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# Analytics of learning tactics and strategies in an online learnersourcing environment

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## Abstract

**Background:** The use of crowdsourcing in a pedagogically supported form to partner with learners in developing novel content is emerging as a viable approach for engaging students in higher-order learning at scale. However, how students behave in this form of crowdsourcing, referred to as learnersourcing, is still insufficiently explored.

**Objectives:** To contribute to filling this gap, this study explores how students engage with learnersourcing tasks across a range of course and assessment designs.

**Methods:** We conducted an exploratory study on trace data of 1279 students across three courses, originating from the use of a learnersourcing environment under different assessment designs. We employed a new methodology from the learning analytics (LA) field that aims to represent students' behaviour through two theoretically-derived latent constructs: learning tactics and the learning strategies built upon them.

**Results:** The study's results demonstrate students use different tactics and strategies, highlight the association of learnersourcing contexts with the identified learning tactics and strategies, indicate a significant association between the strategies and performance and contribute to the employed method's generalisability by applying it to a new context.

**Implications:** This study provides an example of how learning analytics methods can be employed towards the development of effective learnersourcing systems and, more broadly, technological educational solutions that support learner-centred and data-driven learning at scale. Findings should inform best practices for integrating learnersourcing activities into course design and shed light on the relevance of tactics and strategies to support teachers in making informed pedagogical decisions.

KEYWORDS

artificial intelligence in education, learnersourcing, learning analytics, learning strategies, learning tactics, self-regulated learning

## 1 | INTRODUCTION

The concept of learnersourcing refers to a pedagogically supported form of crowdsourcing that mobilizes the learner community as experts-in-training to contribute novel content while being engaged in meaningful learning experiences themselves (Kim, 2015). Learnersourcing has strong roots in learning science and is aligned with contemporary learner-centred approaches (Lambert & McCombs, 1998) such as inquiry-based learning (Edelson et al., 1999), contributing student pedagogy (Hamer et al., 2008) and students as partners (Matthews, 2017), which shift the focus of instruction from the teachers to the learners. Learnersourcing has also been recognized and is increasingly receiving attention as an effective mechanism to support personalisation at scale (Khosravi et al., 2020; Williams et al., 2016). It is worth noting that learnersourcing contributions can be a product of an individual learner's work (e.g., Denny, Luxton-Reilly, & Hamer, 2008) or collaboration among multiple learners (e.g., Yang et al., 2016).

Despite the increasing adoption of learnersourcing platforms in higher education, little is known about students' behaviour on these platforms. Having a deeper understanding of how learners engage with learnersourcing platforms can have various benefits for different stakeholders including assisting tool developers in making data-driven decisions about tool design, educational researchers in evaluating the effects of learnersourcing on learning, educators in making data-informed pedagogical decisions in their teaching and students in regulating their learning. Accordingly, we conducted an exploratory study on trace data originating from using a learnersourcing environment in three courses with a diversity of course and assessment design to examine how students engage with learnersourcing tasks.

To collect the trace data, we use the RiPPLE platform, which enables students to create resources, moderate resources created by their peers or attempt learning resources from a repository of available resources. The three courses used in the study vary in how they integrate RiPPLE into their course design and assessment. One of the courses is a first-year on human biosciences ($N1 = 618$) where the platform was used formatively without any ties to assessment. The second course is a graduate-level course ($N2 = 128$) in quantitative research methods in applied linguistics in which students were expected to create and moderate resources as part of their assessment. The third course is a first-year psychology course ($N3 = 533$) where as part of their assessment, students were expected to create, moderate and attempt learning resources. For the analysis, we use a new methodology from the LA field that aims to represent students' behaviour through two theoretically-derived latent constructs: learning tactics, and the learning strategies built upon them (Fincham et al., 2019; Matcha, Gašević, Uzir, Jovanović, Pardo, et al., 2019). This method is receiving increasing attention within the LA community and has been employed in investigating student behaviour in various learning contexts and modalities (Matcha et al., 2020).

The rest of this paper is organized as follows. Section 2 presents background and related work on learnersourcing and the learning tactics and strategies methodology. Section 3 presents the research questions under investigation. Section 4 presents an overview of the research methodology used in this paper. Section 5 presents the results and findings, answering our proposed research questions. Section 6 discusses implications and limitations of the work. Finally, Section 7 presents concluding remarks and future work.

## 2 | BACKGROUND AND RELATED WORK

### 2.1 | Learnersourcing

Engaging students in learnersourcing has been studied in various communities under various names with a range of aims and objectives. A significant portion of the earlier work has come from the computing education research community, which can be categorized into two groups. One cluster of the work, which is theorized using the contributing student pedagogy (Hamer et al., 2008), has employed the popular Peerwise platform (Denny, Hamer, et al., 2008) to examine students' ability in creating high-quality resources (Denny et al., 2009; Purchase et al., 2010) and its impact on student performance (Denny, Hamer, et al., 2008; Luxton-Reilly et al., 2012). Their findings provide strong evidence that students can create high-quality learning resources that meet rigorous judgemental and statistical criteria (Bates et al., 2014; Galloway & Burns, 2015) and that engaging in learnersourcing can enhance student learning (Khosravi et al., 2019). Other examples focusing on creating content include creating repositories of learning content such as multiple-choice questions (Khosravi et al., 2019), knowledge components (Moore et al., 2020), explanations for programming misconceptions (Guo et al., 2020), solutions to open-ended questions (Wang et al., 2019; Williams et al., 2016), explanations for peer instruction (Bhatnagar et al., 2020), summaries of steps in how-to videos (Weir et al., 2015) and personalized hints (Glassman et al., 2016). These learning repositories can be utilized to develop adaptive and intelligent systems to support the personalisation of education (Khosravi et al., 2019; Williams et al., 2016). The second cluster of work has focused on developing effective peer grading systems where students' assignments can reliably be graded by their peers (Paré & Joordens, 2008; Purchase & Hamer, 2018; Shnayder & Parkes, 2016; Wind et al., 2018; Wright et al., 2015). Reported results indicate that a key challenge in peer grading is motivating peers to grade diligently. To address this challenge, various spot-checking algorithms have been suggested where instructors grade some assignments themselves and assign punishments or rewards to peers based on the diligence of their evaluations (Wind et al., 2018; Wright et al., 2015).

The recent development of learnersourcing tools has enabled researchers to collect the interaction trace data for investigating students' engagement. A common method of examining how students engage with learnersourcing tasks is to report general engagement statistics (e.g., Denny et al., 2009). However, this method considers only one aspect of students' behaviour and does not show whether the time and sequence in which the activities were performed can be informative and help understand the learning process. Alternatively, researchers can consider the dynamics of learning activities over time in their analyses to overcome this limitation.

Prester et al. (2020) conducted a literature review of 97 peer-reviewed papers closely related to learnersourcing, and found that most of the studies could underlie at least one of three philosophical views: (1) entitative view focusing on cause and effect (e.g., the effect of learnersourcing on grades), (2) process view focusing on the occurring of events over time and (3) practice view focusing on practices in education (e.g., best practices). Most of the studies in which the process view was prominent (e.g., de Alfaro & Shavlovsky, 2014) assumed that activities occur over specific stages linearly with the expectation of certain outcomes and effects on entities (Prester et al., 2020). This process view was described as a weak process view as it does not consider the actual process performed by learners (Langley et al., 2013; Langley & Tsoukas, 2010). Some other studies tied the process to specific learning settings (e.g., Hills, 2015).

Based on (Prester et al., 2020) description of the process view, Arruabarrena et al. (2019) work should be an example of the weak process view. In their work, they proposed a general methodology in which learners are connected in an iterative process for generating and evaluating learning content. Their work shows that the proposed methodology enabled students to produce sufficient resources with a high level of satisfaction. Yang et al. (2016) work should be an example of the actual process view in which they explored learners' behavioural patterns using lag sequential analysis. Fourteen significant behavioural sequential patterns were found as evidence of different processes learners employed while engaged in the knowledge creation process used in the study. The authors considered learners' actual process in learnersourcing; however, the context of their study is different to ours. In our work, students created and moderated various types of learning resources individually as part of an assessment or optional learning opportunity. Conversely, in their study, students had to create the teaching contents of the course collaboratively. Also, their study investigated behavioural patterns on the content level, while we investigated learners' behavioural patterns based on learning sessions.

## 2.2 | Interpreting learners' behavioural patterns

Understanding how learning occurs is challenging as the process of learning is complex (Schunk, 2012). Throughout past studies, learners' data collected from diverse educational settings have been utilized to establish theoretical frameworks that could describe different learning-related phenomena. In recent years, with the advancement in educational technology, more coarse- and fine-grained data regarding learners learning have become increasingly available (Romero & Ventura, 2013, 2020). However, this data by itself cannot be used to advance our understanding of the learning and the associated behaviours because they are essentially designed to serve other purposes, such as detecting system faults (Kitto et al., 2020). Instead, they must be transformed into meaningful forms using advanced techniques (e.g., LA methods) and then linked with the existing learning theories to develop expanding knowledge (Wong et al., 2019). Consequently, integrating theoretical learning frameworks with LA starting from developing the data (Kitto et al., 2020) to developing hypothesis and interpreting findings of research (Lodge & Corrin, 2017; Murphy & Knight, 2016) has the potential to develop learning theories and improve the learning process and outcomes. In particular, the use of self-regulated learning (SRL) has been very prominent in LA (Wong et al., 2019).

Models of SRL (Schunk, 2012; Winne & Hadwin, 1998; Zimmerman, 2000) usually state that SRL is an iterative process that is guided by goals and that involves changes in a learner's actions over time. In (Winne & Hadwin, 1998), the SRL model consists of four phases: recognizing the factors related to a task on hand, developing plans for achieving predefined goals, then enacting the plans and finally evaluating the results and the whole process for adaptation. LA provides sophisticated tools and techniques to analyse fine-grained temporal data at the macro- and micro-level in relation to these four phases. Hence, combining SRL and LA by grounding studies that seek a meaningful interpretation of learners' behaviours using trace data in SRL theory is appropriate.

An emerging cluster of research used a learning analytics lens to represent students' behaviour as SRL strategies and tactics (e.g., Fincham et al., 2019; Jovanović et al., 2017; Matcha, Gašević, Uzir, Jovanović, & Pardo,, 2019; Uzir et al., 2020). Weinstein, Husman, and Dierking (2000, p. 727) defined learning strategy as "any thoughts, behaviours, beliefs or emotions that facilitate the acquisition, understanding, or later transfer of new knowledge and skills". This definition is widely accepted and has been adopted by many researchers. Learning strategy can also be seen as a set of different cognitive plans (Pressley et al., 1990; Schunk, 2012) that learners implement adaptively according to their detective, procedural and conditional knowledge to accomplish a task (Schraw & Moshman, 1995; Schunk, 2012). On the other hand, learning tactics are the methods or techniques used to enact a learning strategy's plans in the form of a small number of actions implemented sequentially to information (Winne & Marzouk, 2019). Thus, a learning strategy comprises two or more learning tactics as main components (Derry, 1990; McKeachie, 1988; Winne & Marzouk, 2019).

Matcha, Gašević, Uzir, Jovanović, & Pardo, (2019) have employed process mining, clustering and sequence analysis to uncover and interpret learning strategies and tactics and investigated the association between the strategies and students' performance as well as the association between analytics-based feedback and the selection of tactics and strategies. They found that students utilized various tactics and strategies that indicate approaches to learning, namely deep, strategic and surface (Entwistle et al., 2001). Their findings show that the strategies were associated with students' academic performance; that is to say, the students who implemented the deep and strategic learning approaches performed better than those who implemented the surface learning approach. Also, their findings indicate that the provision of analytics-based feedback was associated with an increase in using the most effective learning strategies (i.e., deep and strategic) and a decrease in using the less effective learning strategy (i.e., surface).

Uzir et al. (2020) attempted to detect theoretically meaningful time management tactics and strategies using clustering and sequence analysis and examined the relationship between the detected time management strategies and learners' performance and personalized feedback. Their findings indicated that learners' behaviours could manifest time management strategies and tactics. Also, they found that the tactics and strategies were positively associated with learners' performance and personalized feedback.

Matcha, Gašević, Uzir, Jovanović, Pardo, et al. (2019) compared three analytical approaches to detecting learning tactics and strategies in MOOC, namely, process, sequence and network. The three approaches differed mainly in the method used to represent the data fed to the clustering algorithms. Thus, unsurprisingly, though the resultant tactics and strategies shared some similarities, they differed in many aspects, suggesting that the results of analysing learning tactics and strategies depend on the data analytics method. Matcha et al. (2020) aimed to examine the generalisability of the methodology used in (Matcha, Gašević, Uzir, Jovanović, Pardo, et al., 2019) by applying it to various contexts. Their findings supported the methodology's generalisability and contributed to gaining further insight into learning tactics and strategies.

### 2.3 | Integrating learning design and LA

Most recently, the idea of integrating learning design and LA (Lockyer & Dawson, 2011) has received great interest from learning design and LA researchers opening up new research opportunities for novel contribution to answering primitive research questions that can lead to the improvement of both fields so that their common goal of improving teaching and learning can be achieved (Macfadyen et al., 2020). Thus, recent research has shown promising findings as evidence of the potential to connect the two fields (Bakharia et al., 2016; Gašević et al., 2016; Nguyen et al., 2017a, 2017b; Nguyen et al., 2018; Rienties et al., 2015; Rienties & Toetenel, 2016; Shen et al., 2020). Two of the several ways by which LA can benefit learning design were mentioned in (Macfadyen et al., 2020): (1) determining the appropriate LA approaches for educators to get actionable insights (Mangaroska & Giannakos, 2019) and (2) informing the learning design decisions based on evidence (Schmitz et al., 2017). In turn, for LA to provide these benefits, LA must consider the learning design as a context to support the interpretation of its resultant outcomes (Lockyer et al., 2013). In this work, the learning design data were not available, yet we considered the course and assessment designs since they can be considered an integral part of the learning design (Shen et al., 2020).

## 3 | AIM AND RESEARCH QUESTIONS

The aim of the presented study is to employ a learning analytics lens to explore how students engage with learnersourcing tasks. We rely on prior research approaches to detect, gain insight and understand students' learning tactics and strategies in a learnersourcing environment. Based on the findings of (Matcha et al., 2020), which suggest that students may use very different tactics and strategies in different course designs, we conduct the study across multiple courses with different course designs. The following two research questions guide our study:

1. What learning tactics and strategies are used by students to engage with learnersourcing tasks across different course and assessment designs?
2. Is there an association between the identified learning strategies and students' performance on the learnersourcing platform?

## 4 | METHODS

This section outlines the methodology we have used for examining students' behaviour in a learnersourcing environment based on the research questions proposed in Section 3.[1] In what follows, Section 4.1 provides an overview of the research tool used for the study. Section 4.2 describes the study contexts and introduces the data sets used in the study. Finally, Section 4.3 details the approach and techniques used for the analysis.

### 4.1 | Tool

This study uses a course-level, discipline-agnostic platform called RiPPLE. At its core, RiPPLE is an adaptive educational system that dynamically adjusts the level or type of instruction based on individual student abilities or preferences to provide a customized learning experience (Khosravi et al., 2019). Instead of the common approach of relying on domain experts to develop the content for an adaptive system, RiPPLE partners with students and employs a learnersourcing approach to engage students in the creation of learning resources. Students can perform three main tasks within the platform: creating, moderating, and answering resources. Figure 1 shows an overview of the process involved for each of these tasks, and Figure 2 illustrates the current interfaces used for these tasks.

*Learner role*: RiPPLE supports three types of resources: multiple-choice questions (MCQs), study notes and worked examples. Figure 2b shows the creation interface for MCQs. After a new resource is created and submitted, the system makes the content available for moderation based on a ranking-based algorithm that considers the learners' knowledge state (i.e., the content is only visible for learners with certain ranks). The moderation interface, including the rubric, is shown in Figure 2c. Once a moderation is received, the system determines whether the content needs additional moderation. If no more moderation is required, the system uses current moderations in a consensus explainable algorithm to decide on the content, updates the status of the resource, and then communicates the decision and provides feedback to the learners involved. On the creator side, the feedback includes whether the resource was approved and how it can be improved for re-submission. On the moderator side, the feedback includes whether the moderation was used in the decision, whether the content was approved and an explanation of the consensus algorithm involved in making the decision (see Figure 2d). If the content is approved, the system makes it available in the platform under the practice section and recommends it to learners based on a ranking-based algorithm (see Figure 2a).

*Instructor role*: The system approves any resources created or imported by instructors without moderation. The system also allows the instructors to moderate any resource and recommends them resources that can best benefit from their moderation. After the system receives a moderation from an instructor on a resource, the resource's status is updated, and a consensus explainable algorithm is used to make the decision. Then, all the moderators receive feedback. However, moderations from instructors are considered final, meaning their decisions are considered the ground truth without considering students' moderations.

[1]Approval from our Human Research Ethics Committee (#2018000125) was received for conducting the study presented in this paper.

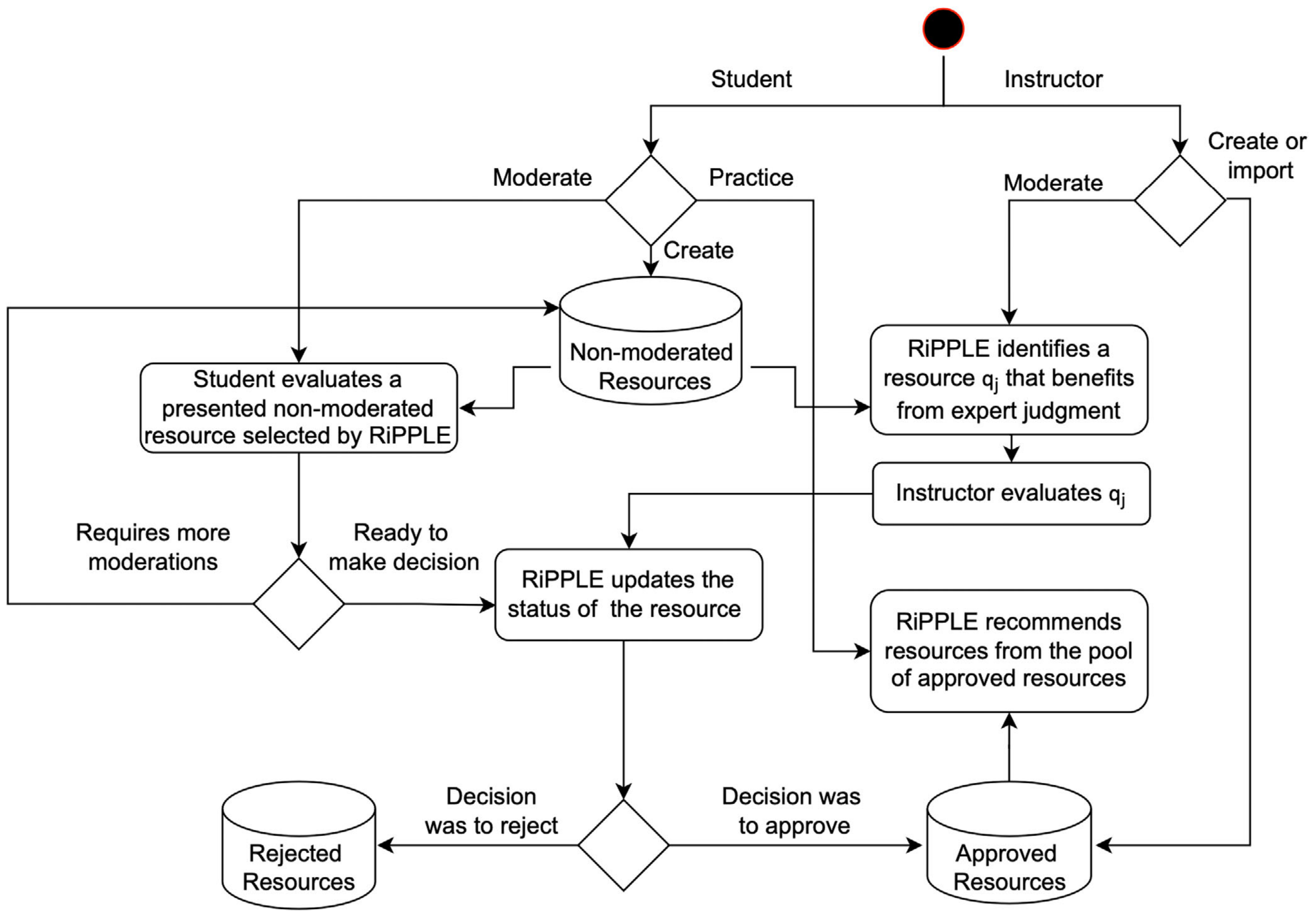


**FIGURE 1** Illustration of the process of learnersourcing on RiPPLE

## 4.2 | Study context

We collected student data from RiPPLE of three courses offered in 2020 at two Australian universities. These courses were offered by different faculties and were on different topics with different course designs. The data sets of the three courses are summarized in Table 1. As a result of the cleaning process and removing outlier sequences, as outlined in Section 4.3.1, some of the students were not included in the final analysis (i.e., students who did not perform any of the three main activities or who only have very long sessions).

*Dataset 1*: This dataset contains data of 618 undergraduate students enrolled in the Human Biosciences course in Semester 2, 2020, lasting 12 weeks. RiPPLE was used formatively, but students were encouraged to use it as a learning source.

*Dataset 2*: This dataset contains data of 128 graduate students enrolled in the Second Language Acquisition course in Semester 1, 2020, lasting 13 weeks. The assessment was scheduled weekly from Week 2 to Week 11 on a pass/fail grading system. Students were instructed to create at least one resource (i.e., learning material/guide as a note) and moderate at least three resources.

*Dataset 3*: Data of 533 undergraduate students enrolled in the Brain and Behavioural Science course in semester 1, 2020, lasting 13 weeks, were collected. RiPPLE was a major part of the course's assessment and contributed to 16% of the total mark. From Week 2 to Week 12, as an exercise, students were instructed to create at least one resource (i.e., MCQ) and moderate at least five resources each week during the second hour of the lecture or outside the class. Only, 8 out of 11 exercises were counted towards their mark. Students were also encouraged to attempt MCQs.

The datasets were available for downloading from the platform as separate reports for each type of activity included in this study. In the reports, the recorded activities were associated with a student id, resource id, resource type and a timestamp.

## 4.3 | Data analysis techniques

### 4.3.1 | Data preprocessing

As an initial step towards exploring the learning tactics and strategies used by the students on RiPPLE, for each student, we used the integrated trace data to generate sequences of activities that represent the user sessions when using the platform. A user session should reflect the time in which the student was engaged with learning activities without interruption (e.g., taking a break). We defined the session as a set of activities in which any two consecutive activities overlap within a 30-minutes time interval (Jovanović et al., 2017). Further, following (Jovanović et al., 2017), the sessions were refined by excluding

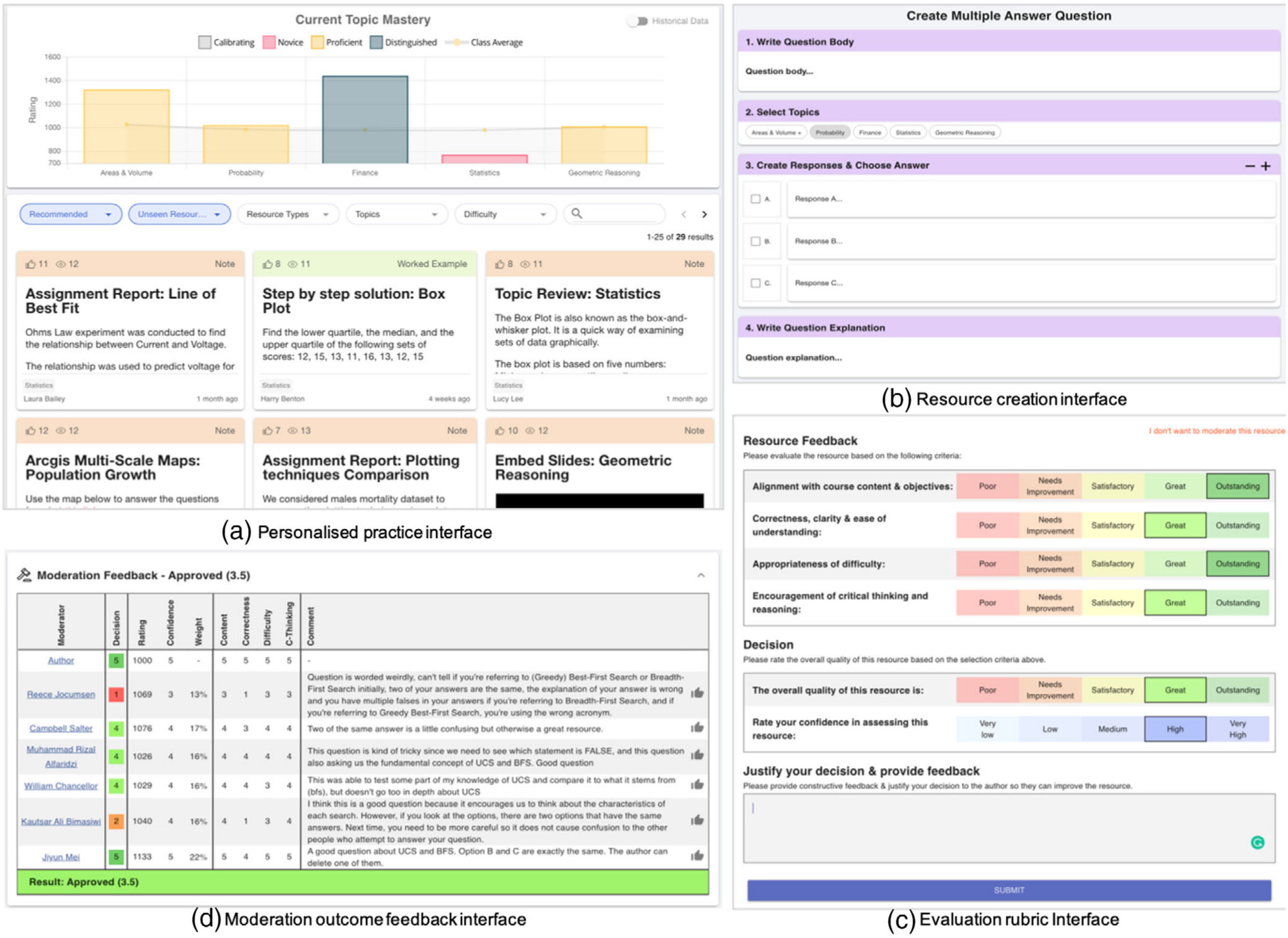


**FIGURE 2** Four of the main interfaces of RiPPLE

**TABLE 1** Summary statistics of the datasets

| | # Participants | | | Activity summary | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Creation | | | | | |
| Course | Actual | Selected | Assessment type | MCQ | MAQ | Note | WE | Moderation | Answering |
| Human Biosciences | 1,432 | 618 | Formative | 264 | 43 | 3 | 2 | 1,279 | 37,970 |
| Second Language Acquisition | 154 | 128 | Summative (weekly) | 6 | 0 | 1,108 | 7 | 3,125 | 16 |
| Brain and Behavioural Sciences | 547 | 533 | Summative (weekly) | 4,695 | 0 | 10 | 15 | 27,296 | 31,675 |

too long sequences (i.e., sequences longer than the 95$^{th}$ percentile). Nonetheless, short sequences with one action length were kept as they could reflect a unique approach to achieving part of the assessment that requires a single activity.

### 4.3.2 | Detection and interpretation of students' learning tactics and strategies

Detecting learning tactics and strategies on RiPPLE was conducted by replicating the approach used in (Matcha, Gašević, Uzir, Jovanović, Pardo, et al., 2019). A learning tactic was regarded as a sequence of activities performed in a single session. LA utilizes methods such as unsupervised machine learning algorithms that can automatically detect similar sequences. Sequences that share high similarities were combined under one umbrella to represent a particular tactic. We used first-order Markov model (FOMM) as an input to the Expectation Maximization clustering algorithm for performing this task. We decided on the number of clusters based on different runs of the algorithm with varying numbers of clusters *k*. First, as the Expectation Maximization algorithm gives different results with each run, the optimal run (i.e., seed value that is associated with the smallest Within Cluster Sums of Squares among 100 runs) was chosen for each *k*. Second, after selecting the best seed for each *k*, the elbow method was

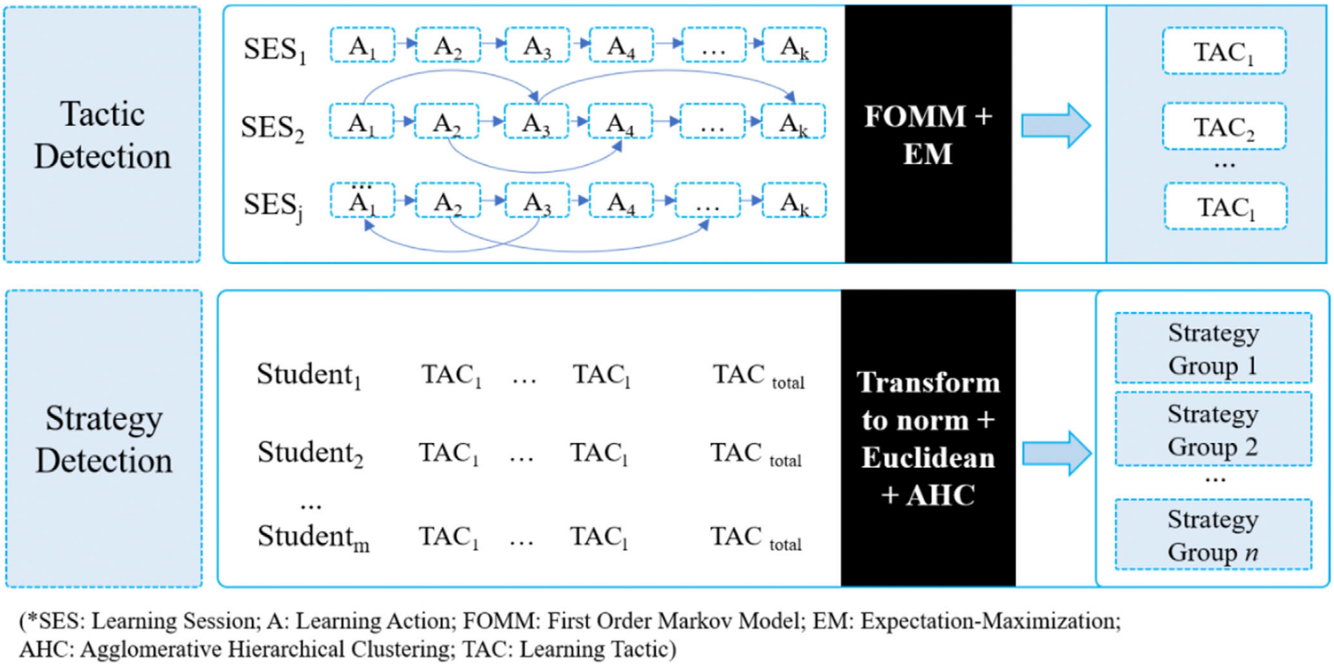


**FIGURE 3** Learning tactics and strategies detection process (Matcha, et al., 2020)

used to choose the best *k*. However, we applied the elbow method for only the course with the most considerable heterogeneity of activities within its sessions; then, we used the same *k* for the other courses' datasets.

Learning strategies were detected based on the tactics identified. For each student, a vector containing a summary of their tactics was created. The summary includes the frequency of each tactic's use plus the sum of these frequencies. After creating the vectors, the agglomerative hierarchical clustering algorithm with Wards' linkage method and Euclidean distance as a metric was used to detect the strategies. We inspected the dendrogram of the course data used to determine *k* for the tactics to determine the strategy's number of clusters. Figure 3 summarizes the process used for detecting the tactics and strategies.

We utilized common approaches used in prior studies to analyse the tactics and strategies. First, descriptive statistics, FOMM and sequence analysis were used to visualize and interpret the identified tactics. Second, besides using descriptive statistics, we looked at how the learning strategies changed over the course study weeks to gain insight into how students employed these strategies differently using process mining with FOMM. We used TraMineR (Gabadinho et al., 2011) and pMineR (Gatta et al., 2017) R packages for sequence analysis and process mining, respectively. In our interpretation, we considered some aspects of the course design (e.g., assessment due dates).

#### 4.3.3 | Relationship between learning strategies and task outcomes on RiPPLE

We hypothesised that students' learning gain is manifested in the practice activity results. Accordingly, the practice activities with the associated outcomes, successful and unsuccessful, were obtained, grouped by the identified learning strategy clusters and then summarized in contingency tables. Based on the contingency tables, the relationship between the learning strategies and the tasks' outcomes was examined using Pearson's chi-square and Cramer's *V* statistics. To examine whether the significant dependency holds true between each pair of the strategy clusters, $2 \times 2$ post-hoc chi-square tests were applied with Bonferroni adjustment.

## 5 | RESULTS

This section investigates and answers the two research questions introduced in Section 3. In what follows, Section 5.1 explores the learning tactics and strategies used by students to engage with learnersourcing tasks. Section 5.2 investigates the association between the identified strategies and students' performance on the platform.

### 5.1 | Response to RQ1

#### 5.1.1 | Learning tactics

The cluster analysis revealed five groups of sequences that best represent the learning tactics. Figure 4 provides an overview of the sequences associated with the tactics.

The tactics differed mainly in the average length of the sessions and the activities' focus. Hence, these factors were used to give the tactic clusters descriptive names. If the median of sequences' lengths within a tactic was less than four, it was considered short, and if it was greater than six, it was considered long. These thresholds were

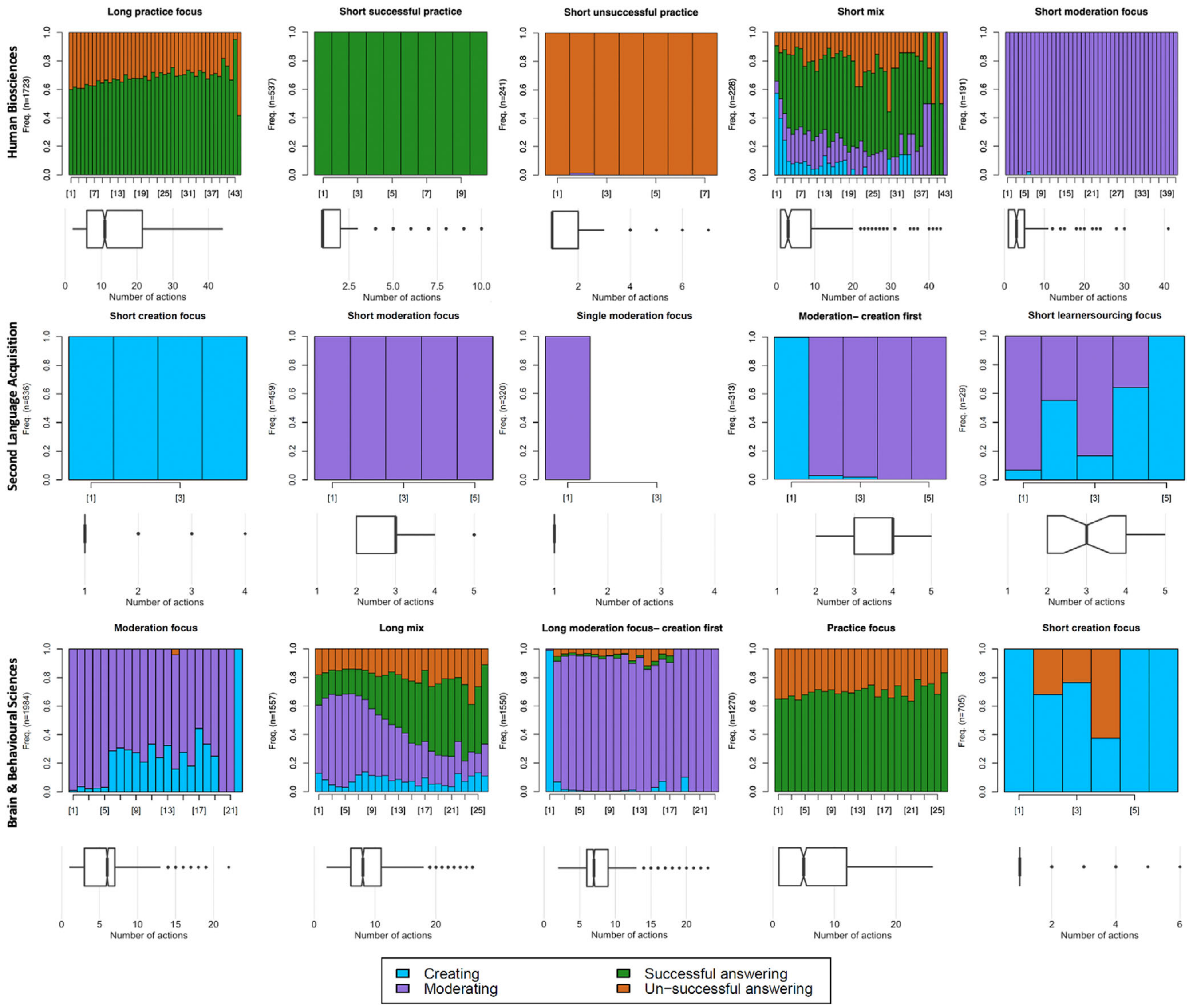


**FIGURE 4** Summary of the sequences identified as learning tactics which includes state distribution for each course. Each bar with a distinct colour represents the probability that an activity *a* occurs in position *i* in a sequence. The boxplots show the distribution of the sequence length

determined by averaging the 40th and 60th percentiles of sequence lengths across the three courses. We categorized the activities into two general categories, practice and learnersourcing. Each of the categories has two types of activities. The practice category includes successful and unsuccessful practices, while the learnersourcing consists of creation and moderation. The focus of the tactic was determined based on the activity that comprises 70% or more of that tactic. If no one type of activity was dominant, the focus was regarded as mix. In the tactic descriptions below, we used Figure 4, FOMM (when applicable) and descriptive statistics.

*Human Biosciences*: Tactics of this course focused on practice activities as three of the five tactics were purely about answering MCQ. The average length of the tactics was six actions per session. However, the data were skewed, suggesting a large discrepancy in session lengths within each tactic.

- *Long practice focus* ($N = 1723$, 59% of all sequences). The median session length was 11 actions. Answering was the only type of activity performed, yet with mixed outcomes, (65%) successful and (35%) unsuccessful. The chance of getting correct answers increases slightly when the session length increases (see Figure 4).
- *Short successful practice focus* ($N = 537$, 18.3% of all sequences). When students used this tactic, they only performed successful practices with a median length of one action.
- *Short unsuccessful practice focus* ($N = 241$, 8.2% of all sequences). When students used this tactic, they only performed unsuccessful practices with a median length of one action.
- *Short mix* ($N = 228$, 7.8% of all sequences). The median session length was three actions. The most performed activity was answering (63%) with a high probability of positive outcomes. An apparent

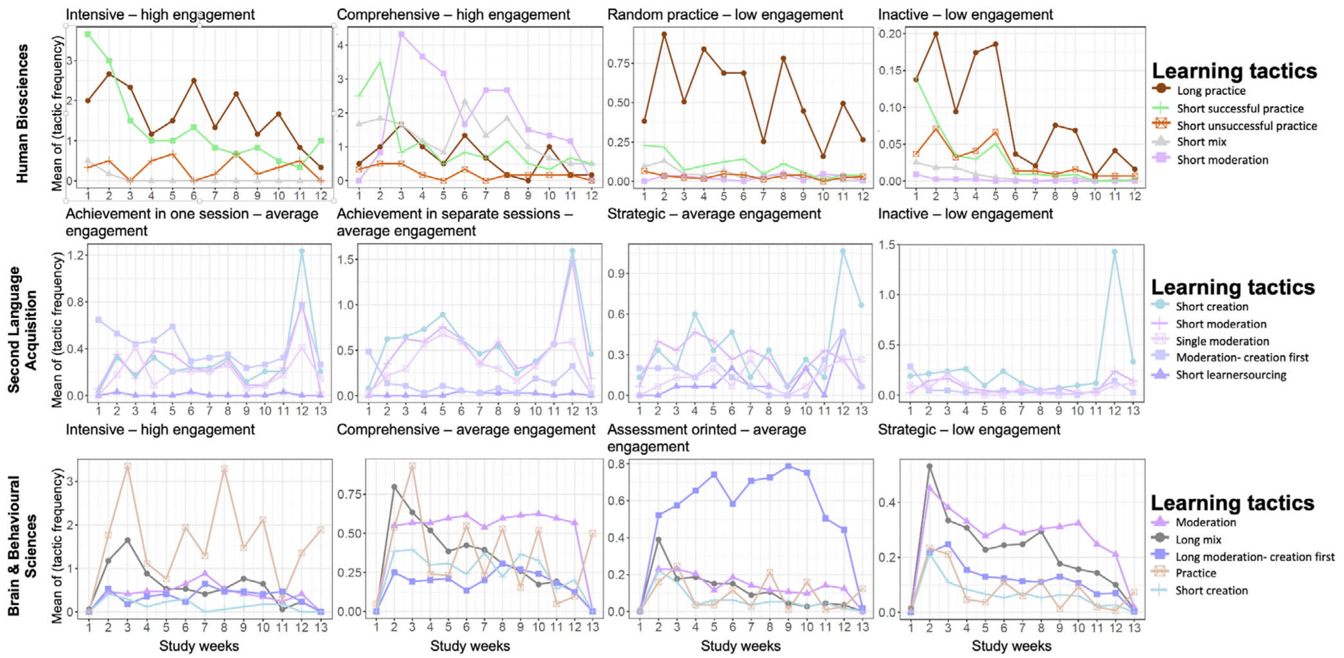


**FIGURE 5** Demonstration of the strategies over time

pattern was that the session began with creating a resource, and the chance of performing an answering activity increases with longer sessions (see Figure 4). FOMM reveals a high occurrence of self-looping (i.e., performing the same type of activity next) and weak interactions between the activities.

- *Short moderation focus* (N = 191, 6.5% of all sequences). The median session length was three actions. This tactic represents short sessions dedicated to moderate learning resources.

The identified tactics showed that students enrolled in this course usually did not utilize multiple types of activity at one time. Accordingly, before starting their learning sessions, they might have had a predefined goal for moderating, creating or practising.

*Second Language Acquisition*: Tactics of this course focused on learnersourcing activities since all the tactics were about creation and moderation. The average length of the tactics was two actions per session.

- *Short creation focus* (N = 636, 36% of all sequences). Creation was the only type of activity performed with a median length of one action.
- *Short moderation focus* (N = 459, 27% of all sequences). Moderation was the only type of activity performed with a median length of three actions.
- *Single moderation focus* (N = 320, 18% of all sequences). Moderation was the only type of activity performed with a median length of one action.
- *Moderation–creation first* (N = 313, 18% of all sequences). The median length was four actions. The most frequent activity was moderation (70%). A prominent learning pattern associated with this tactic is that the session always began with creation followed by moderation (see Figure 6).
- *Short learnersourcing focus* (N = 29, 3% of all sequences). The median length of sessions was three. The most frequent activity was moderation (66%). A prominent learning pattern is that the session began with moderation (93%), followed by either creation or another moderation activity (see Figure 6). However, if the students created a resource, they would most likely end the session (75% based on FOMM).

The short average length of the tactics could indicate that the students devoted their sessions to their assessments as they were required to only complete four tasks per week (see Section 4.2).

*Brain and Behavioural Sciences*: This course had a mixed focus since no consistency was observed in the focus of the tactics. The mean length of the tactics was six actions per session.

- *Moderation focus* (N = 1984, 28% of all sequences). The median length of sessions was six actions. Learnersourcing was the only type of activity performed, focusing on moderation (90%). A prominent learning pattern is that the session began with moderation (99%), and if the session length was greater than five, there was about a 20% chance that the students performed a creation activity (see Figure 4) and then ended the session (79% based on FOMM).
- *Long mix* (N = 1557, 22% of all sequences). The median length of sessions was eight actions. The most frequent activity performed was moderation activity (52%), and the second was answering MCQ (39%). When the session length was larger than six, the chance of performing practice activities was higher (see Figure 6). FOMM showed that three learning patterns were associated with this tactic. The first pattern is that the session began with moderation (48%), and then self-looping was established (68%). The second pattern is that students moderated resources after unsuccessful practice (35%) or

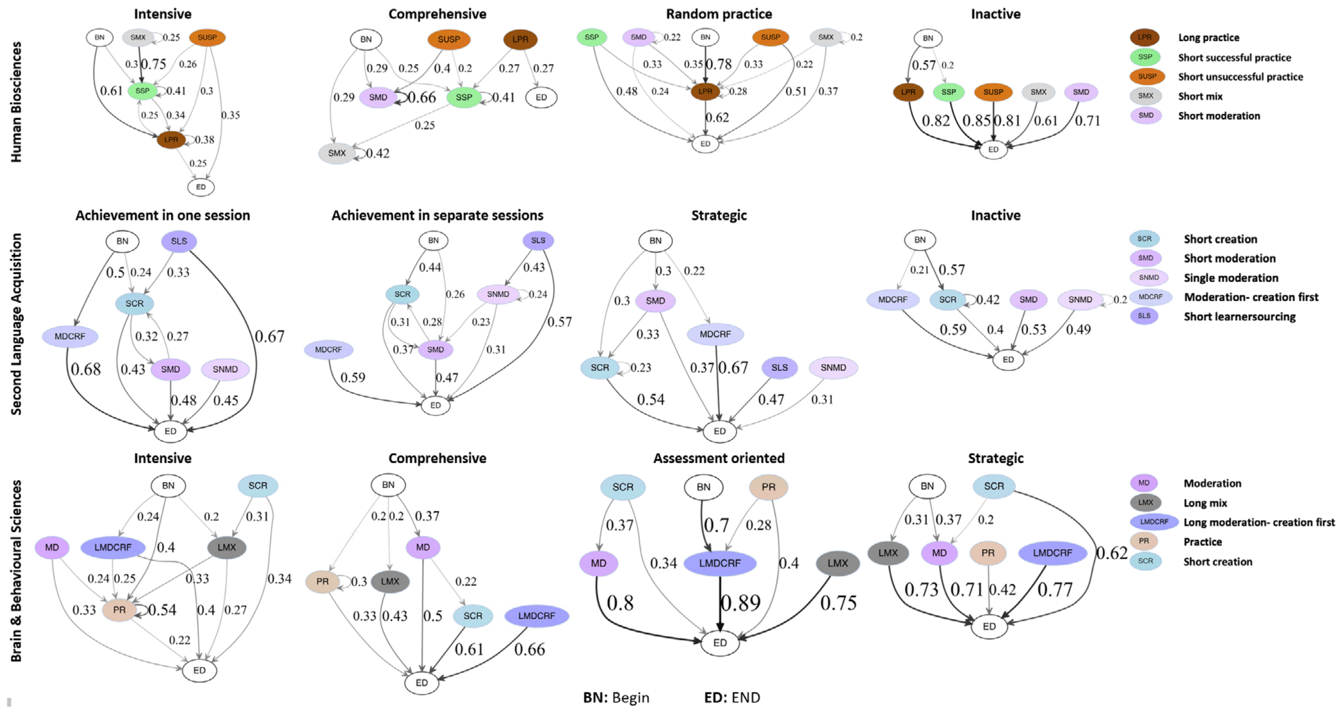


FIGURE 6 First-order Markov model for the learning strategies. The oval shapes represent the activities, the arrows represent the interaction direction, and the fractional number represents the strength of the interaction

creation activities (25%). The last pattern is to perform creation activities at the end of the session (40%).

- *Long moderation—creation first* ($N = 1550$, 21.9% of all sequences). The median length of sessions was seven. A prominent learning pattern is, to begin with, a creation activity (99%) followed by a series of moderations (see Figure 6).
- *Practice focus* ($N = 1270$, 17.9% of all sequences). The median length of this tactic was four. The only activity performed in this cluster was answering MCQs, with the majority ended up with positive outcomes (68%). A prominent learning pattern associated with this tactic is that the session began with successful answering (65%) with a high probability of establishing self-looping (60%).
- *Short creation focus* ($N = 705$, 9.9% of all sequences). This tactic focuses on creation with a median session length of one action.

The variety of tactics with different focuses clearly shows that students used the platform not only for fulfilling the course requirements but also for learning.

### 5.1.2 | Learning strategies

The cluster analysis revealed four groups of students that best represent the learning strategies. Tables 2, 3, and 4 give an overall picture of the strategies' tactic use distribution, which can help distinguish between them. Figure 5 depicts the strategy patterns over the three courses' timelines. Figure 6 shows how students moved from one tactic to another during the study weeks. In Figures 5 and 6, the brownish and greenish colours represent the practice activities, and the bluish and purplish colours represent the learnersourcing activities. The darkness of the colours indicates the session's length (i.e., the darker the colour, the longer the length).

We assessed each strategy group's engagement level based on the activity median distribution across all strategies within a particular study course. Particularly, if the median of a strategy group was less than the median of the medians of all strategy groups by at least 30%, it was characterized by low engagement. If it was greater by at least 30%, it was characterized by high engagement. Otherwise, the engagement level was average.

Below under each course, we describe each strategy. The first sentence in each description indicates why a strategy has a particular name.

*Human Biosciences*: Since RiPPLE was not used for any assessment in this course, we could not provide insight into how the strategies compare to the assessment design.

- *Intensive—high engagement* ($N = 6$ students, 1%): The students had significantly more weekly sessions dedicated to practising than their peers. *Short mix* was used only in Weeks 1 and 2 (see Figure 5). Two prominent patterns were observed. First, the students started the weeks and continued using *short successful practice* (30% and 41%, respectively). Second, the students began the weeks and continued using *long practice* (61% and 38%, respectively) (see Figure 6).
- *Comprehensive—high engagement* ($N = 6$ students, 1%): The students used *short mix* and *short moderation* besides the practice tactics more

**TABLE 2** Descriptive statistics *mdn* (*q1* – *q3*) for the tactics and activities within the Human Biosciences course's strategy groups

| | Strategies | | | |
|---|---|---|---|---|
| Tactics | Intensive | Comprehensive | Random practice | Limited activities |
| Long practice | 19 (16–23.5) | 8.5 (2.3–14) | 6 (4–8) | 1 (0–2) |
| Short successful practice | 13 (9–17) | 11.0 (3–20.5) | 1 (0–2) | 0 (0–1) |
| Unsuccessful practice | 4 (2.5–4) | 1.5 (0–3.75) | 0 (0–0) | 0 (0–1) |
| Short mix | 0 (0–0) | 16.5 (9.25–18.5) | 0 (0–0) | 0 (0–0) |
| Short moderation | — | 19 (8.75–39.75) | 0 (0–0) | 0 (0–0) |
| Overall activities | 309.5 (202.75–337.5) | 305 (215–329.75) | 131.5 (79.25–205.5) | 8 (2–28) |

**TABLE 3** Descriptive statistics *mdn* (*q1* – *q3)* for the tactics and activities within the Second Language Acquisition course's strategy groups

| | Strategies | | | |
|---|---|---|---|---|
| Tactics | Achievement in separate sessions | Achievement in one session | Strategic | Inactive |
| Short creation | 4 (3–5) | 8 (7–9) | 5 (3.5–6.5) | 1 (1–5.75) |
| Short moderation | 3.5 (2.25–4) | 7 (6–8) | 4 (2–5) | 1 (0–2) |
| Single moderation | 2 (1–4) | 4 (1–7) | 2 (0–3) | 0 (0–1) |
| Short moderation-creation first | 5 (4–7) | 2 (1–2) | 2 (1–3) | 0.5 (0–1) |
| Short learnersourcing | 0 (0–0) | 0 (0–0) | 1 (1–1.5) | — |
| Overall activities | 41 (36.25–42.75) | 40 (38–43) | 37 (32–43.5) | 15 (4–38.75) |

**TABLE 4** Descriptive statistics *mdn* (*q1* – *q3*) for the tactics and activities within the Brain and Behavioural Sciences course's strategy groups

| | Strategies | | | |
|---|---|---|---|---|
| Tactics | Intensive | Comprehensive | Assessment oriented | Strategic |
| Moderation | 5 (2–8) | 6 (4–8) | 1 (1–3) | 3 (1–5) |
| Moderation-creation first | 4 (2–6) | 2 (1–4) | 7 (6–8) | 1 (0–2) |
| Mix | 6 (3–9) | 4 (2–6) | 1 (0–2) | 2 (1–4) |
| Short practice | 20 (16–24) | 4 (1–8) | 1 (0–2) | 0 (0–2) |
| Short creation | 2 (1–3) | 3 (2–4) | 1 (0–1) | 1 (0–1) |
| Overall activities | 456 (418–724) | 128 (77.75–203) | 82 (68–108) | 68 (31.5–96.5) |

than their peers. The dominant tactic in this group was the *short moderation*. After Week 3, the use of the tactic decreased gradually. *Short unsuccessful practice* was the least tactic used in this group (see Figure 5). A prominent pattern is that the students started the week with *short moderation*, *short mix* or *short successful practice* and continued using it throughout the week. However, there was a 25% chance that *short successful practice* was followed by *short mix* (see Figure 6).

- *Random practice—low engagement* ($N = 170$ students, 27.5%): The students focused mostly on *long practice*. The second most used tactic was the *short successful* practice. The other tactics were used at a meagre rate (see Figure 5). A prominent pattern is starting and ending the week with *long practice* (78% and 62%, respectively). Meanwhile, the transitions from the other tactics to the *long practice* (>20%) indicate that the tactics were used during the week (see Figure 6).
- *Inactive—low engagement* ($N = 436$ students, 70.5%): The students hardly used the platform. *Long practice* was dominant (see Figure 5). The prominent pattern was, to begin with, and end the week using *long practice* (57% and 82%). The lack of self-looping and interactions between the tactics indicates that the other tactics were used towards the end of each week (see Figure 6).

Overall, we noticed that all the strategy groups used RiPPLE constantly from Week 1, yet the tactics' use decreased over time. The tactics' peaks across the groups were different. This might indicate that the strategies were not related to scheduled course events. *Short mix* and *short moderation* were the tactics least used across all the strategies except for the *comprehensive*. As shown in Figure 6, except for the *comprehensive* group, the strategy groups started the study weeks using the *long practice* tactic.

The high-level of engagement observed in the *intensive* and *comprehensive* groups indicates that the students found RiPPLE a useful learning source (see Table 2). The *comprehensive* group might indicate that the students were interested in higher-order learning activities such as creating and moderating contents. This is evident in the relatively high usage of the *short moderation* and *short mix* tactics.

*Second Language Acquisition*: To assess whether the strategies complied with the course design, we used the course timeline as an indicator. The students had to complete one creation and three moderation tasks every week (see Section 4.2).

- *Achievement in one session—average engagement* ($N = 34$ students, 27%): *Moderation focus—creation first* was the dominant tactic, except in Week 12. *Learnersourcing* was hardly used, and there was no noticeable difference in the other tactics' use (see Figure 5). A prominent pattern is that students started the week using *moderation focus—creation first* (50%) and then stopped performing any activity for the rest of the week (see Figure 6).
- *Achievement in separate sessions—average engagement* ($N = 37$ students, 29%): The students used tactics that focused on a single activity. *Short creation* was dominant in most of the weeks. Students also focused on using *short moderation* and *single moderation* (see Figure 5). A prominent pattern is that students started the week with *short creation* (44%) and then went back and forth between *short moderation* and the *short creation*. There was a higher chance that the week's activities ended with *short moderation* than the *short creation* (see Figure 6).
- *Strategic—average engagement* ($N = 15$ students, 12%): The usage of the tactics throughout the semester seems unpredictable. For most of the weeks, *short creation* and *short moderation* were dominant. Regarding the other tactics, the students were selective. For example, *moderation focus—creation first* was not used from Week 8 to Week 10 (see Figure 5). In contrast to other groups, this strategy group has no prominent pattern regarding the start of the week. The students could start the week with *short moderation* (30%), *short creation* (30%) or *moderation focus—creation first* (22%). If the week started with *short creation* or *short moderation*, the students could still use the platform during the week. However, if the week started with *moderation focus—creation first*, the students stopped using the platform for the rest of the week.
- *Inactive—low engagement* ($N = 42$ students, 33%): The students had a shallow level of engagement (see Table 3). After Week 3, a significant decrease in all tactics, except for *short creation*, occurred. *Short creation* tactic was dominant for most weeks. The *moderation focus—creation first* tactic was the tactic least used, and the *short learnersourcing* was not used at all. A prominent pattern is that the weeks started with the *short creation* tactic (57%), and then the tactic's use was repeated (42%), or no more activities were performed for the rest of the week (40%).

Overall, we noticed that all the strategy groups used RiPPLE regularly from Week 1 to Week 13. In Week 1, all the groups used the *moderation focus—creation first* tactic the most. Also, there was a noticeable drop in the use of the platform among the *strategic*, *achievement in separate sessions* and *achievement in one session* groups in Week 9 due to not having a lecture in that week. For all groups, a sudden increase was observed in Week 12. From Figure 6, a common pattern across the strategy groups is that if the *moderation focus—creation first* tactic was used in a particular week, the students were most likely to stop performing any activity for the rest of that week (>50%).

The *achievement in separate sessions* group used multiple sessions to complete RiPPLE assessment since they focused on tactics of an average length of one action. In contrast, *the achievement in one session* group might have completed their assessment in mostly one session every week using the *moderation focus—creation first* tactic. The *strategic* group might have achieved their assessment using both approaches since their tactics' use differed from one week to another. The dramatic increase in the use of the tactics in Week 12 can be explained as the students had their last chance to fulfil the assessment requirements.

*Brain and Behavioural Sciences*: To assess whether the strategies complied with the course study design, we used the course timeline as an indicator. Students were required to complete five moderation tasks and one creation every week (see Section 4.2).

- *Intensive—high engagement* ($N = 17$ students, 3%): The students had significantly more weekly sessions dedicated to practising than their peers (see Figure 5). *Practice* and *long mix* were the most and second most frequent tactics. *Short creation* was the tactic least used (see Figure 5). The students could start the week with any tactics except the *short creation* and *moderation*. However, the chance to start with *practice* was the highest (40%). From the other tactics transitioning to *practice* (>20%) and *practice* self-looping (54%), it can be inferred that the students used the practice tactic regularly during the week (see Figure 6).
- *Comprehensive—average engagement* ($N = 104$ students, 19.5%): The *moderation* tactic was dominant from Week 4 to Week 12, yet the students also used the *long mix* and *practice* tactics frequently. *Long moderation—creation first* was the tactic least used (see Figure 5). A prominent pattern is that the week started and ended with the *moderation* tactic (37% and 50%). Also, the weeks started and ended with the *long mix* tactic or began and continued with *practice* (see Figure 6).
- *Assessment oriented—average engagement* ($N = 113$ students, 21%): The students seemed to focus on using the tactic that fulfilled their assessment in one session. From Week 2 to Week 12, *long moderation—creation first* was dominant. *Moderation* was the second most frequent tactic used, and the short creation was the least. A prominent pattern is that the week started and ended with *long moderation—creation first* (70% and 89%). Additionally, *moderation* was most likely to be used after *short creation* (see Figure 6).
- *Strategic—low engagement* ($N = 299$ students, 56%): This strategy shares some similarities with the *comprehensive* and *assessment oriented* strategies. Students were active the most in Week 2. Then, the use of RiPPLE dropped significantly till Week 4 and then dropped again from Week 11. *Moderation* was dominant (see

Figure 5). Two main patterns were observed. First, start the week with *moderation* (37%) and then stop performing any activities for the rest of the week (71%). Second, start and end the week with *long mix* (31% and 73%). The weak interaction between the tactics and the lack of self-looping reflect the low engagement and that most tactics were used at the end of the week (see Figure 5).

Overall, we noticed that all the strategy groups used RiPPLE constantly from Week 2 to Week 12. In Week 2, students in all groups used *long mix* with relatively high frequency, but this tactic constantly decreased over time. Students in the *intensive* and *comprehensive* groups increased their use of *practice* significantly in the weeks of module quizzes. From Figure 6, across the four groups, there was a high probability of ending the week after using *long moderation—creation first* (≥40%).

The *intensive* and *comprehensive* groups appeared to use the platform beyond the assessment requirements (see Table 4). The relatively high use of *long mix* and *practice* tactic within these groups is also a hint of this hypothesis. The low use of *long mix* and the high use of *long moderation—creation first* in the *assessment oriented* group might indicate that the students intended to achieve the assessment with minimum effort. The *strategic* group was less active than the other groups (see Table 4). The strategy was similar to the *assessment oriented* in that the students exerted low effort, and it was similar to the *comprehensive* in that the students used a variety of activities.

## 5.2 | Response to RQ2

This section reports the results of the analysis of RQ2 for only datasets in which the practice activity was present, the Human Biosciences and Brain and Behavioural Sciences courses. The following hypothesis of independence was tested and rejected at an alpha level of significance of 0.001:

> **H0.** *There is no relationship between the practice activity's outcomes and the detected learning strategy groups*.

Tables 5 and 6 summarize the results of the chi-square models. The significance of a variable's contribution to the chi-square model was determined by an absolute standardized residual greater than two (Agresti, 2007).

*Human Biosciences*: A chi-square test revealed a statistically significant but negligible association between the strategy groups and the outcomes of the practice tasks $\chi^2$ (3, $N$ = 37,970) = 151.22, $p < 0.001$, Cramer's $V = 0.06$.

The standard residual values for all strategy groups in Table 5 are greater than two. The *inactive* group was the main contributor to the differences with ±9.7 std. The residuals' positive sign indicates that successful outcomes in performing the activities were positively associated with all strategies except the *inactive*. To better understand the differences, we applied post-hoc chi-square where Bonferroni was used to correct the $p$-value. Consequently, significant differences were found between every pair of strategies at an alpha level of 0.01 as follows: *inactive* with *comprehensive* $\chi^2$ (1, $N$ = 11,013) = 77.91, $p < 0.001$; *inactive* with *random practice* $\chi^2$ (1, $N$ = 35,649) = 72.967, $p < 0.001$; *inactive* with *intensive* $\chi^2$ (1, $N$ = 11,952) = 52.442, $p < 0.001$; *comprehensive* with *random practice* $\chi^2$ (1, $N$ = 26,018) = 44.101, $p < 0.01$; *comprehensive* with *intensive* $\chi^2$ (1, $N$ = 2321) = 13.818, $p < 0.001$; *random practice* with *intensive* $\chi^2$ (1, $N$ = 26,957) = 14.498, $p < 0.001$.

*Brain and Behavioural Sciences*: A chi-square test revealed a statistically significant but negligible association between the strategies and the practice outcomes $\chi^2$ (3, $N$ = 31,675) = 225.86, $p < 0.001$, Cramer's $V = 0.08$.

Table 6 shows that the *intensive* group had the largest contribution to the model with ±14.72 std. The residuals reveal a positive association between the *intensive* group and the practice outcomes. Conversely, relative to the *intensive* group, the residuals reveal a negative association between the practice outcomes and all other groups.

Chi-square post-hoc comparisons yielded significant differences only between the intensive group and every other strategy group as follows: *intensive* with *comprehensive* $\chi^2$ (1, $N$ = 18,979) = 120.24, $p < 0.001$; *intensive* with *assessment oriented* $\chi^2$ (1, $N$ = 13,352) = 118.22, $p < 0.001$; *intensive* with *strategic* $\chi^2$ (1, $N$ = 18,664) = 178.33, $p < 0.001$.

# 6 | DISCUSSION AND IMPLICATIONS

*RQ1*: *Tactics and Strategies Detection*. The analysis of students' learning sessions using the SRL lens and LA techniques produced distinctive learning tactics and strategies reflecting the course design across three different courses. This confirms previous research findings on different learning settings (Matcha et al., 2020).

On the tactic level, the results demonstrated that the detected tactics were different in the average length of the tactic and the focus of students' activities comprising that tactic. The consistency in length and focus of sessions within some tactics indicates that the students logged in to the platform with predefined goals to achieve specific tasks. For instance, students might dedicate their sessions to performing only activities required to achieve the whole or part of a scheduled assessment. Tactics with a length shorter than the required number of activities to accomplish a weekly assessment are examples of tactics used to achieve only part of the assessment (e.g., *short creation* and *single moderation*). Tactics with an average length equal to or slightly longer than the required number of activities to achieve a weekly assessment are examples of tactics used to complete the whole assessment in one session (e.g., *long moderation—creation first*). Another example of tactics associated with a predefined goal is the *long practice focus* tactic in the Human Biosciences course and the *practice focus* in the Brain and Behavioural Sciences course. The purpose of these tactics could be to self-test, digest, or review learned topics. This observation is aligned with self-regulated learning as a means of learning tactic where goal orientation is a key characteristic (Winne & Marzouk, 2019).

TABLE 5 Strategy groups by successful and unsuccessful practices for the Human and Biosciences course

| | | Strategies | | | | |
|---|---|---|---|---|---|---|
| | | Intensive | Comprehensive | Random practice | Inactive | Total |
| Successful practice | Observed | 1,186 | 554 | 17,275 | 6,555 | 25,570 |
| | Expected | 1,097.7 | 465.3 | 17,055.9 | 6,951.1 | 25,570 |
| | % of total | 3.1 | 1.5 | 45.5 | 17.3 | 67.3 |
| | Residual (Std.) | 2.7 (4.8) | 4.1 (7.2) | 1.7 (5) | −4.8 (−9.7) | – |
| Unsuccessful practice | Observed | 444 | 137 | 8,052 | 3,767 | 12,400 |
| | Expected | 532.3 | 225.6 | 8,271.1 | 3,370.9 | 12,400 |
| | % of total | 1.2 | 0.4 | 21.2 | 9.9 | 32.7 |
| | Residual (Std.) | −3.8 (−4.7) | −5.9 (−7.2) | −2.4 (−5) | 6.8 (9.7) | – |
| Total activities | | 1,630 | 691 | 25,327 | 10,322 | 37,970 |

TABLE 6 Strategy groups by successful and unsuccessful practices for the Brain and Behavioural Sciences

| | | Strategies | | | | |
|---|---|---|---|---|---|---|
| | | Intensive | Comprehensive | Assessment oriented | Strategic | Total |
| Successful practice | Observed | 7,074 | 6,141 | 2,349 | 5,777 | 21,341 |
| | Expected | 6,508.4 | 6,278.7 | 2,487.5 | 6,066.4 | 21,341 |
| | % of total | 22.3 | 19.4 | 7.4 | 18.2 | |
| | Residual (Std.) | 7 (14.7) | −1.7 (−3.6) | −2.8 (−5.2) | −3.7 (−7.7) | – |
| Unsuccessful practice | Observed | 2,586 | 3,178 | 1,343 | 3,227 | 10,334 |
| | Expected | 3,151.6 | 3,040.3 | 1,204.5 | 2,937.6 | 10,334 |
| | % of total | 8.2 | 10 | 4.2 | 10.2 | 37 |
| | Residual (Std.) | −10.1 (−14.7) | 2.5(3.6) | 4 (5.2) | 5.3 (7.7) | – |
| Total activities | | 9,660 | 9,319 | 3,692 | 9,004 | 31,675 |

On the course level, the results indicated that the tactics were highly distinctive across the three courses. The substantial variation can be seen in the average length of the tactics and the tactics' overall focus, as demonstrated in Figure 4. In particular, the focus of the Human Biosciences course was on the practice activities with long sessions, while the focus of the Second Language Acquisition course was on the learnersourcing activities with short sessions. Differing from both, the Brain and Behavioural Sciences course tactics' focus appears to be on both learnersourcing and practice activities with medium length (Figure 4). Nevertheless, similar patterns were observed across the three courses. First, the Bioscience course and the Brain and Behavioural Sciences course shared similar patterns among their *short/long mix* and *long/practice* tactics. Second, the Second Language Acquisition course and Brain and Behavioural Sciences also shared similar patterns between their *short creation* tactics and their *long/moderation focus—creation first* tactics (see Figure 4). Again, these tactics might differ from each other in terms of their average length. The differences between the tactics are evident that the role of course design in determining how students use the learning platform is crucial.

The results further showed that the detected strategy groups differed in the engagement level and dominant tactic per week across the three courses. The analysis of the courses that tied RiPPLE to their course assessment demonstrated that the learning strategies complied with the assessment design. In the Second Language Acquisition course, the strategy groups used only learnersourcing tactics which appeared to focus on the course's assessment requirements (see Figure 5). In the Brain and Behavioural Sciences course where students applied various tactics, the strategy groups showed that the students were on track with their weekly assessments as the learnersourcing tactics were dominant in most of the strategies and used at a roughly constant rate every week (see Figure 5).

In previous studies (Jovanović et al., 2017; Matcha et al., 2020), the detected learning strategies were linked to well-defined learning approaches (Entwistle et al., 2001): (1) surface approach to learning focusing on the assessment achievement with a low level of knowledge gain, (2) deep approach to learning used to take advantage of all available learning resources to gain a deep understanding and (3) strategic approach to learning combining the surface and deep learning approaches to obtain high achievement with minimum effort. In those studies, the data were collected from learning platforms in which students were provided with the primary learning resources. Thus, linking students' behaviour in this context to the learning approaches was appropriate. In contrast, in the presented study, RiPPLE was not the primary source of learning; instead, it contained one fragment of the learning resources. However, we believe the detected learning strategies can be used as an indicator of using the learning approaches.

For instance, the high level of engagement observed in the *intensive*, *comprehensive* groups in the Human and Biosciences course might indicate applying the deep learning approach since students used optional learning resources. In the Brain and Behavioural Sciences course, the *intensive* and *comprehensive* groups used the platform beyond expected, suggesting that these two groups might have applied the deep learning approach throughout their learning journey. In the meantime, some strategy groups might indicate the use of the strategic approach as the students in these groups increased or decreased the use of some tactics based on a given situation (e.g., module quiz). In the Second Language Acquisition course, the *strategic* group is an example, and in the Brain and Behavioural Sciences course, all the groups could indicate the use of this approach. Nonetheless, the *assessment oriented* group might indicate the surface approach as well.

In the Human and Biosciences course, we observed the common participation inequality phenomenon (Nielsen, 2006) where about 90% of users are lurkers meaning that they do not contribute but instead observe others' contributions. Among the remaining 10%, 9% of users have some contributions, and only 1% account for most contributions. This 90-9-1 rule was observed in the large imbalance sizes of the strategy groups (6,6,170, 436). However, this rule was not observed in the other courses. We posit that the assessment design might contribute to this substantial difference since the assessments tied to the platform in the other two courses provided the students with extrinsic motivation.

The present findings add to the line of research mentioned in Section 2.3 regarding integrating learning design and LA by suggesting that in the context of learnersourcing as an assessment tool, LA can be used to reflect some related and unrelated aspects of the learning design since sequences of assessment tasks can be considered as an integral part of the learning design (Shen et al., 2020), while the course or the learning design plays a crucial role in determining the use of the learnersourcing platform.

With respect to the Second Language Acquisition and the Brain and Behavioural Sciences, the effects of the assessment design can be noted in Figures 4, 5 and 6, which clearly show that two courses from different arts/sciences generated different learning patterns, although the platform was intended to be used to some extent similarly. In the Brain and Behavioural Sciences course, in contrast to the Second Language Acquisition course, it is apparent that the strategy groups used a verity of tactics, and within each group, the tactics' use rate per week was steadier. By looking at some aspects of the two courses' learning designs (i.e., RiPPLE assessment; see Section 4.2), we can see how the course designs were associated with the behavioural patterns as tactics and strategies. Students in the former were encouraged to attempt MCQs on the platform and were given the opportunity to use RiPPLE in the second hour of the lecture. On the contrary, students in the latter were not encouraged to attempt MCQs on the platform nor given a portion of the lecture time to do so. In addition, the types of resources used in both courses were different. In the Brain and Behavioural Sciences course, students were instructed to create different types of resources, yet most students created MCQs. In contrast, in the Second Language Acquisition course, students were required to develop reflections based on the lecture topics as notes.

Unrelated aspect of the learning design can be seen when the student in the Brain and Behavioural Sciences course used the platform in the weeks of the module quizzes. It can also be seen in the Second Language Acquisition course when a drop in the platform occurred during the week of an essay assessment. Besides, it is important to note that the differences in the course levels (i.e., graduate and undergraduate) might have played a substantial role in shaping the tactics and strategies and determining the level of SRL (Artino & Stephens, 2009; Cao, 2012; Park & Yun, 2018; Yun et al., 2020). Hence, it is important to compare large data of different course levels in future research.

*RQ2*: *Association between learning strategies and students' performance on the platform*. The results showed that the detected learning strategies were statistically associated with the practice activity outcomes but with negligible effect size. The negligible effect size of the models can be attributed to the adaptive nature of RiPPLE. Hence, we believe the relationships we found are still meaningful.

In general, across the two courses analysed, the strategy groups that could indicate the strategic or surface learning approaches were associated the most with the practice's negative outcomes, while the strategy groups that could indicate the deep approach to learning were associated the most with the practice's positive outcomes. These results support our assumption (see discussion on RQ1) that the identified strategy groups on RiPPLE can be used as an indicator of the approach to learning that students used outside RiPPLE since previous studies found a positive association between learning strategies that indicate learning approaches and students' academic performance (Matcha et al., 2020).

*Implications*. This study's findings have important implications for learning assisted tool developers, educational researchers, instructors, and students. For learning tool developers, as the learning tactics and strategies are distinctive across different courses, developers might consider designing the tools flexibly, enabling instructors to present the tasks differently. The developers can also consider adding a visualization of the tactics and strategies to assist the instructors in identifying tactics and strategies that students use. Meanwhile, learning strategies and tactics in adaptive learning systems might provide contextual recommendations. For instructors, the design of the assessments can be informed based on learning tactics and strategies detected in the course's past offering. For students, if learning strategies and tactics were provided on the learning platform, students can use them to regulate their learning, especially if they compare their behaviours with their peers or see the association between different strategies and performance. For educational researchers, the finding can open new opportunities to investigate how training students using learning tactics and strategies can improve learners' learning outcomes of learnersourcing activities.

*Limitations*. Since learnersourcing activities require students to engage in higher-order thinking (Lee & Choi, 2017), the tasks they performed might encapsulate sub-learning sequences that must have been performed offline or on other learning sources (e.g., learning management systems) and could not be captured. Additionally, the system did not record activities that did not have outcomes, such as viewing a resource of type "note". So, in the case of the Second Language Acquisition course, students might have used the resources created by their peers on the platform to review or study the course topics. The second limitation is that determining the session's threshold accurately is not possible by either data-driven or domain knowledge approaches. The last limitation is that the presented study used unsupervised machine learning algorithms that require choosing the number of clusters using subjective methods such as examining the dendrogram. Also, these algorithms' results depend largely on the method used to construct the dissimilarity matrix.

## 7 | CONCLUSION AND FUTURE WORK

We employed a novel methodology from the field of LA used to identify self-regulated learning hidden constructs in the forms of tactics and strategies to unveil students' actual learning process to perform instructional tasks on a learnersourcing platform across three courses from different fields. The study's findings provide a novel insight into how students behave in learnersourcing environments and how their behaviours affect their performance in this environment. We identified discrepant learning tactics and strategies within and across the three courses. The learning strategies were statistically significantly associated with the students' performance in the learnersourcing environment. The findings support the generalizability of using this methodology across different contexts (Matcha et al., 2020), and this possibly can suggest the potential of the transferability of the methodology across different domains. Lastly, the findings highlight the dependency between the course and assessment designs and how students behave on educational platforms supporting the potential of the alignment between learning design and LA.

The future direction of this work is to examine whether a feedback-loop based on students' strategies on learnersourcing platforms would improve the quality of their contribution and their learning gain and whether the insight provided by the strategies could support the educators in learning design decision making. In our future work, we will consider using validated survey-instruments to measure students' SRL levels before and after any intervention and consider possible confounders such as personality traits and demographic differences. Finally, we would like to see whether the strategies can be used to improve the personalized learning experience in RiPPLE.

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### CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

### PEER REVIEW

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### DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

### ETHICS STATEMENT

Approval from our Human Research Ethics Committee #2018000125 was received for conducting this study.

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### REFERENCES

Agresti, A. (2007). Contingency tables. In *An introduction to categorical data analysis* (pp. 21–64). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470114759.ch2

Arruabarrena, R., Sánchez, A., Blanco, J. M., Vadillo, J. A., & Usandizaga, I. (2019). Integration of good practices of active methodologies with the reuse of student-generated content. *International Journal of Educational Technology in Higher Education*, *16*(1), 10. https://doi.org/10.1186/s41239-019-0140-7

Artino, A. R., & Stephens, J. M. (2009). Academic motivation and self-regulation: A comparative analysis of undergraduate and graduate students learning online. *The Internet and Higher Education*, *12*(3), 146–151. https://doi.org/10.1016/j.iheduc.2009.02.001

Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. In *Proceedings of the sixth international conference on Learning Analytics & Knowledge – LAK'16* (pp. 329–338). ACM Press. https://doi.org/10.1145/2883851.2883944

Bates, S. P., Galloway, R. K., Homer, D., & Riise, J. (2014). Assessing the quality of a student-generated question repository. *Physical Review Special Topics – Physics Education Research*, *10*(2), 020105.

Bhatnagar, S., Zouaq, A., Desmarais, M. C., & Charles, E. (2020). Learnersourcing quality assessment of explanations for peer instruction. In *Lecture notes in computer science: Vol. 12315. Addressing global challenges and quality education* (pp. 144–157). Springer International Publishing.

Cao, L. (2012). Differences in procrastination and motivation between undergraduate and graduate students. *Journal of the Scholarship of Teaching and Learning*, *12*(2), 39–64.

de Alfaro, L., & Shavlovsky, M. (2014). CrowdGrader: A tool for crowdsourcing the evaluation of homework assignments. In *Proceedings of the 45th ACM Technical Symposium on Computer Science Education* (pp. 415–420). Association for Computing Machinery. https://doi.org/10.1145/2538862.2538900

Denny, P., Hamer, J., Luxton-Reilly, A., & Purchase, H. (2008). PeerWise: Students sharing their multiple choice questions. In *Proceedings of the Fourth International Workshop on Computing Education Research* (pp. 51–58). Association for Computing Machinery. https://doi.org/10.1145/1404520.1404526

Denny, P., Luxton-Reilly, A., & Hamer, J. (2008). The PeerWise system of student contributed assessment questions. In *Proceedings of the Tenth Conference on Australasian Computing Education – Volume 78* (pp. 69–74). Australian Computer Society, Inc.

Denny, P., Luxton-Reilly, A., & Simon, B. (2009). Quality of student contributed questions using PeerWise. In *Computing Education 2009: Proceedings of the Eleventh Australasian Computing Education Conference (ACE 2009), Wellington, New Zealand, January 2009* (Vol. 95, pp. 55–63). Australian Computer Society, Inc.

Derry, S. J. (1990). Learning strategies for acquiring useful knowledge. In *Dimensions of Thinking and Cognitive Instruction* (pp. 347–379). Hillsdale, NJ: Lawrence Erlbaum. https://doi.org/10.4324/9780203771686-15

Edelson, D. C., Gordin, D. N., & Pea, R. D. (1999). Addressing the challenges of inquiry-based learning through technology and curriculum design. *The Journal of the Learning Sciences*, *8*(3–4), 391–450.

Entwistle, N., McCune, V., & Walker, P. (2001). Conceptions, styles, and approaches within higher education: Analytic abstractions and everyday experience. In *Perspectives on thinking, learning, and cognitive styles* (pp. 103–136). Routledge.

Fincham, E., Gašević, D., Jovanović, J., & Pardo, A. (2019). From study tactics to learning strategies: An analytical method for extracting interpretable representations. *IEEE Transactions on Learning Technologies*, *12*(1), 59–72. https://doi.org/10.1109/TLT.2018.2823317

Gabadinho, A., Ritschard, G., Mueller, N. S., & Studer, M. (2011). Analyzing and visualizing state sequences in R with TraMineR. *Journal of Statistical Software*, *40*(4), 1–37. https://doi.org/10.18637/jss.v040.i04

Galloway, K. W., & Burns, S. (2015). Doing it for themselves: Students creating a high quality peer-learning environment. *Chemistry Education Research and Practice*, *16*(1), 82–92.

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002

Gatta, R., Lenkowicz, J., Vallati, M., Rojas, E., Damiani, A., Sacchi, L., Bari, B., Dagliati, A., Fernandez-Llatas, C., Montesi, M., Marchetti, A., Castellano, M., & Valentini, V. (2017). pMineR: An innovative R library for performing process mining in medicine. In A. ten Teije, C. Popow, J. H. Holmes, & L. Sacchi (Eds.), *Artificial Intelligence in Medicine* (pp. 351–355). Springer International Publishing. https://doi.org/10.1007/978-3-319-59758-4_42

Glassman, E. L., Lin, A., Cai, C. J., & Miller, R. C. (2016). Learnersourcing personalized hints. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (pp. 1626–1636). Association for Computing Machinery. https://doi.org/10.1145/2818048.2820011

Guo, P., Markel, J., & Zhang, X. (2020). Learnersourcing at scale to overcome expert blind spots for introductory programming: A three-year deployment study on the python tutor website. In *L@S 2020 – Proceedings of the 7th ACM Conference on Learning @ Scale* (pp. 301–304). ACM.

Hamer, J., Hamer, J., & Cutts, Q. (2008). Contributing student. *Pedagogy*, *40*(4), 19–212.

Hills, T. T. (2015). Crowdsourcing content creation in the classroom. *Journal of Computing in Higher Education*, *27*(1), 47–67. https://doi.org/10.1007/s12528-015-9089-2

Nielsen, J. (2006). Participation Inequality: Encouraging More Users to Contribute. Retrieved from https://www.nngroup.com/articles/participation-inequality/

Jovanović, J., Gašević, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *The Internet and Higher Education*, *33*, 74–85. https://doi.org/10.1016/j.iheduc.2017.02.001

Khosravi, H., Kitto, K., & Williams, J. J. (2019). RiPPLE: A crowdsourced adaptive platform for recommendation of learning activities. *ArXiv:1910.05522 [Cs]*. Retrieved from http://arxiv.org/abs/1910.05522

Khosravi, H., Sadiq, S., & Gasevic, D. (2020). Development and adoption of an adaptive learning system: Reflections and lessons learned. In *Proceedings of the 51st ACM Technical Symposium on Computer Science Education* (pp. 58–64). Association for Computing Machinery. https://doi.org/10.1145/3328778.3366900

Kim, J. (2015). *Learnersourcing: Improving learning with collective learner activity* (Thesis, Massachusetts Institute of Technology). Retrieved from https://dspace.mit.edu/handle/1721.1/101464

Kitto, K., Whitmer, J., Silvers, A. E., & Webb, M. (2020). *Creating Data for Learning Analytics Ecosystems* (p. 43). [Technical Report]. Society for Learning Analytics Research (SoLAR) Retrieved from https://www.solaresearch.org/wp-content/uploads/2020/09/SoLAR_Position-Paper_2020_09.pdf

Lambert, N. M., & McCombs, B. L. (1998). *How students learn: Reforming schools through learner-centered education*. American Psychological Association.

Langley, A., & Tsoukas, H. (2010). Introducing "Perspectives on Process Organization Studies". In T. Hernes & S. Maitlis (Eds.), *Process, sensemaking, and organizing* (pp. 1–26). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199594566.003.0001

Langley, A., Smallman, C., Tsoukas, H., & Van de Ven, A. H. (2013). Process studies of change in organization and management: Unveiling temporality, activity, and flow. *The Academy of Management Journal*, *56*(1), 1–13.

Lee, J., & Choi, H. (2017). What affects learner's higher-order thinking in technology-enhanced learning environments? The effects of learner factors. *Computers & Education*, *115*, 143–152. https://doi.org/10.1016/j.compedu.2017.06.015

Lockyer, L., & Dawson, S. (2011). Learning designs and learning analytics. In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 153–156). Association for Computing Machinery. https://doi.org/10.1145/2090116.2090140

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist*, *57*(10), 1439–1459. https://doi.org/10.1177/0002764213479367

Lodge, J. M., & Corrin, L. (2017). What data and analytics can and do say about effective learning. *npj Science of Learning*, *2*(1), 1–2. https://doi.org/10.1038/s41539-017-0006-5

Luxton-Reilly, A., Bertinshaw, D., Denny, P., Plimmer, B., & Sheehan, R. (2012). The impact of question generation activities on performance. In *Proceedings of the 43rd ACM Technical Symposium on Computer Science Education* (pp. 391–396). ACM.

Macfadyen, L. P., Lockyer, L., & Rienties, B. (2020). Learning design and learning analytics: Snapshot 2020. *Journal of Learning Analytics*, *7*(3), 6–12. https://doi.org/10.18608/jla.2020.73.2

Mangaroska, K., & Giannakos, M. (2019). Learning analytics for learning design: A systematic literature review of analytics-driven design to enhance learning. *IEEE Transactions on Learning Technologies*, *12*(4), 516–534. https://doi.org/10.1109/TLT.2018.2868673

Matcha, W., Gašević, D., Uzir, N. A., Jovanović, J., Pardo, A., Maldonado-Mahauad, J., & Pérez-Sanagustín, M. (2019). Detection of learning strategies: A comparison of process, sequence and network analytic approaches. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming learning with meaningful technologies* (pp. 525–540). Springer International Publishing. https://doi.org/10.1007/978-3-030-29736-7_39

Matcha, W., Gašević, D., Uzir, N. A., Jovanović, J., & Pardo, A. (2019). Analytics of learning strategies: Associations with academic performance and feedback. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (pp. 461–470). ACM. https://doi.org/10.1145/3303772.3303787

Matcha, W., Gašević, D., Uzir, N. A., Jovanović, J., Pardo, A., Lim, L., Maldonado-Mahauad, J., Gentili, S., Pérez-Sanagustín, M., & Tsai, Y.-S.

(2020). Analytics of learning strategies: Role of course design and delivery modality. *Journal of Learning Analytics*, *7*(2), 45–71. https://doi.org/10.18608/jla.2020.72.3

Matthews, K. E. (2017). Five propositions for genuine students as partners practice. *International Journal for Students as Partners*, *1*(2), 1–9. https://doi.org/10.15173/ijsap.v1i2.3315

McKeachie, W. J. (1988). 1—The need for study strategy training. In C. E. Weinstein, E. T. Goetz, & P. A. Alexander (Eds.), *Learning and study strategies* (pp. 3–9). Academic Press. https://doi.org/10.1016/B978-0-12-742460-6.50007-4

Moore, S., Nguyen, H. A., & Stamper, J. (2020). Evaluating crowdsourcing and topic modeling in generating knowledge components from explanations. In *Lecture Notes in Computer Science: Vol. 12163. Artificial Intelligence in Education* (pp. 398–410). Springer International Publishing.

Murphy, P. K., & Knight, S. L. (2016). Exploring a century of advancements in the science of learning. *Review of Research in Education*, *40*(1), 402–456. https://doi.org/10.3102/0091732X16677020

Nguyen, Q., Huptych, M., & Rienties, B. (2018). Using temporal analytics to detect inconsistencies between learning design and students' behaviours. *Journal of Learning Analytics*, *5*(3), 120–135. https://doi.org/10.18608/jla.2018.53.8

Nguyen, Q., Rienties, B., & Toetenel, L. (2017a). Mixing and matching learning design and learning analytics. In *Lecture notes in computer science. Learning and collaboration technologies. Technology in Education* (pp. 302–316). Springer International Publishing.

Nguyen, Q., Rienties, B., & Toetenel, L. (2017b). Unravelling the dynamics of instructional practice: A longitudinal study on learning design and VLE activities. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 168–177). Association for Computing Machinery. https://doi.org/10.1145/3027385.3027409

Paré, D. E., & Joordens, S. (2008). Peering into large lectures: Examining peer and expert mark agreement using peerScholar, an online peer assessment tool. *Journal of Computer Assisted Learning*, *24*(6), 526–540.

Park, S., & Yun, H. (2018). The influence of motivational regulation strategies on online Students' behavioral, emotional, and cognitive engagement. *American Journal of Distance Education*, *32*(1), 43–56. https://doi.org/10.1080/08923647.2018.1412738

Pressley, M., Woloshyn, V., Lysynchuk, L. M., Martin, V., Wood, E., & Willoughby, T. (1990). A primer of research on cognitive strategy instruction: The important issues and how to address them. *Educational Psychology Review*, *2*(1), 1–58. https://doi.org/10.1007/BF01323528

Prester, J., Schlagwein, D., & Cecez-Kecmanovic, D. (2020). *Crowdsourcing for education: Literature review, conceptual framework, and research agenda*. Scopus.

Purchase, H., & Hamer, J. (2018). Peer-review in practice: Eight years of Aropä. *Assessment and Evaluation in Higher Education*, *43*(7), 1146–1165.

Purchase, H., Hamer, J., Denny, P., & Luxton-Reilly, A. (2010). The quality of a PeerWise MCQ repository. In *Conferences in Research and Practice in Information Technology Series* (Vol. 103, pp. 137–146). Australian Computer Society, Inc.

Rienties, B., & Toetenel, L. (2016). The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior*, *60*, 333–341. https://doi.org/10.1016/j.chb.2016.02.074

Rienties, B., Toetenel, L., & Bryan, A. (2015). "Scaling up" learning design: Impact of learning design activities on LMS behavior and performance. In *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 315–319). Association for Computing Machinery. https://doi.org/10.1145/2723576.2723600

Romero, C., & Ventura, S. (2013). Data mining in education. *WIREs Data Mining and Knowledge Discovery*, *3*(1), 12–27. https://doi.org/10.1002/widm.1075

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *WIREs Data Mining and Knowledge Discovery*, *10*(3), e1355. https://doi.org/10.1002/widm.1355

Schmitz, M., van Limbeek, E., Greller, W., Sloep, P., & Drachsler, H. (2017). Opportunities and challenges in using learning analytics in learning design. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data driven approaches in digital education* (pp. 209–223). Springer International Publishing.

Schraw, G., & Moshman, D. (1995). Metacognitive theories. *Educational Psychology Review*, *7*(4), 351–371. https://doi.org/10.1007/BF02212307

Schunk, D. H. (2012). *Learning theories: An educational perspective* (6th ed.). Pearson Retrieved from https://books.google.com.au/books?id=FZq4cQAACAAJ

Shen, H., Liang, L., Law, N., Hemberg, E., & O'Reilly, U.-M. (2020). Understanding learner behavior through learning design informed learning analytics. In *Proceedings of the Seventh ACM Conference on Learning @ Scale* (pp. 135–145). Association for Computing Machinery. https://doi.org/10.1145/3386527.3405919

Shnayder, V., & Parkes, D. (2016). Practical peer prediction for peer assessment. *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, *4*(1), 199–208.

Uzir, N. A., Gašević, D., Matcha, W., Jovanović, J., & Pardo, A. (2020). Analytics of time management strategies in a flipped classroom. *Journal of Computer Assisted Learning*, *36*(1), 70–88. https://doi.org/10.1111/jcal.12392

Wang, X., Talluri, S. T., Rose, C., & Koedinger, K. (2019). UpGrade: Sourcing student open-ended solutions to create scalable learning opportunities. In *Proceedings of the Sixth (2019) ACM Conference on Learning @ Scale* (pp. 1–10). Association for Computing Machinery. https://doi.org/10.1145/3330430.3333614

Weinstein, C. E., Husman, J., & Dierking, D. R. (2000). Chapter 22—Self-regulation interventions with a focus on learning strategies. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 727–747). Academic Press. https://doi.org/10.1016/B978-012109890-2/50051-2

Weir, S., Kim, J., Gajos, K., & Miller, R. (2015). Learnersourcing subgoal labels for how-to videos. In *CSCW 2015 – Proceedings of the 2015 ACM International Conference on Computer-Supported Cooperative Work and Social Computing* (pp. 405–416). ACM.

Williams, J. J., Kim, J., Rafferty, A., Maldonado, S., Gajos, K. Z., Lasecki, W. S., & Heffernan, N. (2016). AXIS: Generating explanations at scale with learnersourcing and machine learning. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale* (pp. 379–388). Association for Computing Machinery. https://doi.org/10.1145/2876034.2876042

Wind, D. K., Jørgensen, R. M., & Hansen, S. L. (2018). Peer feedback with peergrade. In *International Conference on E-Learning, 2018* (pp. 184–192). Academic Conferences International Limited.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In *The educational psychology series. Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates Publishers.

Winne, P. H., & Marzouk, Z. (2019). Learning strategies and self-regulated learning. In J. Dunlosky & K. A. Rawson (Eds.), *The Cambridge handbook of cognition and education* (1st ed., pp. 696–715). Cambridge University Press. https://doi.org/10.1017/9781108235631.028

Wong, J., Baars, M., de Koning, B. B., van der Zee, T., Davis, D., Khalil, M., Houben, G. J., & Paas, F. (2019). Educational theories and learning analytics: From data to knowledge. In D. Ifenthaler, D.-K. Mah, & J. Y.-K. Yau (Eds.), *Utilizing learning analytics to support study success* (pp. 3–25). Springer International Publishing. https://doi.org/10.1007/978-3-319-64792-0_1

Wright, J., Thornton, C., & Leyton-Brown, K. (2015). Mechanical TA: Partially automated high-stakes peer grading. In *Proceedings of the 46th ACM Technical Symposium on Computer Science Education* (pp. 96–101). ACM.

Yang, X., Guo, X., & Yu, S. (2016). Student-generated content in college teaching: Content quality, behavioural pattern and learning performance. *Journal of Computer Assisted Learning*, *32*(1), 1–15. https://doi.org/10.1111/jcal.12111

Yun, H., Park, S., Kim, D., Jung, E., & Yoon, M. (2020). The influence of academic level and course delivery mode on the use of motivational regulation strategies and learning engagement. *Australasian Journal of Educational Technology*, *36*(3), 89–103. https://doi.org/10.14742/ajet.5879

Zimmerman, B. J. (2000). Chapter 2—Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

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