that are not aligned with instructors' needs. ~~Stephens-Martínez, Hearst, & Fox (2014)~~ [20] conducted a survey with 92 MOOC instructors and found that, while instructors were eager to detect timely learners who face problems, they tend to prefer discussion forums more than dashboards as a monitoring resource, since dashboards showed metrics without considering the course particularities. To attain such discrepancies, previous studies proposed following human-centered approaches in the design and development of LA-based solutions with the active involvement of the course instructors [21, 22]. Given this context, ~~Buckingham-Shum, Ferguson, & Martinez-Maldonado (2019)~~ [23] coined the term *'Human-Centred LA'* (HCLA) that considers processes that, among others, position actively the stakeholders in the co-design and/or co-creation of LA tools, including those related to feedback processes, drawing upon their expertise.

Previous works discuss several proposals to facilitate the provision of personalized LA-informed feedback through the active involvement of the human agents in the design of the LA indicators (*i.e.*, LIME, OnTask, SRES, MOOClet framework) [24–27]. These proposals support rule-based feedback, *i.e.*, feedback triggered by "if/then" rules, according to the learners' course performance. However, and despite their positive outcomes, these tools do not guide instructors in the process of reflecting on feedback-related aspects (*e.g.*, feedback type, feedback timing) and do not permit instructors to define contextualization aspects (*e.g.*, difficulty of the tasks). Additionally, these tools do not consider analytics from third-party learning tools that may be involved as learning resources (*e.g.*, Google Docs, Slack). Finally, among the existing proposals, only one was designed taking into account the specific characteristics of MOOCs [27].

Addressing the aforementioned limitations, this paper presents e-FeeD4Mi, a web-based tool that builds on a conceptual framework aimed to assist instructors in the design and automatic deployment of LA-informed feedback in MOOCs. The use of the tool foresees the active positioning of the course instructors in the selection and fine-tuning of the metrics relevant to detect concrete learner behaviors and provide tailored feedback according to the course learning design. The overarching research question guiding this study is: ***"To what extent e-FeeD4Mi can support instructors in the design of personalized and contextualized feedback in MOOCs through its catalogues, process and recommendations?"***.

The rest of the paper is structured as follows. Section 2 outlines the related works, attending feedback in learning processes (Section 2.1) and proposals for personalized feedback that follow human-centered approaches (Section 2.2). Section 3 presents the conceptual framework and the technological tool proposed in this paper. Section 4 describes the methodology that guides the current study, explaining the evaluation context, the study informants, and the data collection methods. Next, Sections 5 and 6 report and discuss the results of the study, respectively. Finally, Section 7 draws the final conclusions and future lines of work.

2. Related Works

2.1. Framing Meaningful Feedback in Learning Processes

Feedback stands among the core elements of learning by fostering the enhancement of learners' performance, the acquisition of more informed learning strategies, the reinforcement of satisfaction and self-awareness [28, 29]. However, according to previous studies, effective feedback requires:

a. *personalized interventions according to learners' needs and characteristics.* According to ~~Koenka & Anderman (2019)~~ [30] and ~~Narciss & Huth (2002)~~ [31], tailoring feedback interventions to individuals' demands impacts positively the learning outcomes, the learners' self-perception, and their course engagement.
b. *alignment with the course design (e.g., feedback according to the learning objectives and course context).* ~~Mory (1996)~~ [32] suggests that the feedback effectiveness varies depending on the learning context, indicating that the same intervention may yield different levels of usefulness in diverse contexts. Thus, the course particularities should be explicitly considered when shaping feedback interventions.
c. *a reflection on the timing of delivering the interventions.* [33–35] highlighted that both delayed and immediate interventions can be beneficial, contingent upon the specific learning objectives they seek to accomplish.
d. *a consideration of different focuses.* While often feedback is linked to the learning outcomes, feedback can serve numerous focuses. ~~Hattie & Timperley (2007)~~ [33] and ~~Henderson et al. (2019)~~ [28] listed several other types of feedback focus apart from the learners' performance, such as interventions aiming self-regulation, motivation/affection, cognitive processes, etc.

Therefore, the design and delivery of meaningful feedback should take into account all factors presented above. These aspects can be addressed easier in small-scale learning settings (*e.g.*, face-to-face classrooms) where teachers can track individual learners' progress and adapt their interventions. However, scaling up feedback interventions in MOOCs, where the learners-teacher ratio gets higher than in a conventional teaching and where the interaction is online, requires special attention [36, 37].

2.2. Instructor-led Personalized Feedback

Building on the need of achieving context awareness, there are several proposals that position course instructors actively in the design of feedback tools by letting them select or define the LA indicators.

~~Burgos and Corbí (2013)~~ [24] introduced LIME, a recommendation model designed to facilitate personalized feedback in both formal and informal online learning contexts. LIME enables instructors to pre-determine a set of rules that trigger various interventions that are automatically delivered to learners. The authors developed a software application called iLIME, which can be integrated into different learning management systems. ~~Liu et al. (2017)~~ [25] proposed SRES, a LA tool designed to deliver personalized feedback in higher education through email messages. SRES allows instructors to establish predefined conditions based on students' course behaviors, such as *"if the number of video rewatches is more than 4 times, send an email message reminder"*. ~~Pardo (2018)~~ [38] suggested a feedback model that enables stakeholders to select data-driven indicators, establish similar if-then conditions, and deliver personalized feedback through email messages to different student cohorts given their course engagement. To facilitate the use of this model, ~~Pardo et al. (2018)~~ [26] developed a web-based tool called OnTask. ~~Reza et al. (2021)~~ [27] introduced the MOOClet framework, which offers the ability for course instructors to provide feedback to learners in the form of explanations and recommendations, based on predefined rule-based conditions. This way, instructors can deliver personalized feedback according to learners' needs and progress.

The above-mentioned proposals support data-driven feedback designed by the course instructors. Nonetheless, the above proposals do not guide the course instructors neither in connecting the LA information with the course design nor in reflecting on the feedback theory. On one hand instructors may need support in bridging the gap between LA and the course learning design -such as the activity difficulty, the collaborative/optional assignments- to effectively integrate LA indicators into feedback interventions [39]. On the other hand, the feedback aspects presented in Section 2.1 can substantially impact the feedback success, however, instructors may not always be aware of these considerations. Therefore, we deem that providing guidance on designing feedback for large-scale contexts may demand a more supportive approach. According to ~~Dimitriadis et al. (2021)~~ [40] the consideration of the course learning design and the pedagogical grounding on educational theories are two key elements when designing human-centered solutions. This way is expected to align the feedback interventions with pedagogical intentions. Additionally, the previous technological proposals, cannot be integrated within existing LMSs and do not consider analytics from third-party tools so widespread in MOOC environments (*e.g.*, Google Docs, Slack). Finally, from the suggested models, only the proposal from ~~Reza et al. (2021)~~ [27] was designed taking into account the specific characteristics of MOOCs. Educational contexts, such as those provided by MOOCs, require a particular attention, as different learner problems can occur due to its massive and online character [41].

3. The e-FeeD4Mi Tool

To address the above-mentioned limitations (*i.e.*, lack of guidance during the feedback design process, and lack of feedback tools connecting LMSs and external tools), we

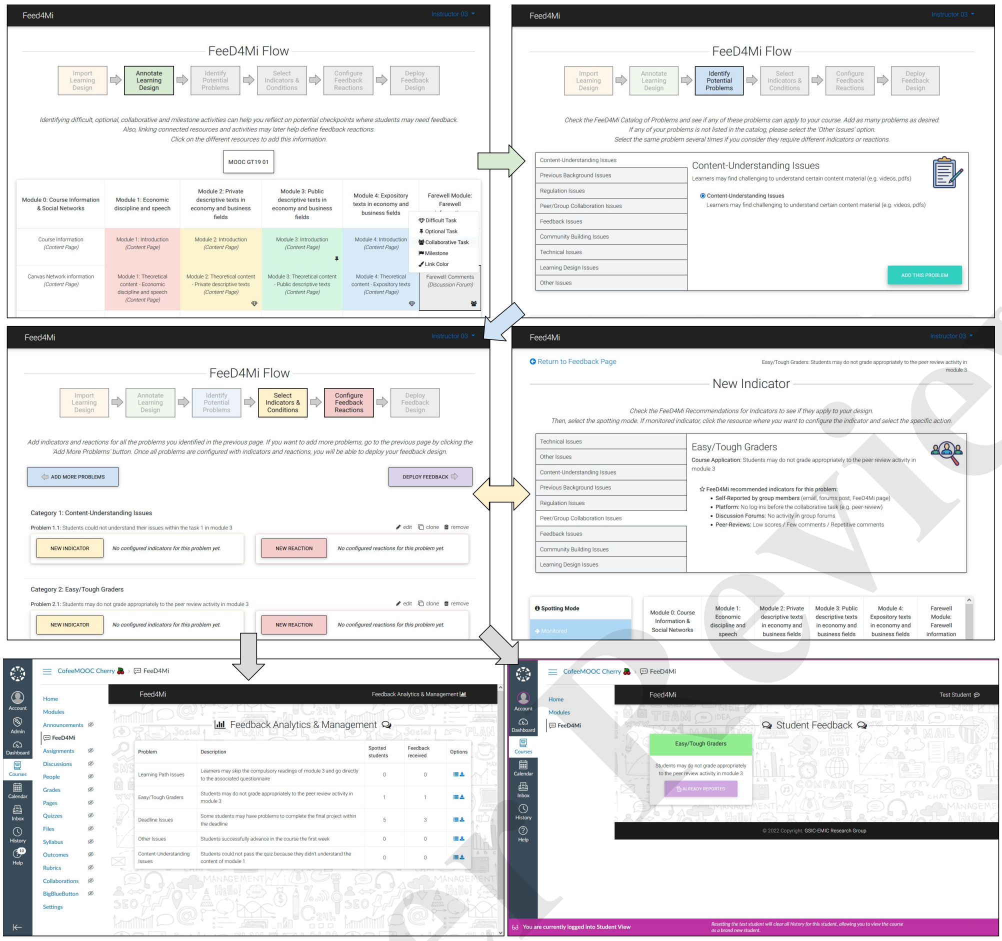

Figure 1. Selection of e-FeeD4Mi screenshots showing its process, catalogues and recommendations to guide instructors in the design of feedback. (A) Annotations in the learning design; (B) Identification of learners' problems; (C) Identification of indicators and reactions; (D) Configuration of indicators; (E) Teacher and (F) Student interface in a Canvas course after implementation.

propose e-FeeD4Mi[1], a web-based tool to support instructors in the design and automatic enactment of personalized LA-informed feedback in MOOCs, within various learning management systems (*e.g.*, Canvas, Moodle) and external tools (*e.g.*, Slack). The tool attends two levels of human-centeredness. That is, on one hand the tool has been built following a participatory approach with MOOC instructors placed as co-designers in prior studies [42]. On the other hand, the use of the tool supports the three human-centered design principles as posed by ~~Dimitriadis et al. (2021)~~ [40] about the consideration of the course design, and the consideration of the learning theories and the active involvement of the course instructors as the main decision-makers for the design of LA-based feedback interventions. Thus, the difference between the e-FeeD4Mi and other proposals lays in the guidance that the tool offers to the instructors in:

a. Reflecting upon their course learning design considering explicitly the course structure and its characteristics (resources, type of activities, etc.) and the po-

[1] e-FeeD4Mi: https://feed4mi.gsic.uva.es/, last access: February, 2024.

tential learner problems, thus contextualizing and personalizing feedback.

b. Selecting LA indicators given learners' course engagement and feedback reactions following the feedback taxonomy of ~~Hattie & Timperley (2007)~~ [33] and the recommendations of ~~Mason & Bruning (2001)~~ [34], ~~Molloy & Boud (2014)~~ [35] and ~~Shute (2008)~~ [43] about the type of intervention (*e.g.*, hint, informal tutoring), the intervention timing (*i.e.*, instant or delayed) and the means via which the intervention will be delivered (*i.e.*, via email, platform notification, course enhancements).

c. Creating if-then rules by fine-tuning the LA indicators and the feedback aspects, such as the timing of the intervention, according to the course design requirements.

e-FeeD4Mi follows a conceptual framework, named FeeD4Mi that consists of a five-dimension process, a set of catalogues and a set of recommendations aimed to guide step-by-step the design of personalized and contextualized feedback interventions in MOOCs. The FeeD4Mi framework is organized around the following dimensions: *(1) Learning Design*, *(2) Learners' Problems*, *(3) Problem Indicators*, *(4) Feedback Rules*, and *(5) Feedback Reactions*. Apart from the dimensions, FeeD4Mi offers:

- A process through which, instructors are expected to start from a reflection on the pedagogical aspects of their course (Learning Design dimension), and on possible struggling behaviours of learners (Learner Problem and Problem Indicators dimensions) to come up with feedback interventions adapted to the different behaviours identified (Feedback Rules and Feedback Reactions).
- Three catalogues containing 15 potential MOOC learner problems (*e.g.*, *difficulty with the activities*, *lack of social interaction*, *collaboration issues*), 33 indicators that describe learner behaviours given their trace data (*e.g.*, *number of video views*, *number of activity attempts*, *forum entries/replies*), and 22 recurrent feedback interventions (*e.g.*, *praising messages*, *badges*, *provision of additional material*, *learners' mentoring*). The catalogues have been informed by existing feedback theories [33–35, 43] and a literature review on LA-informed feedback in MOOCs [44].
- Recommendations about indicators and feedback reactions tailored to the identified potential problems, thus helping instructors to configure optimal feedback decisions by connecting the learner problems with LA indicators and feedback reactions. The recommendations regard *'good practices'* elicited by prior participatory studies with MOOC instructors [42].

e-FeeD4Mi implements the aforementioned process, catalogues and recommendations, hence enabling the configuration of computer-interpretable feedback designs, and the automation of the whole feedback process during course enactment (see Figure 1).

At the technical level, e-FeeD4Mi implements an adapter-based architecture. The adapters are responsible for (1) importing the course information from the LMSs so that instructors can build the feedback upon the underlying learning design of the course with less effort; (2) exporting it to the LMSs by embedding e-FeeD4Mi as an LTI[2] tool in the course, thus enabling single sign on; and, (3) automatically retrieving the log data from the LMS and external tools. This log data is periodically analyzed to test the conditions and, if applicable, perform the feedback reactions defined by the

[2]Learning Tools Interoperability: https://www.imsglobal.org/basic-overview-how-lti-works, last access: February, 2024.

instructors at design time (*e.g.*, send a message if students who were previously active shows no activity in the following lesson). The current adapters use existing APIs to perform all these tasks. Further information about the technical specifications of the tool can be found in [45].

4. Methodology

As previously stated, this RQ guided the e-FeeD4Mi evaluation: ***"To what extent e-FeeD4Mi can support instructors in the design of personalized and contextualized feedback in MOOCs through its catalogues, process and recommendations?"***. The research reported here builds upon earlier work concerning the facilitation of feedback in MOOCs. Prior work indicated the need of MOOC instructors to have conceptual tools to guide them in the design of feedback in MOOCs and of technological tools to automate this process. In the current study we perceive e-FeeD4Mi as the particular way to concretize the components of the FeeD4Mi framework: namely catalogues, recommendations and process. Therefore, we aim to explore a) the usability and implied workload of e-FeeD4Mi in order to check that they are not an insurmountable barrier for instructors and b) the way these components are supporting instructors in the design of personalized and contextualized feedback.

The evaluation followed an interpretive approach [46] to shed light into how MOOC instructors use a proposed LA tool for designing feedback interventions based on their own course designs. We employed a mixed method approach and concretely, a Convergent Parallel Design [47]. According to this design, both qualitative and quantitative data are gathered to provide a more thorough understanding of the evidence gathered. In this case, our aim is to engage a dialogue with the MOOC instructors and to enable a better understanding of how the LA tool serves their learning design needs. To better address the research question, we have followed an anticipatory data condensation process [48] dividing the RQ into the following three subquestions:

- **[Catalogue Expressiveness]**: To what extent did the e-FeeD4Mi catalogues (a) cover the actual instructors' feedback practices, and (b) help identify new problems, indicators, and feedback reactions?
- **[Process Guidance]**: To what extent did the e-FeeD4Mi process support MOOC instructors to design feedback interventions?
- **[Recommendations Usefulness]**: To what extent did the e-FeeD4Mi recommendations provide useful suggestions that were later implemented for the design of personalized interventions?

In addition to these three subquestions, we also explored the instructors' perceived workload of feedback design, and the usability of the proposed tool. We also deem these two topics relevant since, according to ~~Dagnino et al. (2018)~~ [49], instructors tend to adopt or avoid tools (either conceptual or technological) given their usability, and the added workload into their teaching practices. In our case, we want to assess whether e-FeeD4Mi supports MOOC instructors in designing feedback in a usable way without requiring excessive workload.

- **[Perceived Workload]**: To what extent do the participants perceive as manageable the design of feedback with e-FeeD4Mi in terms of workload?
- **[Perceived Usability]**: To what extent is e-FeeD4Mi perceived as usable by the participants?

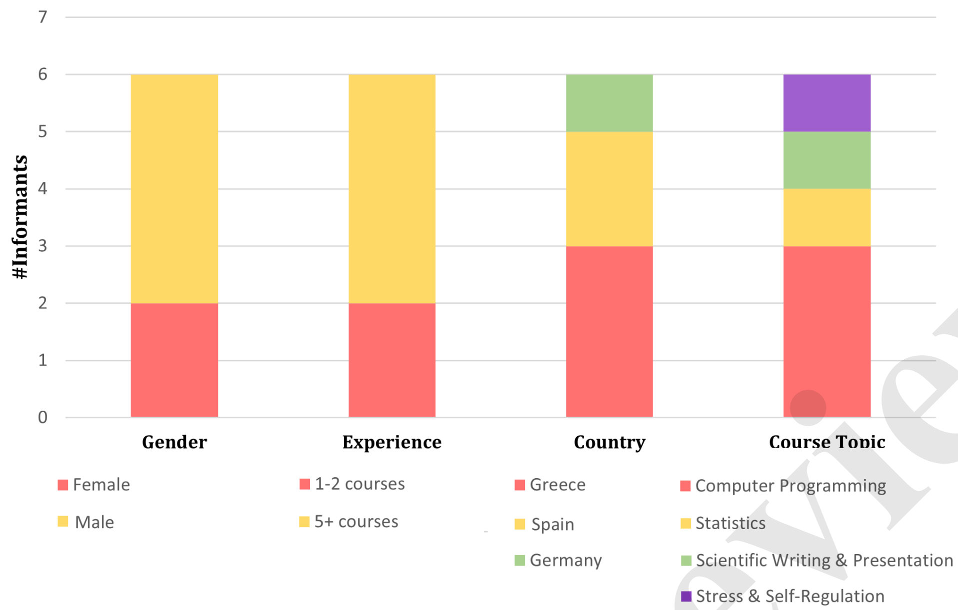

Figure 2. Participants' information regarding their gender, experience, country, and course topic.

Instructor	Platform	Topic	Modality
[Inst#1]	OpenHPI	Computer Programming	Instructor-led
[Inst#2]	EdX	Computer Programming	Self-paced
[Inst#3]	OpenEdX	Computer Programming	Self-paced
[Inst#4]	Coursity	Statistics	Instructor-led
[Inst#5]	Coursity	Scientific Writing & Presentation	Instructor-led
[Inst#6]	OpenEdX	Stress & Self-Regulation	Self-paced

Table 1. Participants' identifier and associated information.

4.1. Informants

The study followed a purposive sample approach. According to ~~Fraenkel et al. (2012)~~ [50] a purposive sample approach describes *"the researchers' judgement to select a sample that they believe, based on prior information, will provide the data they need"*. In our case, the study informants (N=6) were chosen given their experience in MOOCs as course instructors, designing the course material, facilitating learning, and assisting the course learners to overcome their encountered difficulties. By purposely selecting participants, an interpretative study can focus on a relatively small sample size, prioritizing depth of understanding over breadth [48]. This approach aims to enhance the richness and comprehensive exploration of the posed RQ [51]. Figure 2 and Table 1 present participants' profiling information. Briefly, our participants were mostly men, with more than 5 years of experience as MOOC instructors, coming from three different countries and delivering different course modalities (*i.e.*, self-paced, instructor-led).

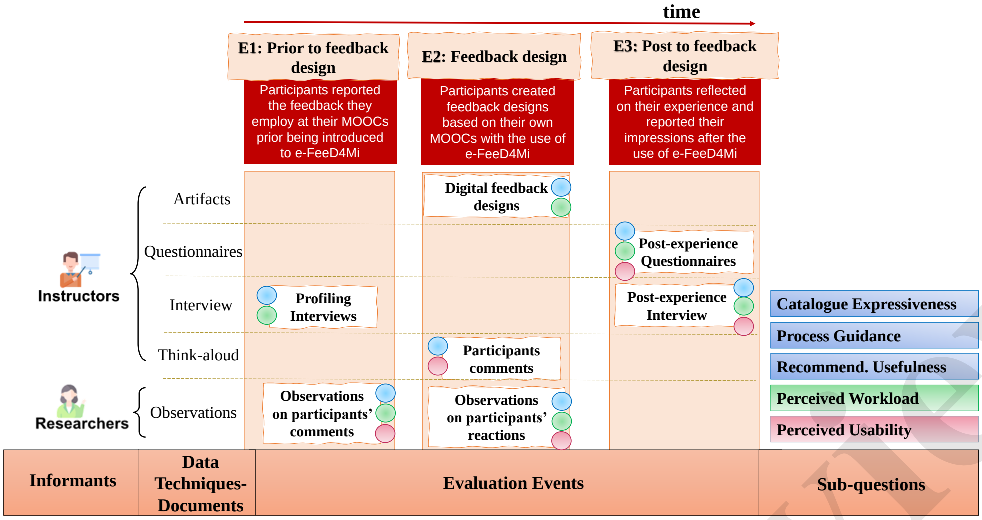

Figure 3. Evaluation events, topics, study informants and data gathering techniques and documents employed during the study.

4.2. Context of the Study

The evaluation consisted of 6 sessions, one per participant, lasting approximately 1h 30min each, where instructors designed personalised feedback interventions using e-FeeD4Mi. Figure 3 depicts the involved sequential events and data-gathering techniques. Further description about the data-gathering techniques can be found in Section 4.3:

E1. **Prior to feedback design:** The first event consisted of gathering participants' profiling information (experience on MOOC teaching). Additionally, we asked participants to describe the feedback strategies regularly used at their own MOOCs, without being introduced to the tool yet. This approach was expected to help us understand the extent to which e-FeeD4Mi can represent the feedback practices of MOOC instructors without being biased by the options offered from the tool. The first event lasted around 15 minutes.

E2. **Feedback design with participants' own course design:** During the second event, participants were introduced to e-FeeD4Mi. We asked them to create feedback interventions applied to their own MOOC designs using e-FeeD4Mi. Participants used the tool for the first time by following the hints and guide it provided. The objective of this event was to understand the extent to which e-FeeD4Mi can satisfy instructors' needs related to the design and creation of feedback interventions. This second event lasted one hour and, among others, we employed a "think aloud protocol", where we asked the participants to express their opinions and reflections throughout the experience.

E3. **After the feedback design:** The third event involved a 15-minutes reflection, during which participants were interviewed about their experience with e-FeeD4Mi and completed two questionnaires regarding its usability (*SUS questionnaire* [52]) and potential adoption (*Net Promoter Score* [53]).

Label	Technique (Evaluation Event)	Aim
[Int]	Profiling semi-structured interviews (E1)	To gather in-depth qualitative insights about the feedback strategies that participants regularly employ at their own MOOCs and compare them with the catalogues supported by e-FeeD4Mi. The semi-structured format provided flexibility to explore the emerging themes while ensuring consistency across the interviews.
[Obs]	Observations (E1, E2)	To provide valuable contextual information and enrich our understanding of participants' behaviors, interactions, and practices in real-world settings. This qualitative data source helped corroborate and contextualize the findings from interviews and questionnaires.
[Art]	Artefacts (E2)	To elicit participants' insights into their instructional strategies, materials, and approaches and to evaluate the expressiveness of the e-FeeD4Mi catalogues. The artefacts served as rich data for triangulation with other data sources.
[Thin]	Think-aloud comments (E2)	To capture participants' thoughts, decision-making, and reasoning in real-time as they engaged with e-FeeD4Mi. This qualitative data source offered valuable insights into instructors' cognitive processes and complemented the data collected through interviews and observations.
[PostInt]	Post-experience semi-structured interviews (E3)	To gather instructors' impressions about their overall evaluation experience and the use of e-FeeD4Mi. The semi-structured format provided flexibility to explore the emerging themes while ensuring consistency across the interviews.
[Quest]	Questionnaires (E3)	To complement the qualitative data by providing quantitative measures of the e-FeeD4Mi usability and potential adoption using two standardized instruments.

Table 2. Data gathering techniques employed in the study.

4.3. Data Collection and Analysis

The data collection process consisted of multiple data sources: semi-structured interviews, standardized questionnaires, observations, instructors' artifacts, and think-aloud comments. The concrete sources permitted the collection of both qualitative and quantitative data and served the objectives and nature of our study. Table 2 outlines the rationale behind each data collection technique.

Content analysis was applied for the qualitative data using inductive (*i.e.*, a set of categories emerged from the participants' answers) and deductive coding (*i.e.* a set of categories predefined given our prior exploratory studies and a literature review on feedback strategies in MOOCs, learner problems in MOOCs and aspects affecting the teachers' adoption of technological tools) [54]. Appendix A presents the applied coding scheme (see Table A1). Two researchers participated in the data collection process, while solo coding was conducted on the qualitative data. Additionally, peer debriefing was employed through regular meetings with a broader research team to discuss the coding decisions, and maintaining transparency in the coding process. The quantitative data gathered were processed using Excel Spreadsheets for descriptive statistical analysis. For the quantitative data we employed the validated instrument

MOOC Instructors	Learner Problems	N	Problem Indicators	N	Feedback Reactions	N
6	100%	5	100%	3	83.3%	6

Table 3. The catalogues expressed in a high degree the problems, indicators and feedback needs reported by the participants.

System Usability Scale[3] (SUS) [52] to measure the tool usability. To permit the interpretation and comparison of the results with other evaluation studies, normally the SUS scores are translated to percentile ranks and letter-grades, as happened in our case (see Section 5.5).

Additionally, we used the *Net Promoter Score* (NPS) item [53] to measure e-FeeD4Mi potential adoption into the participants' future learning contexts. NPS is often applied to measure the potential adoption of a system and is calculated as the percentage of Promoters (*i.e.*, participants selecting 9 or 10 in the likelihood-to-recommend item) minus the percentage of Detractors (*i.e.*, participants selecting 0 to 6). We acknowledge that given the small sample applying SUS and NPS may not provide generalizable results. Yet, as our objective is to better understand the under study phenomenon, we used the results of the SUS and NPS to support our qualitative analysis.

To ensure the credibility and transferability of the current study, we employed the following strategies [55, 56]:

a. *Data Triangulation*, *i.e.*, collecting data from different participants and settings. In the current study we gathered data from 6 different MOOC instructors to complement our findings. Additionally, we gathered data from different evaluation moments (*i.e.*, before, during and after the use of the tool) and data sources to help address the posed questions.
b. *Method Triangulation*, *i.e.*, employing multiple methods to collect data for the same purpose. In the current study, we used various data gathering and analysis techniques. Concretely, we used semi-structured interviews, standardized questionnaires, observations, instructors' artifacts, and think-aloud comments (see Table 2).
c. *Peer Debriefing* among the members of the research team to ensure the alignment of the interview questions with the topics addressed.
d. *Thick Descriptions* of the study context to permit the comparison and transferability to other possible contexts.

5. Results

This section presents the main findings associated with the topics posed above. Each finding is supported with excerpts of evidence in the following format: [data source:informant].

5.1. e-FeeD4Mi Catalogue Expressiveness

The catalogues list potential students' problems, indicators and feedback reactions that might be useful in the design of automatic feedback interventions. Before using the tool, and therefore, the proposed catalogues, the participants

[3]SUS is a standardized questionnaire that requires a minimum of 5 participants.

identified self-regulation challenges, content-related and technical issues as the most common problems reported in forums by the course learners. Additional learner problems, as stated by the participants, were related to peer collaboration (*e.g.*, failing to complete peer reviews), and the request of additional activities for further practice due to the lack of their background knowledge. All these problems, mentioned by the participants before using the tool, are included in the catalogues of e-FeeD4Mi. Some of the excerpts supporting this result are: *"A common issue is that learners have difficulties in understanding some course concepts due to lack of previous knowledge"* [Int:Inst#2] or *"I think that the learners find the activities easy so they tend to disengage"* [Int:Inst#5], *"The students have problems because they do not regulate their learning path and sometimes they miss visiting critical course elements"* [Int:Inst#3]. Regarding the indicators used to detect learners facing the aforementioned problems, participants noted 3 indicators, all of them covered by e-FeeD4Mi: the number of posts in forums, the number of emails sent, and the number of learners' interactions in group activities. Finally, instructors mentioned 6 feedback reactions, out of which 5 are covered by e-FeeD4Mi: the provision of additional material, platform announcements, replies in forums by experts, automated feedback in multiple choice quizzes, and manual feedback in assignments. The aspect not covered by e-FeeD4Mi regards the provision of hints after each answer of a quiz test. Indeed, e-FeeD4Mi supports the provision of hints after completing the whole quiz (and not hints per answer). Table 3 provides a general overview of the extent to which the catalogues contained the problems, indicators, and feedback reactions suggested by the MOOC instructors.

After using the tool, the instructors were requested to check whether the problems, indicators and feedback reactions they usually employ at their courses were covered by the catalogues. Their think-aloud comments served to triangulate the results presented before. For instance, *"All the options I wanted were there"* [Thin:Inst#1], (*"I used e-FeeD4Mi having all the possible learner problems in my mind, and I tried to translate it into the system. The catalogues had everything I needed"* [Thin:Inst#3].

The catalogues helped participants design personalised feedback in unexpected ways. Apart from configuring feedback for addressing struggling learner behaviors, 2 participants created feedback interventions for positive reinforcement due to its suggestion by e-FeeD4Mi. Concretely, the instructors selected the problem of "Reaching critical points/Milestones in the LD" and decided to send motivational messages to learners that fulfil milestone tasks, such as watching a concrete video or successfully completing a difficult activity. That is, *"Seeing now the feedback reactions, I would like to select from the previous problem list, the option of 'when a learner passes this milestone' to give positive feedback to the learners who watched the video of Module 2 because it is crucial for the activities and the rest of the modules. Can I do it?"* [Thin:Inst#5]). Therefore, *"after checking the catalogue of feedback reactions the participant wanted to create what he calls 'positive feedback' saying that this is an option he has not considered to apply at his MOOC before"* [Obs:Inst#5].

The catalogues were perceived as useful for both novice and experienced instructors. 4 participants (2 experienced and 2 novice) highlighted the usefulness of the tool catalogues. Some excerpts evidencing this benefit are: *"I think the more inexperienced you are the more useful the tool is, the more it helps you with ideas"* [PostInt:Inst#3], and *"The catalogues are useful if someone wants to learn from the system, not only an inexperienced person but also an experienced one"* [Thin:Inst#2].

The catalogues need further enhancement. Despite the positive findings, we acknowledge some catalogue limitations as raised by the participants. Three participants found it challenging to interpret some indicators. For instance, *"I needed some* *further explanations to some aspects and items"* [PostInt:Inst#1], *"Some of the indicators could have been labelled more intuitively"* [PostInt:Inst#3]. This result points out the need of studying more usable ways of presenting these catalogues. The inclusion of some examples and further hints could better support the usefulness of the catalogues. Additionally, we observed that despite the different feedback reactions suggested by e-FeeD4Mi (N=22), all instructors at first were inclined towards the solutions they were more familiar with, *e.g.*, personalized messages to learners. This result suggests the possibility of highlighting other types of reactions so that instructors can consider them for improving their feedback design.

5.2. e-FeeD4Mi Process Guidance

The e-FeeD4Mi 5-step process guided instructors in the design of feedback interventions. The evidence gathered showed that the e-FeeD4Mi process fostered participants' reflection on aspects related to feedback, allowing them to jump from one step to another for their convenience. Some excerpts supporting this result are: *"I think it is a well thought out process that supports our reflection on several aspects, it is intuitive to initially think about your course and then connected with learners' problems, etc."* [Quest:Inst#1], *"While configuring indicators, the participant [Inst#2] says that she has noticed a new problem seeing the catalogues of indicators (i.e., Learning Path Issues). She asked if she could add an additional problem now. We replied positively, she configures it, and she returns to the previous page by herself"* [Obs:Inst#2].

Additionally, the first steps of the process (Learning Design and Learner Problem) were highlighted as relevant for feedback design. For instance, *"To tell you the truth, what I found extremely useful in the process is the annotations part, and I would like to have this step for the entire design of the MOOC not only for feedback. I liked that the tool asks me and gives me options about my course LD, thus I would like to have it in general as a guide and be able to add the learning objectives and goals of the course, such as to include the Bloom taxonomy goals"* [PostInt:Inst#5], *"Inst#6 expressed that the colors used during the learning design phase can be useful to mark the different types of activities where there may be different types of feedback"* [Obs:Inst#6].

The process structured the feedback design. Apart from the previous results, three participants explicitly highlighted they liked the structure of the process. Some evidence supporting this result are: *"I definitely liked the process flow, because it structured what you are doing and made a lot of sense to me how we got started with the annotations, later identifying problems etc. I found it super helpful"* [Quest:Inst#6], *"I think the process is well structured and easy. I like that I can easily follow it"* [Thin:Inst#4], *"I liked the indicative flow because it reminded me where I am at all times and what I have to do next and what I did before"* [Quest:Inst#5]. Furthermore, we observed that the process offered flexibility to instructors to employ some dimensions of the tool aspects in different way, i.e., *"Inst#4 uses the red color to annotate 'important' activities/resources while Inst#3 used the colors to connect the content material to the course activities they are useful for"* [Obs:Inst#3] [Obs:Inst#4].

5.3. e-FeeD4Mi Recommendation Usefulness

The instructors adopted the provided recommendations as more reassuring options for feedback design. According to the evidence gathered, 89.48% of the selected indicators and 63.16% of the configured feedback reactions arose from

	Annotations in the LD	Reflection on Learners' Problems	Identification of Indicators	Selection of Feedback Reactions	Total
M	8:48	9:00	19:31	13:36	50:56
SD	1:52	0:58	3:20	2:11	4:06

Table 4. Mean (M) and Standard deviation (SD) of the time spent (min:sec) during each phase (N=6).

the e-FeeD4Mi recommendations [Obs]. Participants' comments and researchers' observations support such a finding. 5 out of the 6 participants stated that the provision of recommendations facilitated them with ideas and suggestions to design feedback strategies more adequately: *"In most cases I found the recommendations informative. I had the feeling I was able to select the best options due to recommendations. I had the best solutions"* [PostInt:Inst#3], *"If you have noticed, I found the recommendations ultra-useful, I have followed them because they gave me the best option. Having default options has been very useful"* [PostInt:Inst#6]. Likewise, the researcher observed the positive perception of a participant while consulting the recommendation list (*"The instructor just commented out-loud that 'The recommendations are very useful', and she says that she finds it difficult in general to think about the most adequate feedback reactions for each problem, so she follows the Recommendations"* [Obs:Inst#6]).

The design of recommendations could be further enhanced. Three participants proposed further ideas for improving the recommendations and their usability within the tool. For instance, *"I would still like to be able to click directly on the recommendations and then fine-tuned them"* [PostInt:Inst#4], *"It would help me to have a set of predefined indicators, such as the performance indicators that can be applied to all courses. Then the user could directly fine-tune these predetermined sets of indicators"* [Thin:Inst#3], *"I think you should not go beyond 7 suggestions of Recommendations, because they are the maximum that a user can have in mind"* [Thin:Inst#2]. All these suggestions will be taken into consideration for the future redesign of the recommendations in the tool.

5.4. Perceived Workload

Instructors perceived as low demanding the use of e-FeeD4Mi in terms of time spent. Before letting participants use the feedback design tool, we asked them about the dedicated workload for feedback design and provision within their current MOOC practice. Four participants reported that usually they dedicate at least 1 hour per day to check the course discussion forums to provide the feedback to the students. Conversely, two instructors stated that during the course run-time they do not provide tailored feedback to their learners due to the lack of time, i.e., *"I do not provide personalised feedback at all. There is no time to follow the learners' individual progress"* [PreInt:Inst#4], *"We provide automated feedback through the closed-ended exercises. This feedback is not personalized because we have a lot of learners"* [PreInt:Inst#5].

Additionally, while all the participants mentioned that MOOC platforms provides dashboards to follow the learners' progress, 5 out of 6 participants do not check the dashboards at all, either due to lack of time or to the lack of useful information provided: *"I have a dashboard, but there are so many learners that I cannot follow all of them and their progress there"* [PreInt:Inst#2], *"We have a dashboard, and we can see what learners are doing, but the data is aggregated. So, we do not check it, because*

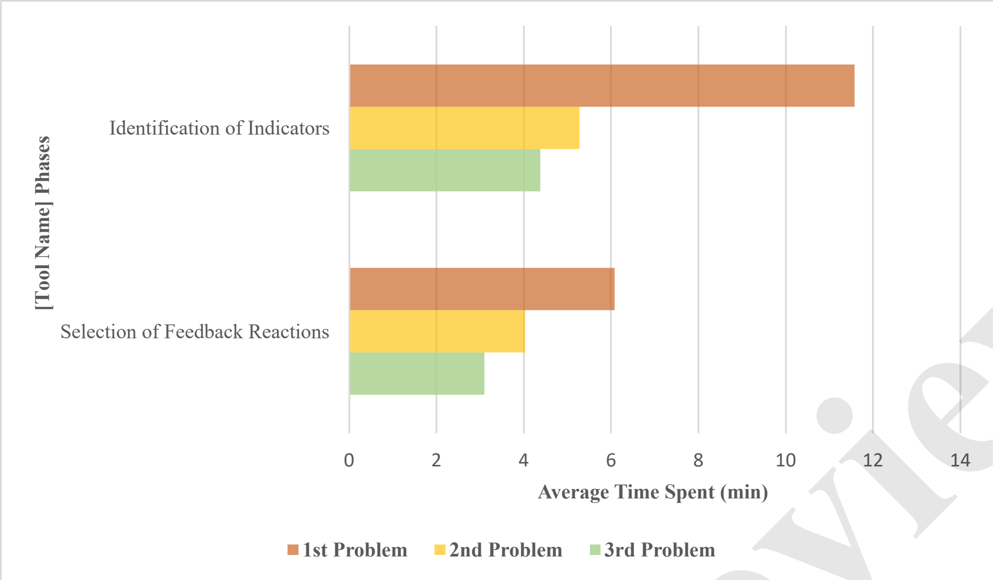

Figure 4. Means of participants' time spent (in minutes) during the configuration of indicators and feedback reactions. Participants were asked to create at least three feedback strategies for three identified learners' problems.

they are not informative" [PreInt:Inst#1]. These results support the usefulness of e-FeeD4Mi to let instructors design their feedback reactions beforehand, and configure the indicators they deem relevant for their courses.

During the second event of the evaluation, participants used the feedback design tool, allowing them to perceive the associated workload of designing and configuring feedback for their courses. During the post interview, participants expressed their satisfaction in terms of associated workload. Some excerpts supporting this result are: *"I think I have spent almost 40 minutes and it's the first time using the tool. I think I would devote such time during my course design"* [PostInt:Inst#5], *"I must say I liked how I could deal faster with tasks, such as delivering feedback or targeting learner challenges, that normally consume a significant portion of my time as an instructor"* [PostInt:Inst#2], *"I liked that in less than an hour using the tool I easily automated feedback for 4 learner problems. Normally in my courses I need at least one hour to treat two learner problems."* [PostInt:Inst#4].

Table 4 presents a synthesis of the time spent during each phase of the e-FeeD4Mi process as recorded in the evaluation study. The evidence gathered shows that within approximately 50 minutes of using e-FeeD4Mi, the instructors were able to design at least three feedback strategies automating feedback interventions to be triggered during the course. More time was dedicated to the identification of indicators, potentially related to the difficulties in interpreting some indicators, as stated by a few participants. Yet, we consider that this additional time spent on this step may be linked to the learning curve of participants in understanding the possible indicators and in reflecting on the most useful ones, i.e., *"I found that there is a learning curve the first time you use the tool, at least for me. So, I felt I spent more time on indicators, because cognitively I had to proceed with them, but designing each following problem was easier than the previous one. I think if I use the tool two more times everything will*

	Inst#1	Inst#2	Inst#3	Inst#4	Inst#5	Inst#6	Avg.
Q1	5	5	4	5	5	4	
Q2	2	1	4	1	2	2	
Q3	4	4	2	5	5	4	
Q4	4	3	3	1	1	1	
Q5	5	4	3	5	4	4	
Q6	1	1	2	1	2	1	
Q7	3	3	4	4	3	3	
Q8	1	1	1	1	1	2	
Q9	5	4	3	4	5	5	
Q10	3	3	4	2	1	2	
SUS Score	77.5	77.5	55	92.5	87.5	80	78.33

Table 5. Individual SUS scores.

be straight-forward and faster" [Quest:PostInt#6]). Indeed, as Figure 4 shows, while during the selection of the first indicators and feedback reactions the time devoted by the participants was high, during the next rounds of creating if/then rules, the devoted time decreased.

Additionally, in two cases, while the participants could finish their tasks earlier, they preferred to continue exploring the tool. For instance, *"It seems that the participant has already understood the tool better and even continues adding several reactions and several indicators for the same problem, although he could finish earlier! We informed him that he can finish his designs and the task, because everything is completed, and this is NOT the case... He asks to use the tool more. He is enjoying exploring the different actions of the different resources"* [Obs:PostInt#6]]. This finding shows that the use of the tool was not perceived as overwhelming.

5.5. Perceived Usability

Instructors perceived e-FeeD4Mi as a usable tool for designing feedback interventions. The perceived usability of e-FeeD4Mi was measured with the SUS questionnaire and complemented with the observations made while participants were using the tool. The average SUS score was 78.33 (minimum value: 55; maximum value: 92.5) and which, according to the scale defined by ~~Bangor, Kortum, & Miller (2008)~~ [57] corresponds to a B+ level of usability, representing a good level of usability.

Looking at the individual scores provided by the participants (see Table 5), Instructor#3 provided the lowest score and Instructor#4 the highest. The self-reported comments of the participants helped us to understand better such scores (see Table 6). Instructor#3 expressed in the post interview his positive impression in automating feedback in MOOCs through the tool (see Table 6-a). Nevertheless, he also stressed a set of reasons for such score: (a) unknowing the actual effect of the designed decisions, (b) lack of enumeration of the required actions within each dimension and (c) lacking reusable options (see Table 6-g, h). Instructor#4 also reported the reasons for such a high score, among which we can mention the ease of use of the interfaces, including the navigation between steps and the selection of problems and indicators (see Table 6-b).

Instructor	Category	Data Source	Excerpt
Instructor#3	Strong Points (x6)	[Thin]	a. I find very useful the automation of commonly used feedback
Instructor#4		[PostInt]	b. I also liked the visualisation of the flow with boxes because they reminded me where I am at all times, what I have to do next and what I did before
Instructor#5		[Thin]	c. It will be an efficient way to summarize my actions as a teacher
Instructor#6		[PostInt]	d. I find interesting the whole idea of having a feedback design tool
Instructor#1		[PostInt]	e. The system has options that cover all my needs from a technical and pedagogical point of view
Instructor#2		[PostInt]	f. I liked the possibility that the tool offers of visualising the workflow and the possibility to select multiple options
Instructor#3	Weak Points (x4)	[PostInt]	g. I basically missed seeing the impact of what I am designing. To that end could serve either additional screenshots or a box with further information to understand what you are designing and how it is applied to the end user
Instructor#3		[Thin]	h. There is the need of organizing feedback design patterns to be saved and reused in similar situations
Instructor#1		[PostInt]	i. I think it would be useful to provide some preconfigured templates for less experienced people
Instructor#2		[Thin]	j. Some of the items in the drop downs could have been labeled more intuitively

Table 6. Selected excerpts of evidence related to the [e-FeeD4Mi] usability.

In addition, Instructors #5 and #6 also rated the tool high. Indeed their self-reported comments indicate that they perceived e-FeeD4Mi helpful for the design of feedback interventions and for guiding the instructor practices (see Table 6-c, d). Instructors #1 and #2 rated the tool considerably high on the SUS scale. Their comments are aligned with the ones raised by the other instructors. For instance, Instructor#2 highlighted the importance of visualizing the different steps at every moment (see Table 6-f), an aspect also mentioned by Instructor#4, while as future enhancements they considered the provision of preconfigured templates for less experienced people and a more intuitive design for some drop-down menus (see Table 6-j).

Attending the potential tool adoption, the NPS score obtained in our case was 67 (with 4 Promoters and 2 Neutrals), indicating participants' likelihood for the tool adoption. In a past study, where the tool was assessed for the first time, the NPS score was much lower (*i.e.*, -18 with 1 Promoter, 7 Neutrals, 3 Detractors), showing the need for improvement before being adopted. This finding indicates the improvement of the tool limitations raised in [42]. The positive score has been complemented with participants' insights. Concretely, all participants (N=6) stated they were interested in including the feedback strategies designed with e-FeeD4Mi in their actual courses. For instance, *"I would like to use the tool even for my own university course. I need the option of sending reminders to a specific cohort of learners, as I designed it now. Normally, I sent messages but to all of the learners because I cannot track specific behaviors in real time"* [Thin:Inst#2], *"I think I would apply the problems. There are problems we normally try to treat manually and with that system we could automate* *them. It is helpful"* [Thin:Inst#1], *"I would apply all the problems we deal with. In fact, I would like to spend more time now with the tool and configure even more problems. If I had to do everything manually, I wouldn't have the capacity to do it and what the tool provides me is that I automate several interventions a priori, so that during the course time I can focus on things that can't be automated anyway"* [PostInt:Inst#5]).

6. Discussion

This section discusses the main findings associated with the RQ that guides this study: ***"To what extent e-FeeD4Mi can support instructors in the design of personalized and contextualized feedback in MOOCs through its catalogues, process and recommendations?"***. The present study served to evaluate e-FeeD4Mi within authentic MOOC designs of an heterogeneous set of MOOC instructors in terms of experience in designing and delivering courses and the course disciplines.

The findings gathered indicated the added value of the e-FeeD4Mi components in guiding instructors and fostering their reflection for the design of feedback in MOOCs. Previous literature indicated as a crucial aspect of a LD tool the provided guidance and support on instructors' reflection [58–60]. In this study, the tool, through its catalogues, could express most of the feedback strategies desired from the participants and at the same time provided further ideas on indicators and feedback interventions. For example, while before using the tool the participants mentioned employing only 3 indicators to detect potentially struggling learners, after using the tool the instructors used more than 15 indicators to monitor learners' behaviors to address expected learner problems. Meanwhile, participants reported difficulties in interpreting or combining some of the indicators. We deem that the provision of examples or further explanations could ease such a challenge.

Concerning the e-FeeD4Mi process, participants' comments and researcher's observations revealed its relevance and effectiveness for both experienced and non-experienced users. Participants stressed the perceived support through the process structure, its flexibility and the step-by-step guidance it offered. Respecting the e-FeeD4Mi recommendations, the evidence gathered indicated its usefulness, since participants mainly followed the provided ideas, both in indicators and in feedback reactions. These positive findings are consistent with prior studies in learning design and orchestration tools for instructors. According to ~~Verbert et al. (2012)~~ [61, 62], conceptual or technological tools which support recommendation techniques seem to be preferred by instructors, given the guidance and the time-affordability they offer. Nevertheless, further studies are needed to enhance further the tool, based on participants' proposals, mainly related with the provision of predefined sets of indicators or the total number of aspects that should be given in order not to overwhelm the user.

At the same time, positive results gathered concerning the e-FeeD4Mi perceived workload and usability. First, participants expressed their satisfaction about the potential of the tool to save time conducting processes that normally are time consuming during the course enactment, such as the feedback provision. Indeed, within a period of 50 minutes and using the tool for the first time, participants were able to design at least 3 feedback strategies according to their course design. Our findings are aligned with the study of ~~Dagnino et al. (2018)~~ [49] who conducted a systematic literature review regarding the needs of teachers in adopting LD tools. The results indicated time as among the most critical parameters for instructors affecting the application or avoidance of tools into their teaching practices. Second, the obtained perceptions about the e-FeeD4Mi usability highlighted the support it offers to automate their feedback decisions, its pleasant interface, and the potential in retrieving the MOOC platform indicators.

The evidence gathered showed a very good tool usability, given the high rate in SUS scale (*i.e.*, 78,33) and a positive NPS value (*i.e.*, 67). Such a finding has been triangulated with the participants' self-reported comments who stated they would like to adopt the designed feedback strategies to their real courses. However, some participants expressed they lacked a clear order of the actions that need to be accomplished within each dimension. Numbering the desired actions within each dimension could contribute to improving the user interface. Our encouraging findings are in accordance with the findings of ~~Dagnino et al. (2018)~~ [49]. Concretely, the examined papers seemed to place the ease of use as among the most desired and valued parameters of ICT and LD tools for instructors. More recent research results derived from empirical evaluation of other LD tools such as Pedagogical Planner [63] and EdCrumble [64] reinforce the importance of required time and ease of use as potential barriers for the adoption of LD tools such as [Tool Name].

6.1. Theoretical and Practical Implications

Building on the context presented above, the contribution of the current paper is twofold. First, this paper introduces e-FeeD4Mi, a web-based tool designed to address the challenge of providing personalized and contextualized feedback in MOOCs through its catalogues, recommendations and process. Unlike alternative approaches that struggle with scalability and lack of pedagogical grounding in LA solutions [17–19], e-FeeD4Mi supports scalability and contextualization by providing semi-automatically LA-informed interventions considering explicitly learning design aspects by involving MOOC instructors actively in the design and finetuning of the interventions (e.g., specify the assignment difficulty, the compulsory/optional tasks). Second, the paper reports an empirical study about the usefulness, usability and workload of the proposed tool (and its associated contributions).

The results show how e-FeeD4Mi guided instructors in the design of personalized feedback interventions in MOOCs. ~~Mangaroska and Giannakos (2019)~~ [39] noted that despite the existence of many LA tools, instructors still need support to connect LA indicators with learning design-related aspects and learning theories. Prior works considered the use of rule-based feedback to target learners' behaviours [24–27]. Nevertheless, none of the previous proposals support instructors to connect the course elements with LA indicators to target concrete learner cohorts. The study results showed that e-FeeD4Mi (and its associated process, catalogues and recommendations) guided instructors in the selection of related LA indicators and their connection with feedback strategies to address potential learner problems. The implications of the paper lay in the context of MOOCs and the broader field of online education and are the following:

(1) Foster the human-centered approaches in the design of LA-driven interventions in MOOCs.
(2) Extend the research and empirical evidence related to personalized feedback in MOOCs.
(3) Promote the feedback literacy in MOOCs and online educational settings.

~~Zheng et al., (2016)~~ [65] highlighted the crucial role of instructors in the learning process and feedback delivery in the context of MOOCs. Yet, ~~Estrada-Molina and~~

~~Fuentes-Cancell (2022)~~ [7] highlighted the obstacles instructors encounter in delivering timely and personalized feedback. While LA can produce data to inform scalable and personalized feedback interventions, MOOC instructors face often challenges in interpreting data-driven insights [8, 42, 66]. The positive experience and perceived usefulness of the instructors with e-FeeD4Mi showcases the potential of placing instructors at the center of the feedback design process, fostering a sense of ownership and agency, ultimately leading to more effective and meaningful feedback interventions in MOOCs. Thus, the lessons learnt by the current study could foster the adoption of human-centered LA-driven interventions, in our case facilitated by e-FeeD4Mi, that could later contribute to a more supportive and responsive learning environment.

Prior research discussed the lack of empirical efforts attending the need of personalized and timely feedback in MOOCs and their implications on learners' engagement [7, 9, 67]. Accordingly, the current paper offers empirical insights of the use of LA addressing the need of personalised and timely feedback in MOOCs. The successful integration of e-FeeD4Mi into the needs of the different MOOC designs opens up possibilities for the future of feedback mechanisms in online learning environments. By leveraging the power of LA and if/then rule-based decisions, instructors can create personalized feedback interventions that are both scalable and contextually grounded, addressing the unique needs of each learner.

Last but not least, the research conducted in this paper may serve for promoting the instructors' feedback literacy within MOOCs and online or massive settings. Concretely, compared to traditional settings, the feedback practices in MOOCs and online settings require an a priori consideration of learners' individual progress through LA, the detection of critical behaviors according to course milestones and the provision of different level, kind and timing of support based on the evidence gathered [34, 68, 69].

7. Conclusions

Despite the benefits of MOOCs in the educational landscape (*e.g.*, free access to education), the provision of personalised feedback concerns still an important challenge due to learners' volume, diversity, and their asynchronous communication [5, 6]. The field of LA provides opportunities for scaling up the feedback interventions, monitoring the learners' progress, and enabling automatic or semi-automatic interventions. However, current the LA solutions employed for scaling feedback interventions, often lack contextual grounding and guidance to course instructors on how to understand and use LA to create suitable interventions [17, 18, 70]. Additionally, there may be a mismatch between instructors' needs and the provided LA information.

Building on this context, the current paper proposes e-FeeD4Mi, a web-based tool that aims to engage MOOC instructors in the design of LA-informed feedback interventions through if/then rule-based decisions. We employed e-FeeD4Mi within the MOOC designs of 6 different instructors and we evaluated its usefulness, added workload and usability as perceived by the participants. The results show a good usability and potential to be adopted by other instructors and offered ideas for further tool enrichment. The positive results obtained confirm that e-FeeD4Mi, through the way its implementing the framework catalogues, process and set of recommendations, enable instructors to create contextualized interventions under potential learners' problems according to their course LD tailored to potentially struggling learners or well-achieving ones. At the same time, the evaluative work revealed certain limitations, such as the need for further guidance on interpreting the catalogue indicators, that should be addressed in future studies.

This study entails certain limitations that can guide future research. To begin with, we acknowledge that conducting 'solo coding' can be perceived as a potential limitation of our study. Nevertheless, to mitigate this issue, we followed the process proposed by qualitative researchers, such as ~~Saldaña (2015)~~ [71]. Concretely, we employed peer debriefing with regular meetings with the research team to discuss and agree upon the coding decisions and to maintain transparency in the coding process. Yet, in our future research we would strive to involve multiple coders to enhance the reliability and validity of the findings. Moreover, it is important to acknowledge that the current evaluation does not yield generalizable outcomes. The current study allowed us to reach a deep understanding of the e-FeeD4Mi use in authentic scenarios. This way, we aimed for a 'naturalistic' generalisation [72], i.e., to inform other cases that employ human-centred approaches for feedback design. Building upon the findings of the current study, we plan to conduct future studies with a larger and more diverse group of MOOC instructors so that the results are generalizable to other contexts. Additionally, we plan to collect maturity indicators of the e-FeeD4Mi impact to enhance the validity of the results.

Furthermore, as part of our future work, we intend to apply the tool throughout the entire life cycle of MOOCs, with a specific focus on the learner's perspective to assess the impact of personalized LA-informed feedback interventions on the learning process and learners' satisfaction. Last, we are interested in studying how the complexity of the different courses (different structure, different number of resources, modules) affect the design of the feedback strategies. In this study we had courses of different structure and resources. Examining how these characteristics may affect the design of feedback in MOOCs might be a relevant knowledge for novice instructors when designing their courses reflecting on feedback.

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Appendix A. Coding Scheme

Category	Code	Modality
Learner Problems	Technical issues	Deductive
	Content-related issues	Deductive
	Peer Collaboration	Deductive
	Heterogeneity due to previous background	Deductive
Problem Indicators	Forums	Deductive
	Emails	Deductive
	Group Activities	Deductive
Feedback	Replies in forums	Deductive
	Automated feedback	Deductive
	Manual feedback	Deductive
	Platform announcements	Deductive
	Provision of additional material	Deductive
	Provision of hints	Inductive
Catalogues Usefulness	Support problems, indicators, and reactions	Inductive
	Creation of new feedback strategies	Inductive
	Support novice/experienced instructors	Inductive
	Other	Inductive
Process Usefulness	Guidance of feedback design	Inductive
	Structure of feedback design	Inductive
	Other	Inductive
Recommendation Usefulness	Adoption of recommendations	Inductive
	Other	Inductive
Tool Workload	Tool Workload	Deductive
Tool Usability	Tool Usability	Deductive

Table A1. Applied coding scheme.

Answers to the comments made by the reviewers of the paper entitled *"[Tool Name]: Human-Centered Design of Personalized and Contextualized Feedback in Massive-Scale Courses*" (ID 233101089)

Research manuscript @ Behaviour & Information Technology

Dear Editor,

We have revised the manuscript "*[Tool Name]: Human-Centered Design of Personalized and Contextualized Feedback in Massive-Scale Courses*" trying to incorporate the minor suggestions made by reviewer #1 (reviewer #2 did not suggest additional changes).

In the following pages, we provide answers regarding the issues raised by the reviewers, and detail the changes done to the manuscript. In our responses, we have employed the following format:

1. The comment of the reviewer is reproduced in **bold**.
2. We provide answers to the reviewer's comment.
3. We have added the new modifications of the new version of the manuscript. The new text editions are enclosed in a box (marking the section and paragraph within the section), stressing what parts have been modified in **bold**.

We believe that these changes adequately address the suggested minor revisions, thus leading to a further improved manuscript. We would like to express again our gratitude to the editor and the reviewers.

Looking forward to your feedback.
Best regards,

The authors.

#Reviewer 1:

R1. The references in the paper use numbers [X Y Z] which is perfectly okay since BIT operates in format-free submissions, however from time to time the in-text citations are both in numbers and in APA style (e.g., Burgos and Corb´ ı(2013) [24], Hattie & Timperley (2007) [33] and Henderson et al. (2019) [28]) this is likely to cause problems. So my advice is to allow minor revisions where the associate editor (AE) will check this, also in this version the authors can remove the [Tool Name] statement and add the tool's name. Since only the AE is going to look at the paper.

Answer: We thank the reviewer for detecting this issue that went inadvertently when compiling the last version of the revised manuscript right before submission.

Action in the manuscript: We have checked the occurrences of this issue and solved them accordingly. We have not included the actual [Tool Name], as suggested by the reviewer, awaiting further instructions from the editor in that regard.

R2. I still have some concerns about how much your contribution is "discussed" VS the published works. One sign is that you only cite two papers Dagnino et al. (2018) and Verbert et al. (2012), just two, and one of them is 10+ years old. Usually, findings must be discussed in detail and interpreted against related published works (e.g., confirming, falsifying, and/or extending them). This step is essential to show your research contribution (how your research adds to, complements, or clarifies the current body of knowledge). This is a very important part of the discussion since it is oftentimes used to clarify the contribution of the paper (i.e., what does the paper add compared to the previously published works). You can consider this point in the minor revisions.

Answer: We agree with the reviewer on the importance of the raised issue. Dagnino et al. (2018) is a literature review, which allows us to frame our findings in the context of the main research works on Learning Design (LD) to that date. But it is true that it would add further grounding to our findings if we check more recent LD literature. Therefore, we have searched for recent papers dealing with the topics raised in the discussion section:

- In the discussion section, we claim that "*Previous literature indicated as a crucial aspect of a LD tool the provided guidance and support on instructors' reflection*". Guidance in LD tools is a topic addressed in a recent empirical paper (Zalavra et al., 2023). We think the empirical results of that paper are well aligned with those of the manuscript (although our manuscript is more focused on the specific aspects of the design of feedback interventions at the MOOC scale).
- In the discussion section, we claim that "*conceptual or technological tools which support recommendation techniques seem to be preferred by instructors, given the guidance and the time-affordability they offer*". The use of recommendations in LD tools is also the topic of (Zalavra et al., 2021). The results of that empirical paper suggest the importance of providing guidance to teachers as designers, something that also arises from the results of our manuscript.
- In the discussion section, we claim that our results (the importance of "short time" and "ease of use" when using LD tools) are well aligned with what Dagnino et al. (2018) identified in the LD literature up to 2018. More recent LD literature, evaluating different LD tools, also reinforces this finding. For instance, (Pozzi et al., 2022) identifies these issues in the "Pedagogical Planner" LD tool, while (Albó et al., 2020) reaches similar conclusions when evaluating the "EdCrumble" LD tool.

Actions in the manuscript: We have added the bibliographic references indicated below, citing them during the Discussion section.

Section 6. Discussion

[...] Previous literature indicated as a crucial aspect of a LD tool the provided guidance and support on instructors' reflection [58, 59, **60]**.

[...]

These positive findings are consistent with prior studies in learning design and orchestration tools for instructors. According to [60, **62]**, conceptual or technological tools which support recom- mendation techniques seem to be preferred by instructors, given the guidance and the time-affordability they offer.

[...]

Our findings are aligned with the study of [49] who conducted a systematic literature review regarding the needs of teachers in adopting LD tools. The results indicated time as among the most critical parameters for instructors affecting the application or avoidance of tools into their teaching practices. Second, the obtained perceptions about the [Tool Name] usability highlighted the support it offers to automate their feedback decisions, its pleasant interface, and the potential in retrieving the MOOC platform indicators. The evidence gathered showed a very good tool usability, given the high rate in SUS scale (i.e., 78,33) and a positive NPS value (i.e., 67). Such a finding has been triangulated with the participants' self-reported comments who stated they would like to adopt the designed feedback strategies to their real courses. However, some participants expressed they lacked a clear order of the actions that need to be accomplished within each dimension. Numbering the desired actions within each dimension could contribute to improving the user interface. Our encouraging findings are in accordance with the findings of Dagnino et al. (2018) [49]. Concretely, the examined papers seemed to place the ease of use as among the most desired and valued parameters of ICT and LD tools for instructors. **More recent research results derived from empirical evaluation of other LD tools such as Pedagogical Planner [63] and EdCrumble [64] reinforce the importance of required time and ease of use as potential barriers for the adoption of LD tools such as [Tool Name]**.

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