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Modeling Micro-Interactions in Self-Regulated Learning: a Data-Driven Methodology

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Abstract

We explore whether interactive navigational behaviours can be used as a reliable and effective source to measure the progress, achievement, and engagement of a learning process. To do this, we propose a data-driven methodology involving sequential pattern mining and thematic analysis of the low-level navigational interactions. We applied the method on an online learning platform which involved 193 students resulting in six interactive behaviours that are significantly associated with learner achievement including exploration of the first week's materials and exploration of the forum. The value of including these behaviours in predictive models increased their explainability by 10% and accounted for an overall explainability of 82%. Performance evaluations of the models indicate 91-95% accuracy in identifying low-achieving students. Other relevant findings indicate a strong association between the reduction of the behaviours over time and student achievement. This suggests a relationship between student interface learnability and achievement: achievers become more efficient at using the functionalities of an online learning platform. These findings can provide context to learning progress and theoretical foundations of interventions against unhelpful learning behaviours.

Keywords: Interactive behavior, Interaction pattern, Self-regulated online learning

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1. Introduction

While online learning platforms provide students with the convenience to access learning materials at any time and location, concerns relating to the self-regulated nature of these platforms are growing. Tracking engagement, achievement, and abandonment features that occur during the learning process has become a rising research topic in the area of learning analytics. The reasons for this are twofold: first, we can provide context for assessment results and differences in student performance by understanding the differences in their level of engagement [35]. This information is valuable for educators as it can be used to identify students who are struggling at an early stage, with previous research suggesting, using performance predictors, that 50% of students who were close to fail or failed could have been identified before the start of the course [83]; second, for those online learning platforms such as connectivist MOOCs (cMOOCs), the absence of an assessment method is one of the challenges of monitoring learning progress. Monitoring these features may provide an assessment-free alternative.

Previous research has associated interactive behaviour with features of learning on Learning Management Systems (LMS) and online search [89, 58], where it was shown that some student interactions are indicators of engagement and can predict knowledge gain. For instance, the number of learning resources visited have been linked to learner achievement [16], the duration of learning sessions can be used to indicate knowledge status [46], properties of search queries such as length or complexity have been linked to learning outcome [84], and the number of resources visited was shown to positively correlate with knowledge gain [27].

User interactions can be classified depending on the level of abstraction, which ranges from low-level physical events (e.g. key press) to high-level task related events (e.g. completing an assignment) [44]. Recent works demand that online learning platforms such as Coursera or Blackboard generate lower level granularity data with rich semantics to allow researchers to extract more interpretable information about what students do in order to create interventions [56, 32]. Established works use coarse-grained features that combine assessment data and user activity [50, 31] suggesting the validity of behavioural data to measure features of learning. Crues *et al.* (2018) [19] provide a comprehensive overview on these features, which mostly include interactions at the same abstraction level, typically coarse grained events such as the number of posts in the forum. Additionally, it has been suggested that both low-level

and high-level interactions should be amalgamated as context may be spread across multiple levels and the composition of these events needs to be taken into consideration to give appropriate interpretations [44]. In the context of online learning, it has also been suggested considering interaction patterns, as the order of interactions can encode valuable information about learning behaviour [17]. Low-level interaction patterns have been described elsewhere as micro-interactions [14], where repeated scrolling, re-visitation, and the number of times a response to an opinion question is changed were helpful in identifying issues such as disengagement, low self-efficacy, and confusion.

Inspired by the above works, we explore these connections in an online learning environment where the lack of formal assessment and the analysis of lower level interactions call for a data-driven approach. Specifically, we investigate whether micro-interactions (i.e. students' interactive behaviours) can be used to measure learning progress, achievement, and engagement. In the context of this work, we define engagement as the student's level of participation in course materials and activities on the learning platform [35], and the number of units completed and whether students received a badge are used to indicate learning progress and achievement respectively. We address the following research questions (RQ):

- **RQ1.** Can we identify micro-interactions that are relevant for online learning?
- **RQ2.** Which micro-interactions are associated with learning progress and achievement?
- **RQ3.** What is the added value of using micro-interactions?

To explore whether interface interactions are associated with learning progress and achievement, higher level task-related behaviours (e.g. watching a video) were generated from UI events (e.g. mouse clicks) by applying data mining techniques and qualitative analysis. Then, we explored the relationship between interactive behaviours and learning progress and achievement. Identifying these relationships provides both additional validation and insights on assessing learning. The contributions of this work are:

- We developed a data-driven methodology to isolate micro-interactions that are indicators of learning progress and achievement. We then showed the feasibility of our approach by applying this method on an online learning platform.

- 73 • Our approach identified six interactive behaviours which can explain
74 82% of the student achievement variation and provide a 91-95% accu-
75 racy in recognising low-achieving students. The added value of non-
76 engagement metrics added a 10% of explainability of student achieve-
77 ment.
- 78 • In the learning platform that serves as a case study of the methodology,
79 we discovered that interactive behaviours involving exploration of the
80 forum, and exploration of the first week materials before leaving the
81 page are significant predictors of student achievement.
- 82 • By discovering negative correlations between the frequency of inter-
83 active behaviours and achievement (i.e. the less frequent, the higher
84 the achievement rate), we were able to associate the learnability of the
85 online learning platform with the learning outcome.

86 2. Related Work

87 This work builds on the metrics of online learning process (e.g. engage-
88 ment, achievement), interactive behaviours to predict the features of learning,
89 and sequential pattern mining to identify interactive behaviours.

90 2.1. Online Learning Metrics

91 In the context of self-regulated online learning, the definition and mea-
92 surement of achievement can be a single (or a combination) of test scores
93 and grades [38, 16], course/personal learning goals [30, 86], and course com-
94 pletion [72]. In a recent study, student achievement was measured as person-
95 alised learning objectives, and the rates of receiving a certificate significantly
96 improved for students whose learning objectives include receiving a certificate
97 when compared to the entire course population [74].

98 Engagement has been established to be closely related to learning [51,
99 69, 90] in that the more students engage with activities the better they per-
100 form [50], while low-achieving students show lower level of engagement [24].
101 It has been suggested that low-achieving students receive fewer gamified
102 badges and are less engaged than other students [24]. It has also been shown
103 that evaluating engagement is key to assessing student retention, learning
104 progress, and test performance [11, 19, 71, 78]. Engagement is often mea-
105 sured by learner activities, and the amount of participation in online learning

106 forums and the interaction with lecture videos are two of the most com-
107 mon measures of engagement. Motivation has shown to be a significant
108 predictor of engagement [12], and it was found that motivation can predict
109 behavioural, emotional, and cognitive engagement [79]. Previous work sug-
110 gests that awarding badges has the potential to increase student motivation
111 as it provides clarity of the learning goals and guidance on how to reach
112 them [43, 1].

113 Approximately only 10% of registered students complete an online course
114 [54]. Hence, another frequently explored topic is student dropout/abandonment.
115 Dropouts in online courses refer to the students who discontinue their par-
116 ticipation in the course, while abandonment refers to passive participants —
117 students who do not unregister and continue the course without being active
118 participants [73]. Many studies have investigated the reasons students drop-
119 out, the most common reasons being lack of intention to complete, personal
120 circumstances, bad course design, limited digital skills, unmet expectations,
121 and negative prior experiences [62, 37].

122 *2.2. Modeling Student Interactions*

123 Interactive behaviours and patterns refer to how the learners interact
124 with an online learning platform and how these behaviours are exhibited
125 over time. These factors have been the focus of previous works which involve
126 assessment and prediction. Web navigation behaviours, for example, have
127 been used to predict the next page students are likely to explore [65], their
128 level of engagement/participation [71], the likelihood to dropout [85], and
129 their level of competence [21, 48, 29]. Similarly, student interactions have
130 been used to evaluate participation behaviours in online collaborative learn-
131 ing [20], as well as to predict gaming behaviours in an intelligent tutoring
132 system [59]. Further to this, informed by learning design, a recent study
133 analysed interactive patterns to better understand student behaviours such
134 as resource transition and review [77], and interaction patterns together with
135 self-regulated learning strategies and self-reported variables were found to be
136 accurate predictors of learner types [55].

137 It has also been suggested that learning is associated with interactive
138 behaviours such as browsing patterns (e.g. how students transition through
139 different tasks) [36], click patterns [66], exploration strategies (including how
140 students interact with videos) [3], exploration choices [48], and problem-
141 solving strategies [91, 40]. Research has shown that students' grades can be

142 accurately predicted using internal-course interactions combined with stu-
143 dent activities and behaviours beyond the learning platform [70]. These
144 works suggest that there are opportunities to relate online interactive be-
145 haviours with learning.

146 2.3. Sequential Pattern Mining

147 Sequential pattern mining (henceforth SPM) algorithms identify interac-
148 tion patterns by extracting the sequential combination of interaction data
149 that generates the most frequent patterns for a given *support* (i.e. the per-
150 centage of sequences that exhibit the pattern). SPMs have traditionally been
151 used in retail where understanding shopping patterns can help increase profit
152 by improving product allocation and display [5].

153 SPM algorithms generally produce three types of patterns: frequent,
154 closed, and maximal sequential patterns. Frequent patterns are sub-sequences
155 with frequencies exceeding a specified minimum support. Closed sequential
156 patterns are frequent sequential patterns that are not strictly included in
157 other sequential patterns having the same support. Finally, maximal sequen-
158 tial patterns are frequent sequential patterns that are not strictly included
159 in other frequent sequential patterns. For instance, both pattern A $\{i,j\}$ and
160 pattern B $\{i,j,k\}$ are frequent with their support counts being 0.3 and 0.2,
161 respectively. We assume that for pattern A, its only frequent super pattern is
162 B. In this case, pattern A is a closed pattern as its only super pattern is less
163 frequent than itself. However, pattern A is not a maximal pattern as its su-
164 per pattern B is also frequent. The pattern B would be a maximal pattern if
165 it has no super patterns which are frequent. For mining sequential patterns,
166 CM-SPADE generally has the best performance [33], while CM-ClaSP and
167 CloSPan are generally better suited for mining closed sequential patterns,
168 and so is VMSP for maximal sequential pattern mining [34].

169 SPM is frequently used in the area of educational data mining; to iden-
170 tify sequences of events that can distinguish stronger/weaker groups in an
171 online collaboration environment [67], and to extract learning features to
172 classify learner groups [81]. It has been used in recent e-learning studies to
173 improve online learning platforms, investigate online collaboration, and ex-
174 plore self-regulated learning [26, 67, 25]. Previous work has also used SPM to
175 mine student behaviours from length and correctness of steps taken in online
176 programming courses [45]. Compared to other similar purpose data mining
177 techniques such as process mining, SPM is more general as it can be applied
178 to various types of sequences. Both techniques were evaluated qualitatively

179 and quantitatively to predict dropouts in online learning, and it was shown
180 that SPM is better suited to handle the data produced by learning processes
181 for predictive purposes [22].

182 **3. Study: Setting, Apparatus and Data collection**

183 Interaction data was extracted from an online learning platform con-
184 structed as a cMOOC (connectivist Massive Open Online Course), a type
185 of MOOC that focuses on participatory learning with an emphasis on collab-
186 oration and creation. The platform targeted a specific student group, early
187 career researchers. The courses took place in three waves and ran for four
188 weeks each time: 12 November–16 December 2018, 21 January–17 February
189 2019, and 17 June–14 July 2019. The learning topic was open science and
190 open research methods. The learning materials were divided into four weeks
191 and three learning modules including 63 micro-learning units. The three
192 modules were:

- 193 • Data and information literacy: how to search, evaluate, and manage
194 digital information.
- 195 • Communication and collaboration: how to use technologies to interact,
196 share, communicate, and collaborate.
- 197 • Content creation: how to develop, integrate, and apply copyright to
198 digital content.

199 The learning materials included text, videos, illustrations, links to online
200 resources, etc. The platform provided a news page with updates about new
201 modules, a wiki page where students share their reflections collaboratively,
202 and a forum where students discuss the learning materials. Within each page
203 there was a main area containing the learning materials and a left sidebar
204 with links to other pages. For certain learning units the contents also included
205 videos. 193 out of 382 students gave their consent to having their interactions
206 collected. When each wave of the MOOC was finished, an online survey was
207 sent to the students, which had a low response rate (10%). Hence, we should
208 be careful making generalisations from the sample: the majority of students
209 were based in the EU, the gender ratio was balanced and most of them
210 were researchers or PhD students in natural sciences, engineering, and social
211 sciences. We did not associate the demographic data to interaction data.

212 The platform was instrumented to generate low-level event interactive
 213 data, including browser window events such as page loads, and mouse and
 214 keyboard interactive data. Some of the events contain additional informa-
 215 tion, such as mouse coordinates for mouse events. We captured a total num-
 216 ber of 281,087 interactive events of the types listed in Table 1 using Wev-
 217 Query [8]. The low-level interface events generated directly from the platform
 218 captured student interactions in detail, which can lead to outputs that con-
 219 tain noise such as unintended/unnecessary student actions [23]. A series of
 220 pre-processing steps were conducted to combine or transform such events.
 221 For example, events which typically follow each other such as mouse-up and
 222 mouse-down, were combined and renamed as mouse-press. Key-down were
 223 renamed depending on whether they were commands (i.e. return key) or an
 224 alphanumeric key and same consecutive events were also merged. To ensure
 225 the interpretability of the event sequences, we grouped them by topic, i.e. the
 226 homepage, weekly material page, wiki page, forum, news page, and settings.
 227 Each recorded event had a corresponding timestamp, URL of the Web page
 228 where the event takes place, and the specific DOM element that triggers the
 229 event. Hence, a **event-node-URL** triple represented each event. For exam-
 230 ple, **mouseinorout+main+wiki+multi** indicates multiple mouse movements
 231 in the main area of the wiki page.

232 We computed two indicators of learning: the badge status and the num-
 233 ber of units completed. The instructors of the course awarded an ‘Open
 234 Science Aficionado’ badge to those students that conducted weekly assign-
 235 ments. The specific requirements of the badge were to achieve at least 12
 236 out of 24 attainable points from the following activities: vote on other stu-
 237 dent’s forum post (1 pt.); comment on other student’s forum post (2 pt);
 238 complete weekly assignment (3 pt.). On the weekly assignment of week 1,
 239 students had to read an article about the opportunities and challenges of
 240 Open Science. On week 2, students had to use social media to share ideas,
 241 ask for advice and find research partners to run a research project. Week 3
 242 was about sharing research using workflows involving DOIs, ORCID, open
 243 data repositories such as Zenodo and use of Altmetrics. Finally, on week 4,
 244 students had to design a research plan using what they had learned in the
 245 previous weeks. While the data of all the participants was used for pattern
 246 analysis, we excluded 53 students from the predictive modeling analysis as
 247 the first wave of the course did not award any badge, leaving 140 students
 248 for the analysis involving badges and 193 for progress analysis.

Table 1: Example of captured student interface events.

Type	Events	Description
Mouse	mousedown	Start of mouse click action
	mouseup	End of mouse click action
	mousemove	Mouse movement
	mouseover	Hovering into target
	mouseout	Hovering out from target
	doubleclick	Double mouse click
	mousewheel	Mouse wheel interaction
Selection	select	Selection of page content
	cut	Content cut
	copy	Content copy
	paste	Content paste
Keyboard	keydown	Start of key press action
	keyup	End of key press action
	keypress	Key press action
Window	load	Page is loaded
	resize	Browser window is resized
	unload	Window is closed
	windowfocus	Browser tab gains focus
	windowblur	Browser tab loses focus
	scroll	Change of scroll state
Other	change	Input element state change
	contextmenu	Opening of context menu

249 4. Methodology

250 We propose a three-step methodology to mine interaction data, analyse
251 sequential patterns, and generate interactive behaviours of interest. First,
252 we benchmark sequential pattern mining algorithms and different versions of
253 our dataset to identify the combination yielding the most *representative* and
254 *informative* patterns. Once we set the parameters, we run the algorithms
255 and extract the sequential patterns. Second, we apply thematic analysis to
256 interpret and group the extracted patterns, transforming low-level interac-
257 tions into higher-level interactive behaviours. Third, the interaction patterns
258 that fall under the emerging themes are used to build user models.

259 4.1. Benchmarking Algorithms and Datasets

260 The success criteria for this stage aim at maximising the number of pat-
 261 terns generated and the sequence length. We benchmarked a number of
 262 SPM algorithms including CloSpan, CM-ClaSP, CM-SPADE, CM-SPAM,
 263 and VMSP, which were provided by the SPMF Java library [34].

264 To find representative patterns we maximised the number of patterns
 265 generated by a higher number of users. Each of the input sequences was
 266 constructed with a single student’s interaction events across all active ses-
 267 sions. To assess how representative a set of patterns are, we explored the
 268 value space of the *minimum support* parameter (i.e. the percentage of stu-
 269 dents that exhibit a given sequence) in the 0.35–0.8 range as values above
 270 0.5 yielded a small number of patterns and the number of patterns increases
 271 dramatically when the support decreases below 0.4. To maximise the amount
 272 of information, we maximised the length of the pattern. Longer sequences
 273 entail more events, and thus more information. Single-event sequences were
 274 therefore excluded.

275 To explore interaction patterns over time, we split our dataset into ses-
 276 sions. Sessions were split by 5, 30, and 40 minutes of inactivity in between
 277 two consecutive events which is in line with what is suggested in the liter-
 278 ature [47]. This resulted in three different datasets: **gap-5**, **gap-30**, and
 279 **gap-40** respectively. We compared the medians of sequence size of the three
 280 datasets with minimum support of 0.35–0.5. The number of patterns and
 281 their lengths were plotted for each dataset to identify intersections that max-
 282 imised the criteria for representativeness and sequence length.

283 4.2. Thematic Analysis

284 Thematic analysis is a widely used qualitative analytic method for iden-
 285 tifying, analysing, and reporting patterns (themes) within, typically, qualita-
 286 tive data [13]. While the use of thematic analysis has been used to evaluate
 287 online learning platforms [57, 63, 6, 64], we employ thematic analysis to sys-
 288 tematically find themes on the patterns produced by the SPM algorithms in
 289 the previous stage and reduce the high number of sequential patterns (and
 290 address **RQ1**), being the first of its kind to adopt this method. We adopted
 291 the most common form of thematic analysis, a six-step process described by
 292 Braun and Clarke [13]: familiarising with the data, coding where we consid-
 293 ered the sequential patterns generated as initial codes, and generating the
 294 themes. We conducted an inductive approach to determine themes as the
 295 data-driven nature of this research. We first followed the semantic approach

Table 2: Example of theme generation process. The first column gives examples of the initial codes (i.e. sequential patterns). The second column shows the sub-themes generated from initial codes. The third column shows the final themes (i.e. interactive behaviours) generated from the sub-themes.

Codes	Sub-themes	Final themes
load+week.1 windowfocus+week.1 mouseinorout+main+week.1+multi scrollorwheel+week.1+multi mouseinorout+sidebar_left+week.1+multi video+week.1	load and open the week 1 page multiple mouse movement at week 1 main area multiple scrolling in week 1 page multiple mouse movement at week 1 left sidebar video activity in week 1 page	Explore the week 1 page main area, left sidebar, and interact with videos
windowfocus+week.1 mouseinorout+main+week.1+multi mouseinorout+main+sidebar_left+week.1+multi video+week.1	open the week 1 page multiple mouse movement at week 1 main area multiple mouse movement at week 1 left sidebar video activity in week 1 page	
load+home windowfocus+home mouseinorout+main+home+multi blurfocus_leavepage+home	load and open homepage multiple mouse movement at homepage main area leave home page	Explore the homepage main area then leave page

to transform each code into a sub-theme as a sentence describing the explicit interaction. After the generation of sub-themes, we followed the latent approach with assumptions about the underlying behaviours and determined the final themes. Each theme was created with a combination and transformation of the sub-themes. Examples of this process can be viewed in Table 2 where the codes are results from the sequential pattern mining (i.e. patterns detected in low-level events) and the final themes are the interactive behaviours student exhibit. The interpretation of the behaviours reveals the strategies used by students such as interacting with videos and forums. An independent coder was involved in the thematic analysis. The inter-rater reliability was particularly high, Cohen’s $\kappa = 90\%$. This may be due to the fact that sub-theme and theme analysis was conducted under a set of agreed rules: for example, **load+windowfocus** was defined as ‘explore’ rather than ‘load’, ‘focus’, or ‘view’, which reduced ambiguity.

4.3. Modeling Student Interaction

To investigate **RQ2**, the behaviours identified through thematic analysis and their corresponding interaction patterns were sought in the original dataset for occurrences of each behaviour within each session for each student. These occurrences were represented in $m \times n$ matrices, where m is the number of students and n the number of sessions exhibited by the student. For instance, the matrix for behaviour B can be represented as follows:

$$B = \begin{bmatrix} f_{11} & f_{12} & \dots & f_{1n} \\ f_{21} & f_{22} & \dots & f_{2n} \\ \dots & \dots & f_{ij} & \dots \\ f_{m1} & f_{m2} & \dots & f_{mn} \end{bmatrix}$$

where f_{ij} is the frequency or number of occurrences of behaviour B for $student_i$ in $Session_j$. Since not all students have the same number of sessions, $f_{ij} = NA$ on those cells that do not have sessions.

To identify which behaviours were associated with indicators of learning, we computed descriptive statistics of the frequencies including the mean, median, and sum of occurrences. We also considered the sessions where students were ‘inactive’ (i.e. $f_{ij} = 0$), as dwell time is indirectly related with achievement through engagement [88, 53]. Also, to show the evolution of interactive behaviours, we computed the frequency trend to indicate the general direction in which the number of occurrences is developing. To calculate the trend, we calculated the mean, median, and sum of the occurrences across 3, 5, and 10 surrounding sessions. This is in consideration of the accuracy of calculated trend for a relatively sparse dataset where long periods of inactivity exist. The trend is calculated using two methods: the coefficient of its correlation with the session number variations, and the slope in a polynomial equation with the horizontal line representing the increase of session number [61]. The trend, a combination of the aforementioned correlation and slope, was categorised in six levels of strength ranging from strong negative trend to strong positive trend. In total, we included 46 features for each behaviour as listed in Table 3. We then conducted correlation and regression analysis between these features, and the number of units completed (indicator of progress) and the badge status (indicator of achievement).

5. Results

Benchmarking. None of the five SPM algorithms was found to be problematic in terms of execution time and memory usage. As far as the number of patterns was concerned, for all of the datasets, CloSpan produced the fewest patterns while CM-SPADE produced the most. The ranges of sequence size under the minimum support of 0.5–0.8 was 2–4 for CloSpan and 2–8 for CM-SPADE, CM-ClaSP, and VMSP. In consideration of the next step of the methodology, it was more efficient to select a maximal sequential pattern mining algorithm to eliminate the possible overlapping sequences.

Table 3: Description of the features of interactive behaviours.

Feature	Description
Average	The average of occurrences across all sessions
Sum	The sum of occurrences across all sessions
NumGap	Number of consecutive inactivity sessions
MaxGap	Maximum number of consecutive inactivity sessions
Inactiv	Number of inactivity sessions in total
AvInactiv	Proportion of inactivity sessions in all sessions
Epi_not0	Number of active sessions
Episodes	Number of online sessions in total
Average_not0	Average of occurrences across all active sessions
Median	Median of occurrences across all sessions
T+3/5/10+mean/median/sum	Trend calculated as coefficient with the mean/median/sum of 3/5/10 surrounding sessions
P1+3/5/10+mean/median/sum	Trend calculated as slope with the mean/median/sum of 3/5/10 surrounding sessions
S+3/5/10+mean/median/sum	Trend strength of T3/5/10
Sp+3/5/10+mean/median/sum	Trend strength of pl3/5/10

348 We therefore performed our analysis using the maximal sequential pattern
349 mining algorithm – VMSP on the three datasets.

350 The dataset with sessions separated by 40 minutes of inactivity (i.e.
351 gap=40) is the one that generated the longer sequences exhibited by the
352 largest number of students. This was measured as the point at which mini-
353 mum support and sequence length are both maximised – which was 0.43 for
354 minimum support. As a result, a total number of 110 patterns were generated
355 with a sequence length range of 2–10.

356 *Thematic Analysis.* From the initial 110 patterns, 23 themes emerged from
357 the thematic analysis, as shown in Table 4, including the exploration of the
358 homepage, wiki, and the learning materials of week 1. Video and forum
359 activities, which are known to be associated with learning [18, 10, 15] were
360 involved in six and five of the 23 interactive behaviours, respectively. Explo-
361 ration of the left bar menu, which contains the links to different resources, is
362 also a recurrent element suggesting intent to explore pages. We also found
363 that ‘leaving a page’ is present in four of the interactive behaviours, sug-
364 gesting the action of clicking a link provided in learning materials or the
365 student being distracted from the course (i.e. withdrawing from exploring its

Table 4: Interactive behaviours generated from thematic analysis.

Index	Interactive behaviour
1	Visit the wiki page
2	Explore the wiki page and left sidebar
3	Explore the week 1 page main area, left sidebar, and interact with videos
4	Explore the week 1 page main area, left sidebar, and forum main area
5	Explore the week 1 page main area then leave page
6	Explore the week 1 page main area and interacting with videos
7	Explore the week 1 page main area and left sidebar then leave page
8	Explore the week 1 page main area and left sidebar
9	Explore the week 1 main area and forum main area
10	Explore the week 1 page main area
11	Explore the homepage main area, left sidebar, and interact with videos
12	Explore the homepage main area and interact with videos
13	Explore the homepage main area and left sidebar
14	Explore the homepage main area then leave page
15	Explore the homepage main area and week 1 page main area, left sidebar, and interact with videos
16	Explore the homepage main area then week 1 page main area and interact with videos
17	Explore the homepage main area then week 1 page main area and left sidebar
18	Explore the homepage main area and left sidebar then week 1 page main area and interact with videos
19	Explore the homepage main area and left sidebar then week 1 page main area
20	Explore the homepage main area and left sidebar then forum main area
21	Explore the homepage main area
22	Explore the forum main area and left sidebar
23	Explore the forum main area

contents). Eight interactive behaviours were found to involve interactions on different pages including homepage, materials of week 1, and forum.

Modeling Student Interaction and Analysis. For each of the 23 emergent behaviours, we computed the Spearman and Kendall correlation tests between the features in Table 3 and the two indicators of learning we extracted: the badge status and the number of units completed. We found moderate to strong significant correlations $|\rho, \tau| > 0.45$ between the features of six of the behaviours and the badge status as shown in Table 5. We found no significant correlations between the behaviours and the number of completed units.

From the features in Table 3, **Episodes**¹ (i.e. the number of online sessions in total) correlates positively with whether students received a badge ($\rho = 0.42, p < 0.001$), which is in line with literature that suggests the more active a student is, the more likely a badge will be awarded [41, 78, 46]. The highest positive correlation was yielded by the **NumGap** feature of B_6

¹All of the features are computed for each of the behaviours but Episodes, which is behaviour agnostic.

Table 5: Behaviours and corresponding features correlated with achievement, where correlation coefficients $| > 0.45|$ and $p < 0.001$.

Id	Interactive behaviour	Correlated feature	Spearman’s ρ	Kendall’s τ
B_1	Explore the week 1 page main area, left sidebar, and forum main area	NumGap	0.55	0.54
		Epi_not0	0.47	0.45
B_2	Explore the week 1 page main area then leave page	S10mean	-0.48	-0.47
		T10mean	-0.50	-0.49
B_3	Explore the week 1 main area and forum main area	NumGap	0.48	0.46
B_4	Explore the homepage main area and interact with videos	NumGap	0.49	0.46
B_5	Explore the forum main area and left sidebar	NumGap	0.57	0.55
		Sum	0.51	0.49
		Pl10sum	-0.49	-0.46
		Pl5sum	-0.49	-0.46
B_6	Explore the forum main area	NumGap	0.61	0.57
		Epi_not0	0.58	0.53
		S3sum	-0.72	-0.71
		S5sum	-0.64	-0.63

380 ($\rho = 0.61$, $p < 0.001$), which indicates a relationship between obtaining a
381 badge and the number of continuous sessions where the forum’s main area
382 was not explored. On the other hand, the highest negative correlation was
383 **S3sum** ($\rho = -0.72$, $p < 0.001$) for the same behaviour, suggesting a rela-
384 tionship between achievement and a decrease in the exploration of the forum
385 over time.

Table 6: Comparison between models including all the features (**AllFeatures**) and models including engagement features only (**EngFeatures**)

	Cox & Snell R^2			Nagelkerke R^2		
	AllFeatures	EngFeatures	Diff	AllFeatures	EngFeatures	Diff
Best	0.43	0.38	+0.05	0.82	0.73	+0.09
Average	0.42	0.35	+0.07	0.81	0.67	+0.14
Median	0.42	0.36	+0.06	0.81	0.69	+0.12

386 For the six interactive behaviours that yielded coefficients above 0.45
387 with badge status in Table 5, we included in a regression analysis the top
388 two strongly correlated positive/negative features of each behaviour as long
389 as they were not variations of the same feature (e.g. **S3sum** and **S5sum** for B_6)
390 to prevent overfitting. These were the dependent variables of the regression

analysis, while badge status was the dependent variable. As dependent variable is binary, we used logistic regression analysis. The logistic models with 1–6 predictors were computed following the stepwise backward and forward techniques, where **Model 1** has the highest explainability (81.8%, Nagelkerke R^2) about whether a student received a badge:

$$- 9.44 + 1.52B_1 - 1.08B_2 - 1.15B_3 - 0.04B_4 - 1.06B_5 + 2.40B_6 \quad (1)$$

The goodness-of-fit test (Hosmer–Lemeshow test) yielded a value of 0.246 and was insignificant ($p = 0.993$), suggesting that the model fits the data well. Two descriptive measures of goodness-of-fit presented are Cox and Snell $R^2 = 0.43$ as well as Nagelkerke. These indices are variations of the R^2 concept defined for Ordinary Least Squares regression (OLS) model.

According to **Model 1**, the log of the odds of receiving a badge is negatively associated with the exploration and withdrawal of the week 1 page main area ($B_2, p = 0.01$), the exploration of the week 1 main area followed by the exploration of the forum ($B_3, p = 0.37$), the exploration of the homepage followed by the interaction with videos ($B_4, p = 0.96$), and the exploration of the forum main area and left sidebar ($B_5, p = 0.36$). Those behaviours that were positively associated with receiving a badge include the exploration of the week 1 page main area, left sidebar, and the forum main area ($B_1, p = 0.30$), and the exploration of the forum main area ($B_6, p = 0.01$). The statistical significance of individual regression coefficients were tested using the Wald chi-square statistic. According to the results, only B_2 's **S10mean** ($p = 0.01$) and B_6 's **NumGap** ($p = 0.01$) were significant predictors of badge status.

In other words, the more students revisited (**S10mean**) week 1 materials to then leave the learning platform without interacting with any other section of the MOOC (B_2), the less likely they were to receive a badge. This could be because this behaviour models those who got stuck in week 1, try to catch up several times but make no further advances in the course. We confirm that the number of consecutive sessions in which the forum was not explored (**NumGap** on B_6) is a strong predictor of badge status. The odds of students exhibiting B_2 (**S10mean**) not receiving a badge were 3, whereas the odds for those exhibiting B_6 (**NumGap**) receiving a badge were 11.

Some of the features included in our previous regression analysis are closely related to engagement, including the number of inactive sessions. We

425 know from previous work that dwell time is related to engagement [88, 53,
426 41, 78]. To investigate the added value of including non-engagement met-
427 rics in the models and address **RQ3**, we computed a baseline model with
428 those features in Table 3 that are known indicators of engagement. Similar
429 to the previous analysis, the variable that contributed most was the number
430 of consecutive sessions (**NumGap**) in which the forum was not explored (B_6).
431 The model with the highest explanatory power (Nagelkerke $R^2 = 72.8\%$) for
432 whether a given student receives a badge is:

$$- 6.52 + 0.36B_1 - 0.001B_3 - 0.23B_4 - 0.62B_5 + 1.85B_6 \quad (2)$$

433 where only B_6 is a significant predictor of achievement ($p = 0.001$). We
434 computed R^2 values of the top-20 performing models for both analyses: i.e.
435 the models including all features (**AllFeatures**) and the models including
436 only engagement features (**EngFeatures**) —see Table 6. Our results indi-
437 cate that including non-engagement behaviours in the models adds a 9% of
438 explainability in the best case and a 14% on average for the Nagelkerke R^2 .

Table 7: 10-fold cross validation of the original dataset.

Classifiers	Precision	Recall	F1 Score	Accuracy	Accuracy Change
K Nearest Neighbour	0.65	0.60	0.62	0.94	+0.06
Naive Bayes	0.72	0.80	0.73	0.92	+0.04
Decision Tree	0.72	0.75	0.69	0.93	+0.05
Random Forest	0.85	0.75	0.78	0.94	+0.06
Logistic Regression	0.77	0.75	0.73	0.94	+0.06
Support Vector Machine	0.90	0.55	0.67	0.94	+0.06
AdaBoost	0.48	0.50	0.48	0.91	+0.03
Multi-layer Perception	0.57	0.60	0.56	0.93	+0.05
Bagging	0.90	0.60	0.70	0.95	+0.07
Gradient Tree Boosting	0.75	0.60	0.65	0.94	+0.06

Table 8: 10-fold cross validation with oversampling.

Classifiers	Precision	Recall	F1 Score	Accuracy	Accuracy Change
K Nearest Neighbour	0.58	0.85	0.66	0.89	+0.01
Naive Bayes	0.57	0.95	0.69	0.89	+0.01
Decision Tree	0.78	0.70	0.69	0.93	+0.05
Random Forest	0.75	0.75	0.71	0.92	+0.04
Logistic Regression	0.73	0.85	0.73	0.91	+0.03
Support Vector Machines	0.63	0.85	0.71	0.91	+0.03
AdaBoost	0.72	0.80	0.73	0.94	+0.06
Multi-layer Perception	0.66	0.85	0.71	0.93	+0.05
Bagging	0.57	0.90	0.65	0.89	+0.01
Gradient Tree Boosting	0.62	0.65	0.59	0.92	+0.04

439 We then conducted 10-fold cross validation using a variety of classifiers.
 440 As the distribution of students with and without a badge is imbalanced, only
 441 12% (17 out of 140) of the participants received a badge with a 1:7.2 ratio,
 442 to avoid losing information in majority examples to undersampling [42] and
 443 overly-optimistic estimates [76], we performed oversampling during the cross
 444 validation procedure. Synthetic Minority Oversampling Technique (SMOTE)
 445 coupled with Tomek Links was performed as the combination of algorithms
 446 was suggested to prevent overfitting [76]. Stratified k-fold cross validation
 447 was used to ensure that the proportion of positive to negative examples is
 448 kept in the folds. The results for the 10-fold cross validation on the original
 449 dataset and with oversampling are shown in Tables 7 and 8, where the ac-
 450 curacy change (difference between the accuracy of the model and the default
 451 distribution percentage which is the students without a badge out of all the
 452 students), precision, recall, and f1 score are tabulated. We focus on the pre-
 453 cision and accuracy as the importance of identifying students with tendencies
 454 to fail is greater than identifying students who are likely to succeed. For the
 455 original dataset (without oversampling), the accuracy of the models identify-
 456 ing failing students is 91-95%, 3-7% higher than using random selection (i.e.
 457 the percentage of students without a badge, 88%). The Bagging classifier
 458 yields the largest increase in accuracy across the two sets of results (7%),
 459 with precision being 0.90.

Figure 1: Graphical representation of the number of the active users for each session (brown line), the average of occurrences for each session among students who received a badge (blue line), the average of occurrences for each session among students who did not receive a badge (purple line).

To investigate the occurrences of the behaviours over time, we analysed the occurrences of the 23 behaviours in each session for the students that eventually received a badge and students who did not. The number of the active students for each session was plotted alongside the average of occurrences for each session among the students who received a badge and the students who did not (data had been smoothed using LOESS Curve Fitting). Based on our observations of the visualisations as shown in Figure 1, we classified these behaviours into four clusters:

1. Behaviours of both groups evolve similarly over time (Figure 1a).
2. Behaviours were exhibited more by students with the badge (Figure 1b).
Among the six behaviours included in our models, B_1 , B_3 , B_5 , B_6 are in this cluster.

- 472 3. Behaviours of both groups evolve similarly for most sessions, with sig-
473 nificant differences only at specific sessions (Figure 1c). Behaviours B_2
474 and B_4 are classified in this cluster.
- 475 4. Behaviours were exhibited more by students without the badge for most
476 sessions, with significantly higher peak for badge holders in specific
477 sessions (Figure 1d).

478 6. Discussion

479 We revisit the research questions formulated at the outset:

480 **RQ1.** *Can we identify micro-interactions that are relevant for online learn-*
481 *ing?*

482 We utilised sequential pattern mining and thematic analysis to find implicit
483 regularities that are associated with learning including achievement and unit
484 progress. Our methodology allowed us to investigate micro-interactions in
485 different abstraction levels by grouping fine-grained interaction patterns into
486 higher level behaviours. Our findings suggest that micro-interactions can
487 potentially be used to predict achievement.

488 **RQ2.** *Which micro-interactions are associated with learning progress and achieve-*
489 *ment?*

490 We confirmed existing findings on an online learning platform and discovered
491 that interactive behaviours involving exploration of forum, and leaving the
492 online platform after the exploration of the week 1 materials are significant
493 predictors of student achievement. Further to this, our findings provide more
494 clarity on these behaviours: first, the less students abandon week 1 materials,
495 the more likely they are to receive a badge; second, the number of consecutive
496 sessions where the forum’s main area was not explored was strongly related
497 to obtaining a badge. While the first behaviour confirms that withdrawal is
498 directly related to the (lack of) achievement, it is unexpected that the less the
499 forum is explored the more likely students are to achieve a badge [7, 19, 71].
500 This may be due to the forum being perceived as a collaborative tool within
501 the context of a cMOOC, which was used as a resource for students who were
502 struggling. Hence, not required by advanced students.

503 The interactive behaviours include regularities such as exploration of the
504 forum and interactions with videos. Forum participation and video interac-
505 tions have been thoroughly investigated in previous research [75, 82, 10, 49],
506
507

perhaps as they are the most representative of a classic classroom structure. The other frequent elements, for example exploration of homepage, week 1 materials, and leaving week 1 materials are within expectation: exploring the week 1 materials and leaving may be interpreted as distraction from the learning material and abandonment of the course, which resulted in low achievement. This is in line with the visualisations in Figure 1d illustrating the decrease of interactions over time and previous research indicating that participation tends to drop rapidly within the first week [28].

We found that a decrease in exploring the forum is a strong predictor of achievement while the visualisations show that successful students were more active in the forum. The findings may seem contradictory as they indicate that the levels of participation in forums decreased over time for students who received a badge while still remained higher compared to other students throughout the sessions. More forum activities suggests that the student is more likely to receive a badge, which is in line with related studies showing that forum participation positively affects the learning outcome [7, 19, 71]. Our findings can be explained in that, in sessions when students were less active in the forum, they were conducting other learning activities in the platform. It may also be the case that as students use the forum to make progress and learn, they depend on the forum less and become more autonomous learners.

We did not find strong relationships with the number of units completed. This may be because obtaining the badge involves a set of diverse activities and it is more informative than student progress. The models can be used to develop, for instance, browser extensions to capture interface interactions in real time and predict student learning trajectory to provide feedback and guidance to students and course leaders.

535

RQ3. *What is the added value of using micro-interactions?*

Features of engagement (e.g. the number of inactive sessions) are the strongest predictor of achievement according to our analysis. The explainability of models built with engagement features is as high as 72.8%. By comparing the models from two regression analysis containing different features, we discovered a 10% contribution to the explainability of student achievement from features of behaviours other than engagement, and perhaps learnability. When analysing the performance of the models, results indicate a 3-7% increase in accuracy in identifying students who will not receive a badge versus random selection (i.e. the percentage of students who did not re-

ceive a badge) suggesting that micro-interactions implicitly capture learning processes. This can be explained in that the relationship between cognitive engagement and learning outcomes is mediated by user activity [32]. Consequently, it can be argued that the user activity in online learning platforms contains behavioural markers that are indicators of cognitive processes and learning outcome.

6.1. *The Role of User Interface Learnability*

In general, beyond the decrease in the interactions of successful students with the forum, we discovered that students exhibited decreasing trends of participation throughout the online sessions. The decrease can be expected as engagement typically decreases over time on online learning platforms. The correlation results showed that most of the trends are negatively correlated with student achievement, which means that the less a student exhibits these behaviours, the more likely they are to receive a badge. As the trend features were calculated using windows of 3/5/10 sessions, the trends can be considered as fluctuations, which is confirmed by the visualisations of occurrences, as shown in Figure 1a. More fluctuations may mean that students exhibited different interactive behaviours at the same time. As students engage with the platform they become more familiar with the platform, and consequently they become more proficient at navigating and using it. This finding may further support our assumption that interface learnability has an effect on the learning outcome as measured by student achievement. Usability has been investigated in online learning settings to evaluate different platforms and to provide insights on the design of platforms and the learning resources [87, 80]. Although it has been suggested that there is no widely-agreed definition for learnability, it can be described as ‘the ability to improve performance over entire usage history’ based on a taxonomy provided in [39]. Learnability as an important and perhaps fundamental component of usability [2, 60], has not been thoroughly discussed in online learning platforms.

The plausible association between *becoming a more efficient user* and student achievement may suggest that the easier a learning platform is to use, the better students learn. It may also suggest that students who are more familiar with the learning platform or skilled navigators are better at learning. This opens up new research avenues into analysing the learnability of platforms and student learning outcome.

581 *6.2. Implications*

582 **Methodological implications.** Previous research has identified the chal-
583 lenges of using sequential pattern mining algorithms in educational stud-
584 ies [68]: 1) the generation of excessive patterns with limited relevancy and
585 value, and 2) the involvement of domain experts for filtering and labeling
586 purposes. For the first challenge, we proposed a benchmarking process to
587 select the most suitable algorithm, dataset and algorithm parametrisation so
588 that we maximise how informative and representative the results are. The
589 second challenge is relatively common in data mining and analysis scenarios.
590 Through a number of established methodological steps, thematic analysis fa-
591 cilitates the work of domain experts.

592

593 **Theoretical implications.** We found that micro-interactions can be be-
594 havioural markers of online learning. Whether these micro-interactions are
595 universal is unknown but they are probably not generalisable across online
596 platforms. However, they provide further explainability in terms of inter-
597 pretability and predictability of what students do.

598

599 **Implications for practice.** Despite the current demands on the use of rich
600 interaction data [56], existing data analysis procedures in online learning do
601 not contemplate low-level events. This may be due to the lack of infrastruc-
602 ture to do so although, actually, there is an availability of these tools [8]
603 which facilitate low-level data collection. However, computing patterns and
604 building student models require programming and data science expertise.
605 While they are not widespread and their coverage is limited, tools such as
606 WevQuery-PM [9] can lighten this burden.

607

608 *6.3. Limitations*

609 As each online learning platform is designed for different purposes and
610 audiences, there may be limitations to the extent of the generalisability of
611 our conclusions, which is a common issue in online learning [4]. It is well known
612 that the models defined for MOOCs are typically valid within the scope of
613 the MOOCs under scrutiny: early career researchers on a cMOOC. There
614 are no universal models as students, learning contents, and course designs
615 differ [58]. Hence, researchers emphasise on methodological approaches to
616 build student models [52]. We contribute to such body of knowledge with
617 this novel approach.

618 Also, compared to other online learning platforms, the sample size is
619 relatively small due to the fact that the platform was targeting an specialised
620 student group, early career researchers. We counterbalance this limitation
621 with the large amount of data points collected, which give us an in-depth
622 understanding of student behaviour.

623 While students interactions with the platform are used to predict whether
624 they will receive a badge or not, achieving a badge is also rewarded partly for
625 these same interactions. It could be argued, however, that low-level interac-
626 tions used in analysis contain many more varieties of higher level interactions
627 (such as viewing the video content and wiki page) than those used to give
628 out the badge. Further to this, the criteria for receiving a badge includes
629 activities and assignments which are not captured in these low-level interac-
630 tions.

631 7. Conclusion

632 We propose a three-step methodology to determine if there are implicit
633 micro-interactions that are associated with indicators of learning. To suggest
634 its feasibility, we apply the methodology in an online learning platform. From
635 the generated dataset, we extracted frequent student interaction patterns
636 using sequential pattern mining algorithms. To handle the sheer numbers
637 of patterns we applied thematic analysis to group the patterns into themes
638 that represent interactive behaviours. Then we sought the presence of these
639 representative behaviours in the original dataset to build student models
640 that represent such behaviours. Finally, we conducted statistical analysis
641 between features derived from the models and indicators of learning including
642 achievement and unit progress.

643 We identified features from six interactive behaviours that strongly cor-
644 related with achievement that explain 72% of the student achievement vari-
645 ation, which was 10% higher when non engagement features were included.
646 The models with the interactive behaviours were 3-7% more accurate at iden-
647 tifying students who will not receive a badge than random selection. It would
648 have not been possible to obtain the increases in explainability and accuracy
649 without our data-driven approach. This increase involves deeper insights
650 gained from the relationship between student achievement and learnability
651 of the student interface. In summary, our data-driven approach provides
652 self-regulated learning platforms with a fresh perspective on measuring in-
653 dicators of learning, and has revealed connections between platform/student

654 learnability and learning outcome.

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