Transferring effective learning strategies across learning contexts matters: A study in problem-based learning

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Learning strategies are important catalysts of students' learning. Research has shown that students with effective learning strategies are more likely to have better academic achievement. This study aimed to investigate students' adoption of learning strategies in different course implementations, the transfer of learning strategies between courses and relationship to performance. We took advantage of recent advances in learning analytics methods, namely sequence and process mining as well as statistical methods and visualisations to study how students regulate their online learning through learning strategies. The study included 81,739 log traces of students' learning related activities from two different problem-based learning medical courses. The results revealed that students who applied deep learning strategies were more likely to score high grades, and students who applied surface learning strategies were more likely to score lower grades in either course. More importantly, students who were able to transfer deep learning strategies or continue to use effective strategies between courses obtained higher scores, and were less likely to adopt surface strategies in the subsequent course. These results highlight the need for supporting the development of effective learning strategies in problem-based learning curricula so that students adopt and transfer effective strategies as they advance through the programme.

Implications for practice or policy:
- Teachers need to help students develop and transfer deep learning as they are directly related to success.
- Students who continue to use light strategies are more at risk of low achievement and need to be supported.
- Technology-supported problem-based learning requires more active scaffolding and teachers' support beyond "guide on the side" as in face-to-face.

Keywords: learning strategies, problem-based learning (PBL), learning analytics, sequence mining, process mining

Introduction

Problem-based learning (PBL) originated in the Health Sciences Centre at McMaster university in Canada in 1969 as the McMaster Philosophy (Servant-Miklos, 2019). Since then, the approach has gained increasing adoption within medical education as well as other disciplines, for example, economics, philosophy and law (Hmelo-Silver, 2004). PBL can be considered a form of collaborative learning where students work in small groups on problems (Yew & Goh; 2016). These problems are typically ill structured and mimic real-life scenarios (Albanese & Dast, 2014; Hmelo-Silver, 2004; Taylor & Miflin, 2008). The problems are supposed to act as triggers for the PBL process. Students are supposed to meet with a teacher – often referred to as a tutor – to read the problem, identify relevant knowledge and generate hypotheses about possible solutions (Albanese & Dast, 2014; Schmidt, 1983). Analysing the problem helps students identify their knowledge limitations and what they need to learn. Teachers act as facilitators to guide students through the group meetings. Then, students are supposed to work independently, in a self-directed manner, to achieve their learning goals. By the end of the week, students have to meet to discuss what they have learned, reflect on the process and give feedback to each other (Hmelo-Silver, 2004; Savery & Duffy, 1995; Schmidt, 1983).

Compared to traditional forms of learning, PBL may enhance medical students' ability to transfer knowledge to new problems and to achieve a more coherent understanding (Hmelo-Silver; 2004; Schmidt, 1983). PBL aims to foster self-directedness and medical students' responsibility for their own learning, to take the initiative in deciding what and how to learn with or without the help of teachers and to implement appropriate learning strategies towards the achievement of their learning goals (Loyens et al., 2008). As PBL adoption has grown, several implementations of PBL have also emerged that vary from the aforementioned process (Taylor & Miflin, 2008). One of the major changes is the inclusion of technology to facilitate or support the implementation of PBL.

Using online technologies, for example, online discussion forums to deliver PBL, affords learners a media-rich platform that allows PBL scenarios to be closer to reality. More importantly, technology helps students communicate, build communities and extend their knowledge and understanding through the multiplicity of opinions. Since contributions are permanent, students can repeatedly access information, search for solutions and re-iterate through difficult problems. Various types of technologies are being integrated into PBL in order to support learning, enhance the learning experience, improve learning quality and encourage the learning engagement, such as virtual reality (VR), mixed reality (MR) and augmented reality (AR). VR, MR and AR are considered as emerging technologies that enhance the learning by integrating virtual objects such as 3D models, audio, video and other types of interactive multimedia (Abdulllah et al., 2019). Research has examined how such technologies can enhance learning experiences and quality of learning. For instance, Fidan and Tuncel (2019) implemented an AR application to support PBL. Based on their quasi-experiment, they found that integrating AR to support learning design based on PBL improved the students' learning performance. The most common and well-known technology-integrated learning is the use of massive open online courses, distance learning and online learning. It has been reported that using asynchronous online learning enables students to participate in learning activities at their own pace and time (Taradi et al. 2005). Overall, technology-supported PBL seems to be as effective as face-to-face PBL regarding knowledge outcome and may offer better results in terms of knowledge acquisition and potential improvement in attainment of skills (Tudor Car et al., 2019).

However, online learning – including technology-supported PBL – has its own affordances and constraints that require students to have effective learning strategies. Such strategies are increasingly needed with the growing use of technology-enhanced learning, which is rather demanding (Greene et al., 2011). Online learning requires students to have technological skills, learn independently and navigate through large amounts of information on their own (Bond et al., 2020). Furthermore, online learning requires students to manage their time efficiently, prioritise their learning and manage distractions. It lacks the classroom social interactions with the peers and the teacher, and therefore, students may suffer from isolation or feel unmotivated to engage in meaningful learning activities (Martin & Borup, 2022). The lack of easy interaction – compared to the classroom – guidance and scaffolding by teachers may also add to the difficulties that online learning incurs on students.

Learning strategies

Three types of learning strategies are often recognised (Dolmans et al., 2016; Hattie & Donoghue, 2016):

- *Surface learning strategies* are related to acquiring knowledge, memorising and fulfilling the requirement of the task.
- *Deep learning strategies* are more concerned with deeper understanding, analysis, critical thinking, holistic processing and linking information to previous knowledge. To acquire deep learning strategies, students may go through surface strategies and oftentimes use both strategies together to approach their learning (Hattie & Donoghue, 2016).
- A third type of strategy that is increasingly recognised is *transfer strategies*, which reflects on how a learner can adjust strategies between different contexts, that is, develop autonomous skills for independent functioning and learning (Hattie & Donoghue, 2016).

Students with effective learning strategies are able to set learning goals based on their awareness of what they have learned and what they need to learn, to monitor learning and learning achievement, to evaluate their learning processes and to use and adjust – that is , transfer – their learning strategies into new contexts (Sandars & Cleary, 2011; Saqr et al., 2023; Stegers-Jager et al., 2012). Efficient students can – and always – use the three types of learning strategies according to their learning needs with no strict order. As such, students may start learning with surface strategies, build on previous learning, connect complex ideas and progress to deep learning and transfer such approach to new problems. Research has shown that students who use deep learning strategies are more likely to have better academic achievement; have better skills managing their learning resources, time, and effort; and consequently are more likely to graduate and assume their professional roles (Hattie & Donoghue, 2016; Stegers-Jager et al., 2012).

Although learning strategies are of paramount importance to the success of learners, many current implementations of PBL do not emphasise the development of effective learning strategies but rather aim to enhance active, self-directed learning and intrinsic motivation, which in turn promote deeper learning (Loyens et al., 2008). A literature review of existing research has found that PBL implementations have produced a mixed effect on the development of deep learning strategies (Dolmans et al., 2016). Thereupon, prominent scholars have called for incorporating self-regulating learning strategies in teaching and learning (Sandars & Cleary, 2011). As Sandars and Cleary (p. 875) put it “self-regulation theory offers an exciting potential for improving academic and clinical performance in medical education”.

Traditional educational research gathers the information on students’ learning strategies by using self-report instruments such as questionnaires. Zhou et al. (2012) and Gašević et al. (2017) argued that questionnaires reflect the intention of using learning strategies rather than the actual use. Technology-supported PBL enables automatic recording of the actual learning actions performed by students while interacting with the learning materials (Srivastava et al., 2022; Zhou et al., 2012). However, such data is immense and unstructured. Hence, it requires learning analytics techniques to extract the insights from log data.

Learning analytics

Research in medical education have harnessed the potentials of learning analytics to predict under-achievers (e.g., Saqr et al., 2017), study the factors behind the success of technology-supported PBL (e.g., Saqr et al., 2020; Saqr & Viberg, 2020) or evaluate students’ approach to online video lectures (e.g., Lau et al., 2018). However, few studies in medical education, if any, have harnessed the potentials of novel methods – such as process and sequence mining (discussed below) – that enable the study of learning as a process. Studying the learning process offers window to the the temporal and sequential aspects of the "when" and "what" actions students are performing, and therefore, these methods have been used to mine students' learning strategies (Ahmad Uzir et al., 2020; López-Pernas et al., 2021).

Sequence mining is concerned with the analysis of temporally ordered data such as students' online activities, offering a rich toolset for representing, visualising and finding the patterns in students' data (Romero & Ventura, 2020). More importantly, sequence mining can be integrated with other methods such as clustering. Combining clustering with sequence mining offers a method for finding patterns within the data based on their temporal and sequential similarities, which is particularly useful for analysing students' learning that unfolds in time. A rising number of studies have harnessed this combination – that is, sequence mining and clustering – to discover subgroups of distinct behaviour that could be considered as manifestations of students' learning tactics and strategies (Ahmad Uzir et al., 2020; López-Pernas & Saqr, 2021; Saqr & López-Pernas, 2021).

Process mining is a relatively new method for discovering, mapping and visualising a process, for example, processes that underlie students' learning strategies. Process mining offers visually intuitive graphs that show, for example, the most common activities, frequency of transitions, intervals between activities and the overall map of connections between students' activities; therefore, process mining has been used frequently to chart the processes that characterise students' strategies, compare different strategies and find gaps in students' use of strategies (Ahmad Uzir et al., 2020; López-Pernas et al., 2021; Peeters et al., 2020). Recently, process and sequence mining have gained traction in the educational community at large and, in particular, to study students' learning strategies (e.g., Ahmad Uzir et al., 2020; Matcha et al., 2019).

Both sequence and process mining methods are used to analyse temporal data. Nevertheless, they approach the analysis from different perspectives. That is, sequence mining is primarily concerned with the sequence and order of events, while process mining is more concerned with transitions and mapping the overall process. Also, sequence mining focuses on the sequential data with the aim of discovering common patterns in sequences, while process mining focuses on the analysis of event logs to model transitions between different states based on the history of events. Therefore, sequence mining can be used to detect common patterns of learning behaviours based on similarities of sequences of actions that correspond to learning sessions (Ahmad Uzir et al., 2020; López-Pernas & Saqr, 2021).

The present study takes advantage of the recent advancements in process and sequence mining to mine students' learning strategies from trace data. Learning strategies are operationalised according to Azevedo et al. (2008) as sequences of time-ordered learning activities and tactics that students use to engage with their learning tasks (Knowles, 1977). Learning tactics are elements of learning strategies that students use within a limited time scale to perform a task or parts of the task (Saqr et al., 2021). Research has shown that sequence mining and process mining can be used to extract the learning tactics and strategies from trace data. Furthermore, research has demonstrated that learning strategies extracted from log data are representative of deep learning, surface learning and transferred learning strategies (Fincham et al., 2018; Jovanovic et al., 2017; Matcha et al., 2019).

Motivation for this study

There is limited knowledge on how online course design is related to students' usage of learning strategies in technology-supported PBL settings and more importantly how students transfer strategies across courses. In this study, we aimed to use learning analytics methods (i.e., sequence and process mining and clustering) to study how medical students use learning strategies, how different implementations are related to students' choice of strategies in technology-supported PBL, how students transfer strategies between courses and how the adoption and transfer of strategies are related to performance. To that end, we studied the same student cohort in two different PBL courses with the same course structure and design but different implementations (the first course hads technology-supported PBL with no teacher, whereas the second course was facilitated by teachers). The research questions (RQs) was as follows:

(1) What are the learning tactics and strategies that students adopt in courses with similar designs but different implementations (tutor-supported blended PBL vs tutor-less blended PBL)?

Given the same students, the same course pedagogical underpinning and course design with different course implementations (teacher facilitation vs no teacher facilitation), we aimed to explore the tactics and strategies that the same students used to approach their learning in different course implementations. Furthermore, we aimed at investigating how the students transfer their learning strategies when moving across the different courses.

(2) How is the adoption of different learning strategies and the transfer thereof related to academic performance?

This question investigated how students' transition patterns between different courses related to their academic performance.

Method

Course information

Our intention was to compare different PBL implementations in order to examine how they were associated with students' learning strategies as well as to examine if and how students' strategies differed in different PBL implementations. To control, as much as possible, the factors that might affect students' selection of strategies and their course performance, we chose two successive courses with related curricula, similar pedagogical approaches, similar teaching methods and similar assessment methods, taken by the same group of students. The two courses included in the study were Man and Environment (MAE) and Growth and Development (GAD); both were first-year courses and followed each other in order. MAE can be considered as the first course in the program, and GAD is the next following course. Whereas the courses were focused on different subject matter, they comprised similar components, that is, an integrated curriculum of basic science subjects that included the anatomy, physiology, histology and pathology of their subjects. For instance, in MAE, students learned about the anatomy, physiology, histology and pathology of the human body and environment, and in GAD, they studied the anatomy, physiology, histology and pathology of human growth and development (Table 1). As such, courses were fairly similar in content, curriculum and teaching methods with rather similar difficulty levels but with different durations. The main difference was that, in the MAE course, students were organised into face-to-face PBL groups and were instructed (though it was not mandatory) to continue the PBL process online with the same group structure but without the tutors. However, technology-supported PBL usage was limited. In turn, in the GAD course, the tutors facilitated the online discussions. Put another way, the main difference between the two courses is that GAD online interactions were facilitated by the teacher.

Table 1
Weekly topic covered in the course

Characteristic	MAE	GAD
Description	Focuses on the interaction between human and environment, including diseases caused by interaction with the environment, e.g., excess temperature, chemicals, food or waterborne diseases, pathogens, how this affects human homeostasis, immune system and adaptation.	Focuses on aspects of human growth, including the basic sciences of human reproduction, intrauterine development, early childhood development, immunisation schedules, the physical and physiological changes of adolescence.
Course duration	11 weeks	6 weeks
Modality	Blended learning	Blended learning
Online PBL facilitation	No	Yes
Timing	End of first semester	Start of second semester

The curriculum in the two courses was an integrated PBL approach that follows the Maastricht seven jumps approach (Wood, 2003). Each week, students – in small groups – were asked to study an ill-structured problem which was designed to stimulate their learning inquiry.

The small groups met in class on the first day of the week, read the problem, extracted the learning objectives and concluded the meeting by identifying learning goals. After the first face-to-face meeting, students would continue their interactions in an online forum where they discussed the problem, co-constructed knowledge and shared learning resources (Figure 1). On the last day of the week, students would meet again face-to-face to discuss what they have learned and reflect on their process of learning and group performance. As such, the PBL approach can be thought of as technology-supported or blended PBL. The PBL process is expected to continue online most of the week and offered students a platform where they can discuss the learning objectives of the weekly problem (Saqr, 2018). The collaborative process also helped students access diverse ideas and opinions, and propose and learn alternative solutions and explanations. The permanence of content allowed learners to repeatedly access, process and re-iterate through the complex problems. Also, students can search for resources, gather information and exchange knowledge with peers and get feedback on their contributions. In contrast to the face-to-face component, which is limited in time and place, the online forums allowed an asynchronous access that is self-paced at students' convenience. As such, most of the PBL process (apart from initial reading and setting discussion goals) and all the interactions around the problem were designed – yet not mandatory – to be online, and students were expected to participate in the process all over the week as shown in Figure 1. The curriculum relied on a learning management system (LMS) as a platform for the PBL discussions as well as for delivering the course instructions, objectives, news and announcements, and all course learning resources (i.e., lectures). The course also offered a formative assessment quiz on a weekly basis. The teaching in the course followed the theme of the weekly problem, and so did the evaluation.

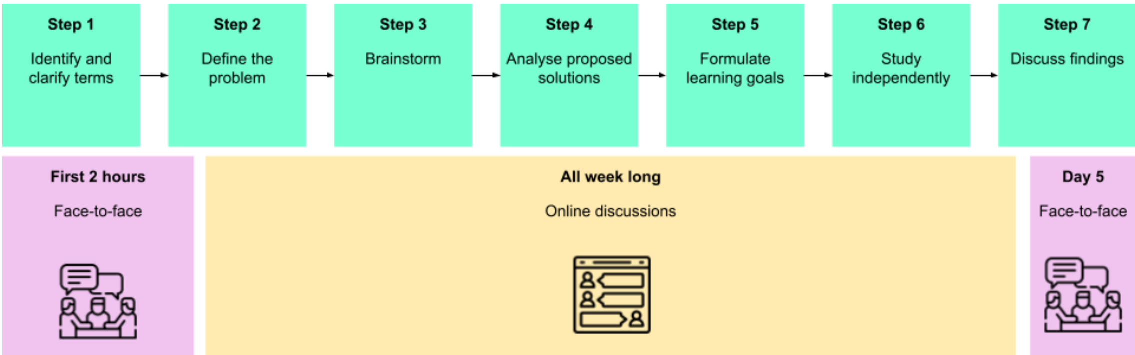

Figure 1. Summary of the PBL seven jumps approach (Wood, 2003) and its implementation in our context

Data collection

This research was approved by the Research Ethics Committee of Qassim University. The university privacy guidelines and policies of dealing with students' data were strictly followed. A total of 139 students who were enrolled in both courses in the academic year 2018–2019 participated in the study. The traces of students' online learning actions, together with the corresponding timestamps, were recorded in the LMS, which are referred to as "trace data".

In our study, trace data were retrieved from the Moodle LMS for the 139 students. The logs were cleaned from non-learning actions, for example, clicks on profile or chat pages. Similar logs were coded in the same way, so clicks on the main course page were coded as *Course_view*; clicks on lectures, links to lectures, or folders or compressed files of learning resources were coded as *Learning_resources_view*. Interactions between students regarding learning actions were coded as *Social interact*, and students' posts asking for support were coded as *Support*. The type of the form was recognised from the title of the forum. That is, the name of the forum is available in the log data.

Table 2 presents the full detail of learning actions recorded in the trace data. The study consisted of 81,739 log traces of students' learning related activities. MAE had 46,752 log entries over 12 active PBL weeks, whereas GAD had 34,987 over 6 weeks. The number of *PBL_Interact* actions in GAD was 2,041, the number of *PBL_Read* was 15,481, which was relatively higher than MAE where *PBL_Interact* was 133 and *PBL_Read* was 1,638. Such a stark difference highlights the divergence between the two courses regarding the course enactment. A detailed distribution of all the learning actions per student is shown in Table 3, including the mean, standard deviation, first and third quartiles as well as the total number of actions for both courses.

Table 2
Description of the Moodle LMS actions available in the trace data

Action	Description
Course_view	Students viewed the course front page, which had links to lectures, forums and all other actions; it also had a section that listed the recently added materials and course announcements.
Evaluate	Students accessed the formative assessment.
Instruction_view	Student viewed or read the course instructions (course booklet, course objectives, assessment criteria).
Learning_resources_view	Students accessed the learning resources (lectures, or lecture presentations, videos or book chapters).
PBL_Interact	Students posted content or replied to posts in the PBL forums.
PBL_Read	Students read the PBL forum discussions.
Social_interact	Students read or responded to the social forum discussion that was unrelated to the course content.
Support	Students asked questions in the support forum or viewed answers for course-related questions.

Table 3
Summary statistics of the learning actions recorded in the LMS for each course

Action	GAD					MAE				
	Mean	SD	25%	75%	Total	Mean	SD	25%	75%	Total
Instruction_view	9.0	5.3	5.0	11.0	1245	21.7	16.4	10.0	28.5	3017
Course_view	62.8	37.5	39.0	78.5	8733	105.8	67.6	61.0	137.5	14702
Learning_resources_view	35.2	18.6	22.5	43.0	4898	131.8	63.8	94.0	158.5	18323
Evaluate	12.8	12.6	2.5	19.5	1784	37.5	29.1	16.0	54.0	5219
Support	1.6	3.4	0.0	2.0	222	8.1	13.1	0.0	9.0	1121
Social_interact	4.2	4.7	1.0	6.0	583	18.7	23.4	3.0	24.5	2599
PBL_Read	111.4	66.3	65.0	146.0	15481	11.8	13.5	3.5	16.0	1638
PBL_Interact	14.7	10.6	7.0	21.0	2041	1.0	1.7	0.0	1.0	133

Data analysis

RQ1: What are the learning tactics and strategies that students implement?

- **Tactic detection**: We started our analysis by detecting students' learning tactics from the log data of their online activities. A learning tactic is defined as a sequence of learning actions performed by a student to complete a learning task (Saqr et al., 2021). We adapted the method proposed by Matcha et al. (2019), depicted in Figure 2. The first step was to group together the learning actions in the trace data into learning sessions. A learning session is an uninterrupted sequence of learning actions with a time gap of less than 10 minutes between an action and the next. This gap corresponds to the 98th percentile of the time gap between two successive learning actions in the examined courses (Jovanovic et al., 2017). After grouping the actions together, learning sessions contained at least one learning action and a maximum of 753 actions. We excluded the outliers including the overly short and overly long learning sessions. As a result, we included 12,446 learning sessions containing from 2 to 47 learning actions per session in this study

(Jovanovic et al., 2017). The obtained sequences of learning sessions represented the process of students' learning by using the first order Markov model to formulate the process of learning.

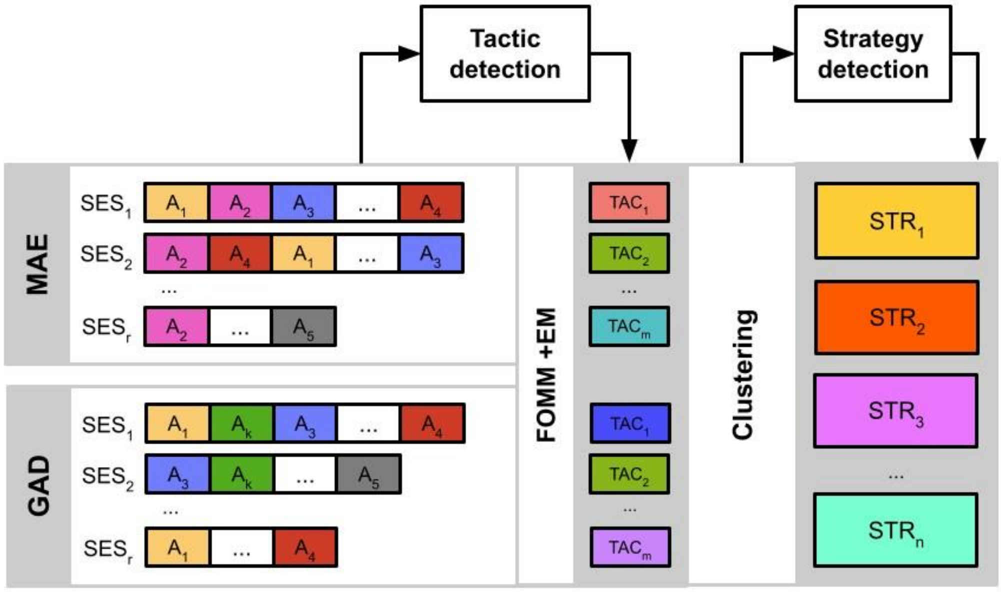

Figure 2. Summary of the process to detect tactics and strategies.
Note. FOMM stands for first order Markov model. EM stands for expectation–maximisation algorithm.

We used the expectation-maximisation algorithm (Ferreira & Gillblad, 2009) to cluster together learning sessions with similar learning actions (Jovanovic et al., 2017; Matcha et al., 2019). Each cluster constitutes a learning tactic with similar sequences of learning actions. To investigate the detected learning tactics, we used the distribution plot to examine the distribution of learning actions for each tactic group at each time point.

- **Strategy detection:** We used the detected learning tactics to identify learning strategies using the methods of Saqr et al. (2023). That is, we first computed the frequency of each tactic and the total number of tactics used. We then used these data as an input to the agglomerative hierarchical clustering (AHC). To use the AHC, the dissimilarity matrix is needed, which we computed by using the Euclidean method, whereas we computed the distance between clusters by using the Ward method (Murtagh & Legendre, 2014). As the result of applying AHC, students with similar usage of learning tactics were grouped together, thus forming clusters with shared learning behaviour, indicative of the adopted learning strategies as defined in Derry (1988).
- **Analysis of detected strategies**: In order to understand the students' learning behaviours and learning strategies, we used a process mining based on the R package bupaR (Janssenswillen et al., 2019) to illustrate the students' tactic regulations. Process mining allows us to examine the transition of learning tactics and the time spent (Ahmad Uzir et al., 2020; López-Pernas et al., 2021). To formulate the learning process, we used the following items as an input to the algorithm: case ID, activities and timestamp. The case ID referred to the learning sessions; the activities referred to tactics performed at a particular timestamp. We created two process mining plots for each strategy, a frequency-based process mining which demonstrate the frequency of transitions over time (Ahmad Uzir et al., 2020). We plotted students' transitions of strategy use from one course to another using a transition plot and computed the statistical significance using a chi-square test and plotted using multi-way contingency plot (mosaic plot). The mosaic plot is an area of proportional visualisation that shows the observed versus the expected frequency with colours indicating statistically significant associations – red for negative association and blue for positive association – (Hofmann, 2008).

RQ2: Adoption and transfer of learning strategies and relation to performance
We used a non-parametric (Kruskal-Wallis test) analysis of variance (ANOVA) to examine the relation between grades and strategies since grade distribution violated the normality assumption and the homogeneity of variance required for ANOVA. We used the epsilon-squared (ε^2) effect size to assess the magnitude of the difference in grades among the strategies. According to Cohen (1992), a value of $\varepsilon^2 < 0.02$ represents a very small effect size; $0.02 \leq \varepsilon^2 < 0.13$ represents a small effect size; $0.13 \leq \varepsilon^2 < 0.26$ represents a medium effect size, and a value of $\varepsilon^2 \geq 0.26$ represents a large effect size. Pairwise comparisons were performed using Dunn test with Holm's correction for multiple testing. We employed a Mann-Whitney non-parametric rank-sum test to compare the grades in the GAD course between the two implemented strategies. We used the rank-biserial correlation effect size to assess the magnitude of the difference in grades between the two strategies.

According to Cohen (1988), a value of $r < 0.1$ represents a very small effect size; $0.1 \leq r < 0.3$ represents a small effect size; $0.3 \leq r < 0.5$ represents a medium effect size; and a value of $r \leq 0.5$ represents a large effect size.

Results

RQ1: What are the learning tactics and strategies that students implement? [H2]

Learning tactics
The initial step in the analysis was to mine students' sequences of activities using clustering into homogeneous groups of similar activities, that is, to discover the learning tactics. The clustering yielded four distinct tactics:

- **Tactic 1 – Learning resource oriented** (n = 4,274): Most learning sessions belonged to this tactic. The most dominant learning action in this tactic was *Learning_resources_view*. As presented in Figure 3, learning sessions corresponding to this tactic often started by viewing the course main page (*Course_view*), followed by accessing the learning resources for example, lectures. The median number of learning actions in each session was 3 (median (Q1, Q3) = 3(2,5)). This tactic was associated with 784 (18.3%) sessions from the GAD course and 3,490 (82.7%) sessions from the MAE course.
- **Tactic 2 – PBL oriented** (n = 2,822): Most learning actions in this tactic were related to the PBL aspect of the course (*PBL_Read* and *PBL_Interact*). As presented in Figure 2, students often began these sessions by viewing the course and then accessing the PBL problems in the online forum. The number of learning actions per session was higher than in Tactic 1 (median (Q1, Q3) = 6(3,12)). The majority of learning sessions were from the GAD course (N = 2455 sessions), while a smaller number of learning sessions from MAE were categorised as PBL oriented (N = 367 sessions).
- **Tactic 3 – Evaluation and resource oriented** (n = 1,964): This tactic involved three main learning actions, including *Course_view*, *Evaluation*, and *Learning_resources_view*. The predominant action was *Evaluation*. The learning patterns were slightly different between the two courses. That is, MAE had more diverse learning actions (median (Q1, Q3) = 5(3,9)), whereas the GAD course showed that students focused on evaluation and less on accessing the learning resources compared to MAE.
- **Tactic 4 – Diverse** (n = 3,386): Students exhibited diverse learning actions, including *Course_view*, *Learning_resources_view*, *Social_interact* and *Instruction_view*, with moderately long session (median (Q1, Q3) = 5(3,9)). This tactic was associated with 766 sessions from the GAD course and 2,620 sessions from MAE.

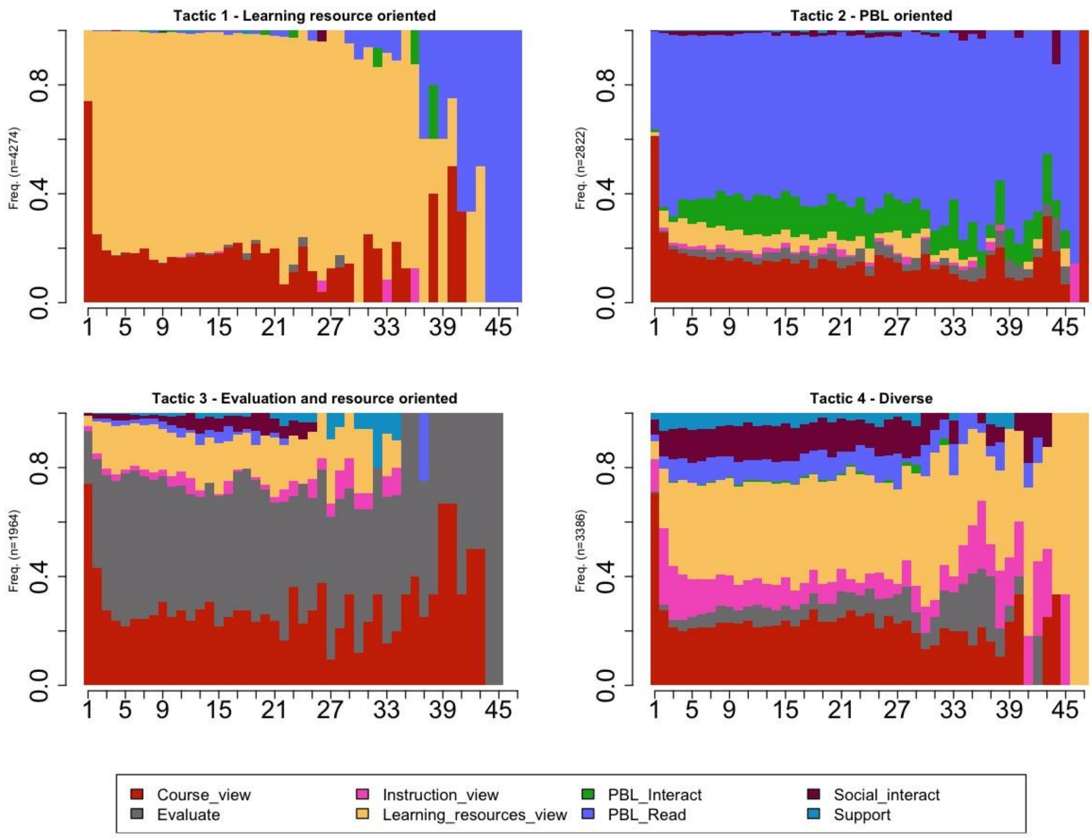

Figure 3. Temporal distribution of learning actions in each detected learning tactic

Table 4 shows a detailed comparison between two courses and the number of identified tactics. The PBL tactic was prevalent in the GAD course where PBL was scaffolded compared to the MAE course. The next step was to use the identified tactics to identify course strategies using clustering.

Table 4
Summary statistics of the learning tactics for each course

Tactic	**GAD**					**MAE**				
	Mean	**SD**	**25%**	**75%**	**Total**	**Mean**	**SD**	**25%**	**75%**	**Total**
Diverse	5.51	2.79	4.00	7.00	766	18.85	13.23	9.00	25.50	2620
Learning resource oriented	5.64	3.84	3.00	8.00	784	25.11	13.63	14.00	34.00	3490
Evaluation and resource oriented	3.47	3.65	1.00	5.00	483	10.65	8.77	5.00	14.00	1481
PBL oriented	17.66	9.90	11.00	24.00	2455	2.64	2.61	1.00	4.00	367

Learning strategies

The second step in the analysis was to cluster students' learning tactics, discovered in the previous step, into course strategies. The clustering yielded four strategies across the two courses.

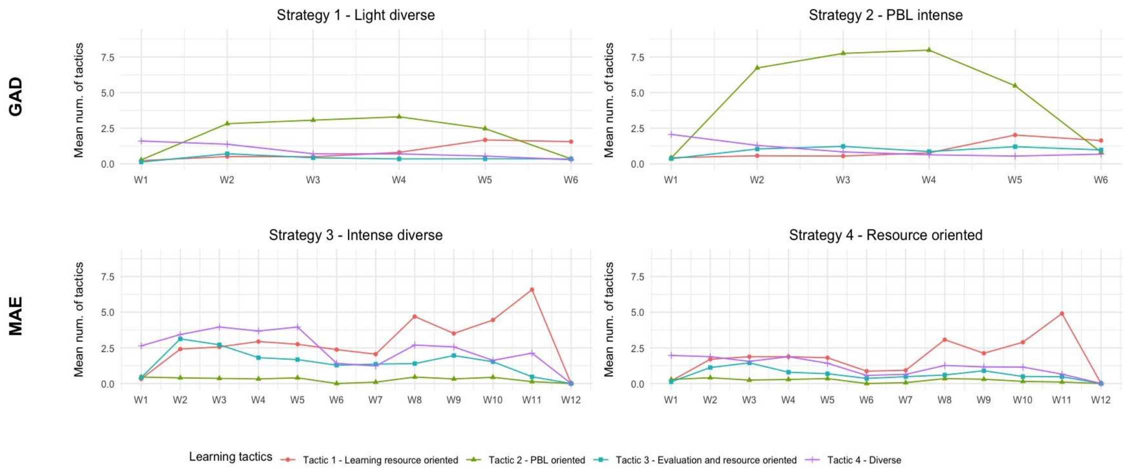

Figure 4. Weekly evolution of the learning tactics used in each learning strategy

- **Strategy 1 – Light diverse**: The overall pattern of this strategy group showed a moderate level of engagement, with students using the *PBL oriented* tactic, *Learning resource oriented* tactic and *Diverse* tactics. The examination of the weekly trend in Figure 4 shows that students who adopted this strategy used the *Diverse* tactic at the beginning of the course. This indicates that students might be exploring the learning contents and attempting to find the most suitable learning actions as exhibited by using the *Diverse* tactic, that is, participating in several learning activities in one learning session. In Week 2, the students' level of engagement with the *Diverse* tactic slightly dropped, and their use of the *PBL oriented* tactic increased. They frequently visited the activities related to PBL, especially from Week 2 to Week 5. The *Learning resource oriented* tactic can be seen as gradually increasing as the course progressed. The majority of these patterns can be observed from the GAD course, in which 66.9% of students exhibited this learning strategy whereas, in MAE, only 13.7% of students did. The process mining plot in Figure 5 (left) shows that most students (71%) started with the *Diverse* tactic. However, their most common tactic throughout the course was the *PBL oriented* tactic (49% of the sessions), and they transitioned to PBL frequently from other tactics, from *Diverse* (42%), from *Evaluation and resource oriented* (33%) and from *Learning resource oriented* (25%). The temporal process mining plot in Figure 5 (bottom) shows a median time between tactics of around one day, with longer transitions from/to the *PBL oriented* tactic than between the other tactics.

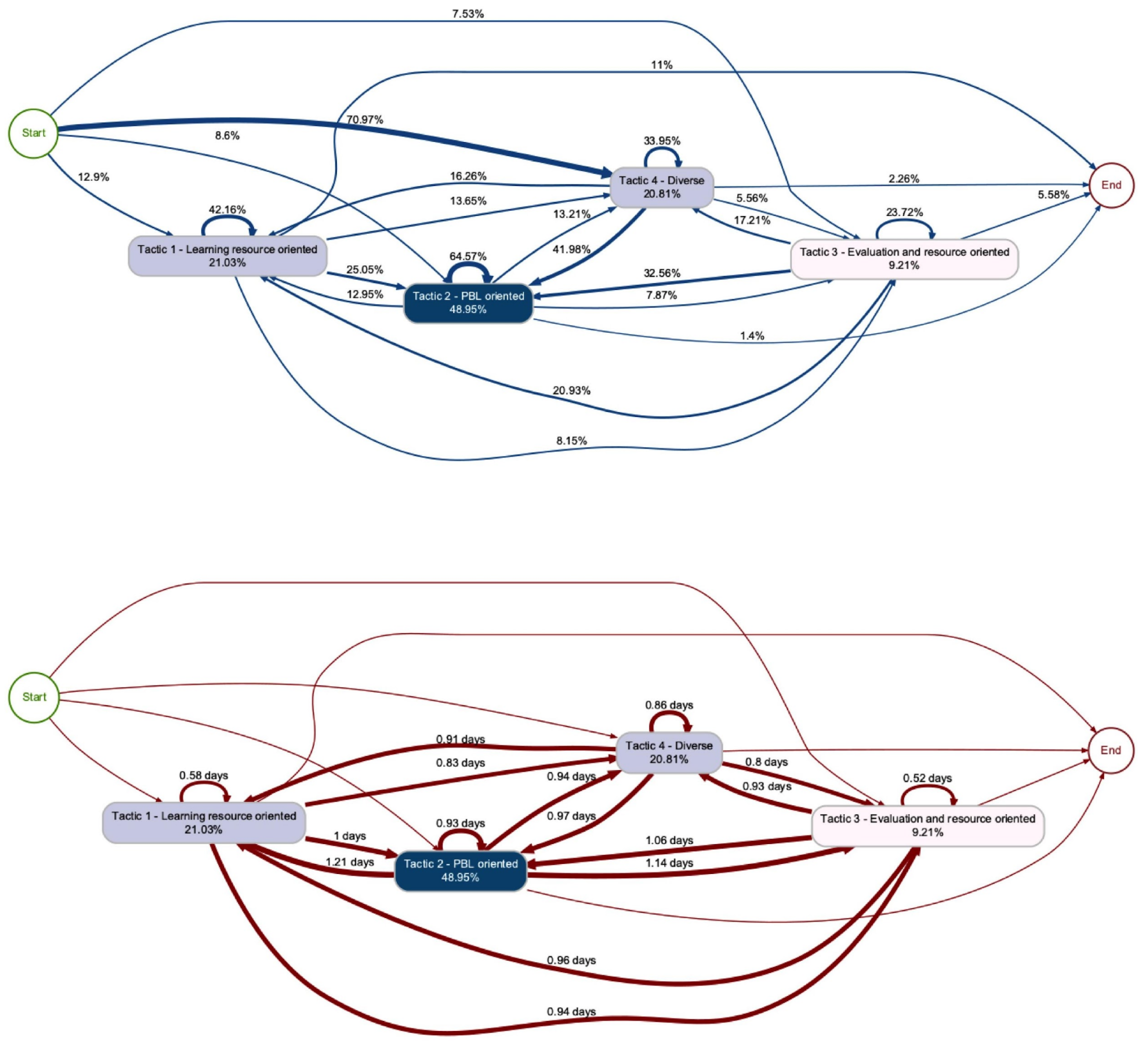

Figure 5. Process models for the learning processes of the Light diverse strategy

- **Strategy 2 – PBL intense:** The overall pattern of this strategy group was the use of the *PBL oriented* tactic, which had a larger presence than in any other strategy. The use of *Evaluation and resource oriented* tactic was higher than in *Light* diverse strategy, which reflects the focus of the students on the PBL activities and on the evaluation indicating higher level of regulation. This strategy has only been observed in students who participated in the GAD Course. The examination of the weekly trend plot in Figure 4 shows a continuous high level of engagement across all weeks especially with PBL oriented tactic and less so with other tactics.

The process mining plot in Figure 6 shows that students with this strategy were focused on PBL, as the *PBL oriented* tactic accounted for 62% of the tactics. What is more, after using the *PBL oriented* tactic, students were more likely to return to this tactic 75% of the time. Other employed tactics were comparatively less present with percentages that were around 12%–13% each (Figure 6 – left). The process mining temporal plot shows that the transition times between different tactics (Figure 6 – bottom) were relatively short (between 0.5 and 0.8 days), and the time to repeat a tactic was short, especially for the *Evaluation and resource oriented* tactic, which was 0.16 days (approximately 4 hours), indicating students' emphasis on evaluating their knowledge.

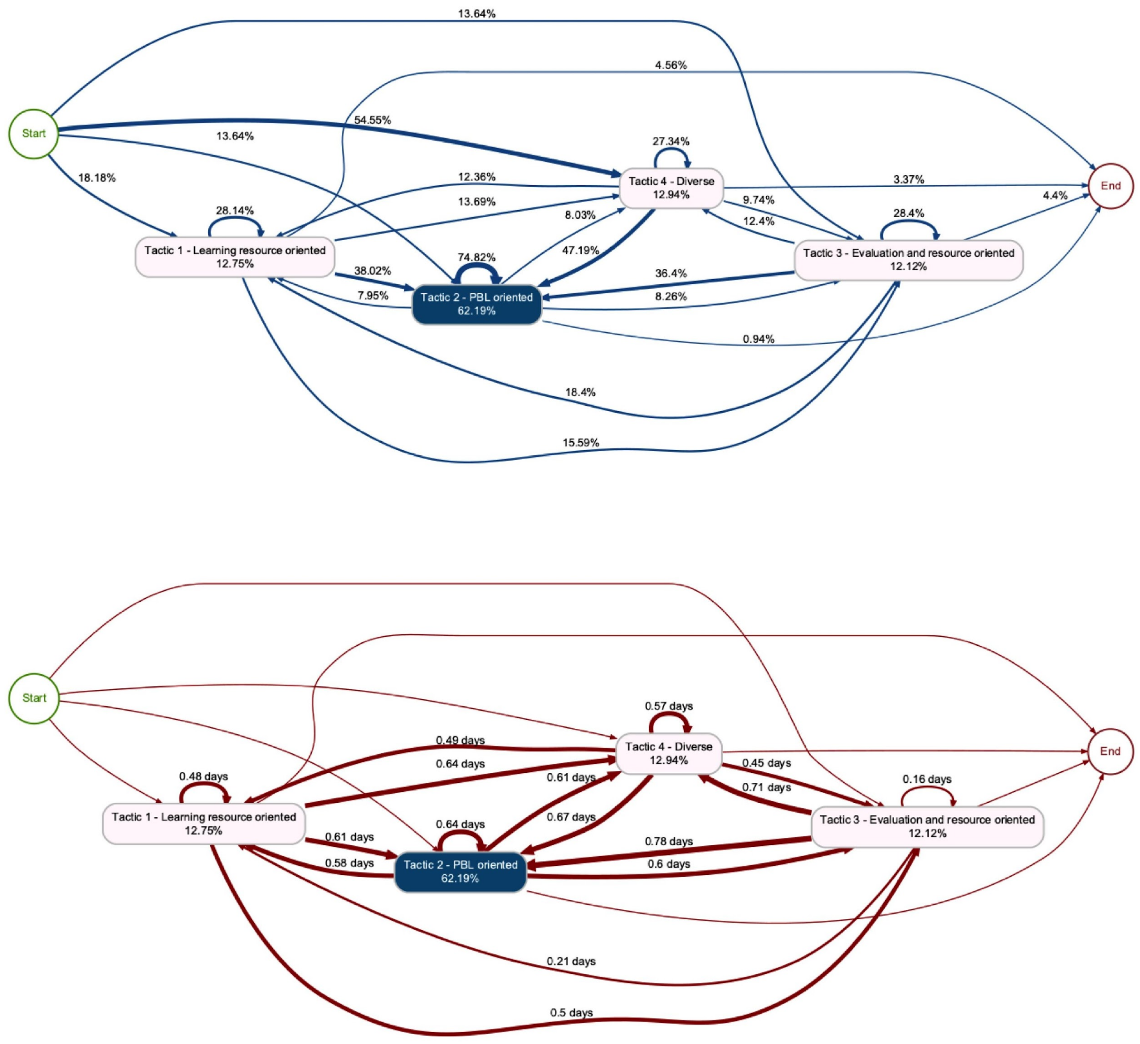

Figure 6. Process models for the learning processes of the *PBL intense* strategy

- **Strategy 3 – Intense diverse:** This strategy showed that students used a variety of learning tactics. Students used the *Diverse*, *Evaluation and resource oriented* as well as the *Learning resource oriented* tactics most of the time. The weekly temporal trend in Figure 4 shows that the usage of the Diverse tactic was highest from the first until the fifth week. Students increased the application of the *Learning resource oriented* tactic, especially, during Weeks 8–11, that is, before the exam. It is worth noting the use of the *PBL oriented* tactic was relatively low. This strategy was only observed in students from the MAE Course, where 38.13% of the students used this strategy.

The process mining of this group (Figure 7) showed a diverse picture with several instances of the *Learning resource oriented* tactic (41%), *Diverse* tactic (34%), and *Evaluation and resource oriented* tactic (21%) with very few occurrences of the *PBL oriented* tactic (4%). The transitions were also distributed between tactics with no predominant pattern (Figure 7 – left). The process mining temporal plot shows very short transition times mostly between 0.5 and 0.8 days (Figure 7 – bottom). The transition times were all relatively close to each other except for the *PBL oriented* tactic, which had a “loop”; that is, students transitioned from *PBL oriented* to *PBL oriented* again, in a median of 0.41 days, a time shorter than all other tactics.

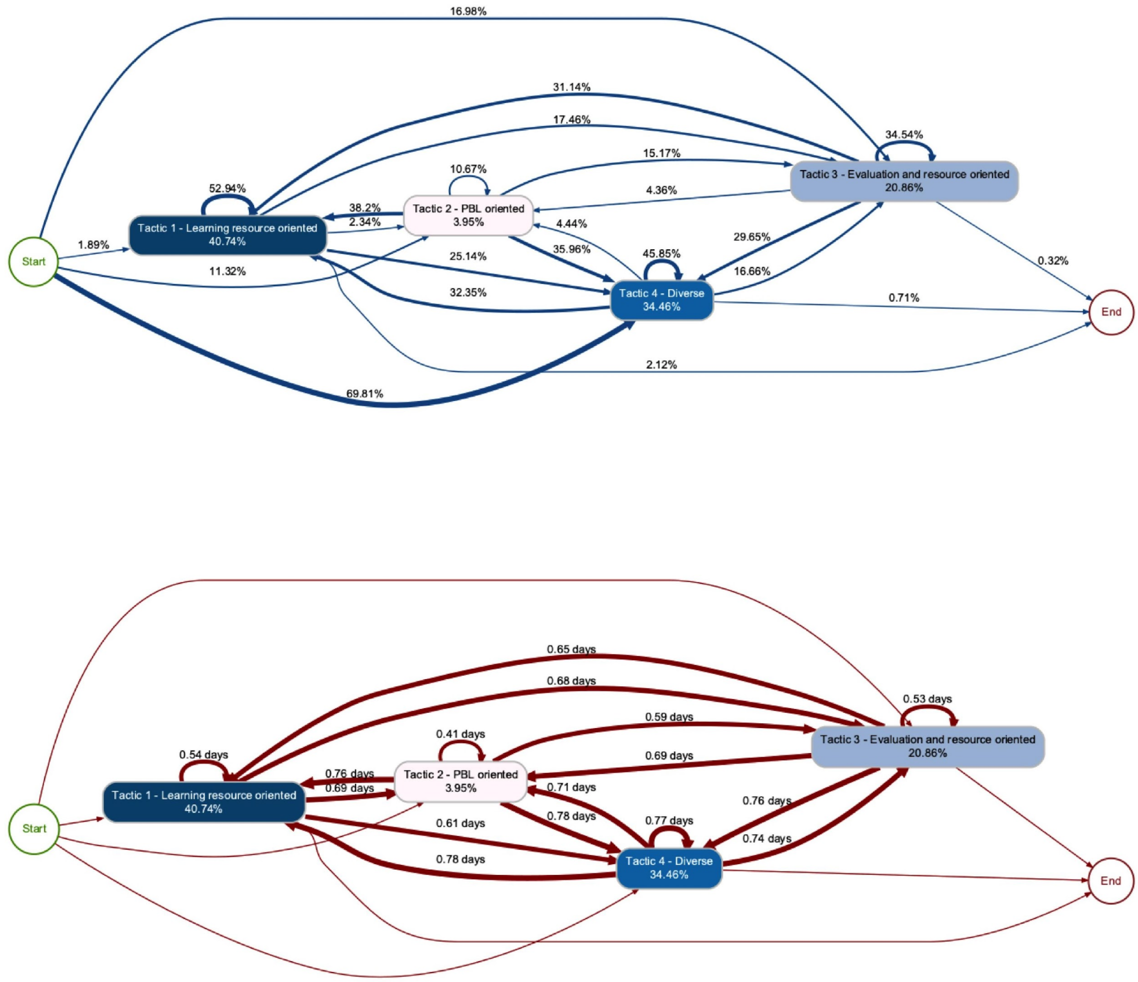

Figure 7. Process models for the learning processes of the Intense diverse strategy

- **Strategy 4 – Resource oriented:** This strategy showed lower level of engagement. Students focused on *Learning resource oriented* and *Evaluation and resource oriented* tactics most of the time. The application of all tactics dropped as the course progressed, except for the *Learning resource oriented* tactic which can be seen as highly used during Weeks 8–11, that is, before the exam. Some 48.2% of students enrolled in the MAE course applied this strategy, whereas in the GAD course only 1.4% of students were in this group. The process mining in Figure 8 shows that students in this strategy group were mostly focused on the *Learning resource oriented* (48%) and the *Diverse* tactics (31%) and less so on the *PBL oriented* (5.41%) or *Evaluation and resource oriented* (16.1 %) tactics. For students in this group, it took slightly longer to shift from one tactic to another compared to other strategy groups, with a median time over 1 day in most of the cases (Figure 8 – bottom). It is worth noting that the shortest transition time was from *PBL oriented* to *PBL oriented* again at 0.27 days (approximately 6.5 hours).

Students in the *Intense diverse* strategy had the highest scorers in the MAE course with a mean final grade (μ) of 83.09 [80.04, 86.14], and so had the students with the *PBL intense* strategy in the GAD course μ = 83.63 [80.02, 87.24] (Table 5). A Kruskal-Wallis test confirmed that grades differed by strategy in the MAE course, and this difference was statistically significant ($p < 0.001$) with a large Cohen (1992) effect size ($\varepsilon^2_{\text{ordinal}} = 0.27$ [0.18, 1.00]). A Mann-Whitney test confirmed the same in the GAD course, although with a small effect size Cohen (1988) ($r_{\text{biserial}}^{\text{rank}} = -0.29$ [-0.46, -0.09]), $p < 0.001$.

Table 5
Summary statistics for course grades for each learning strategy

					95% CI	
Course	**Strategies**	**N**	**Mean**	**SD**	**Lower**	**Upper**
GAD	Light diverse	93	74.78	18.62	71.00	78.57
	PBL intense	44	83.63	12.22	80.02	87.24
MAE	Intense diverse	53	83.09	11.34	80.04	86.14
	Light diverse	19	62.01	13.25	56.05	67.96
	Resource oriented	67	73.65	13.62	70.39	76.91

RQ2: Adoption and transfer of learning strategies and relation to performance

According to Kruskal-Wallis test, transitioning from one strategy to another made a statistically significant (p ¡ 0.01) difference in students' grades with a large effect size ($\varepsilon^2_{ordinal}$ = 0.27 [0.18, 1.00]). Students who used the *Intense diverse* strategy were most likely to transition to a *PBL intense* strategy (66%), indicating their ability to adapt strategies between courses to effective strategies in the following courses. Those students were the highest scoring among all students (Table 6) with μ = 78.62 [75.25, 81.99]. Pairwise comparisons (using Dunn test with Holm's correction for multiple testing) showed that this group's grades were statistically significantly higher than those in other groups except for the group who transitioned from a *Resource oriented* strategy to *PBL intense*, who scored μ = 70.39 [66.21, 74.56]. Students who used the *Light diverse* strategy were the lowest scoring students in both courses. They scored μ = 62.01 [56.05, 67.96] in the MAE course and μ = 74.78 [71.00, 78.57] in the GAD course. Such differences were statistically significantly different from other groups in both courses. Students who continued to use the *Light diverse* strategy scored the lowest grades μ = 59.85 [48.50, 71.21] among students who transitioned to the GAD course. The highest proportion of transitions was for students who transitioned from *Resource oriented* to *Light diverse* (53% of all students), and they scored μ = 78.75 [74.23, 83.27], the second lowest average final grade. Students with the *Resource oriented* strategy scored an average final grade μ = 73.65 [70.39, 76.91], and their transition to *PBL intense* was associated with slightly higher grades (μ = 78.85 [74.23, 83.27), whereas their transition to *Light diverse* was associated with slightly lower grades (μ = 75.47 [70.53, 80.41]). However, these differences were not statistically significant.

Table 6
Summary statistics for course grades for each transition between learning strategies

				95% CI	
Strategies	**N**	**Mean**	**SD**	**Lower**	**Upper**
Intense diverse → Light diverse	23	84.22	8.31	80.63	87.82
Intense diverse → PBL intense	29	87.67	9.59	84.02	91.32
Light diverse → Light diverse	17	59.85	22.09	48.50	71.21
Resource oriented → Light diverse	53	75.47	17.92	70.53	80.41
Resource oriented → PBL intense	13	78.75	7.49	74.23	83.27

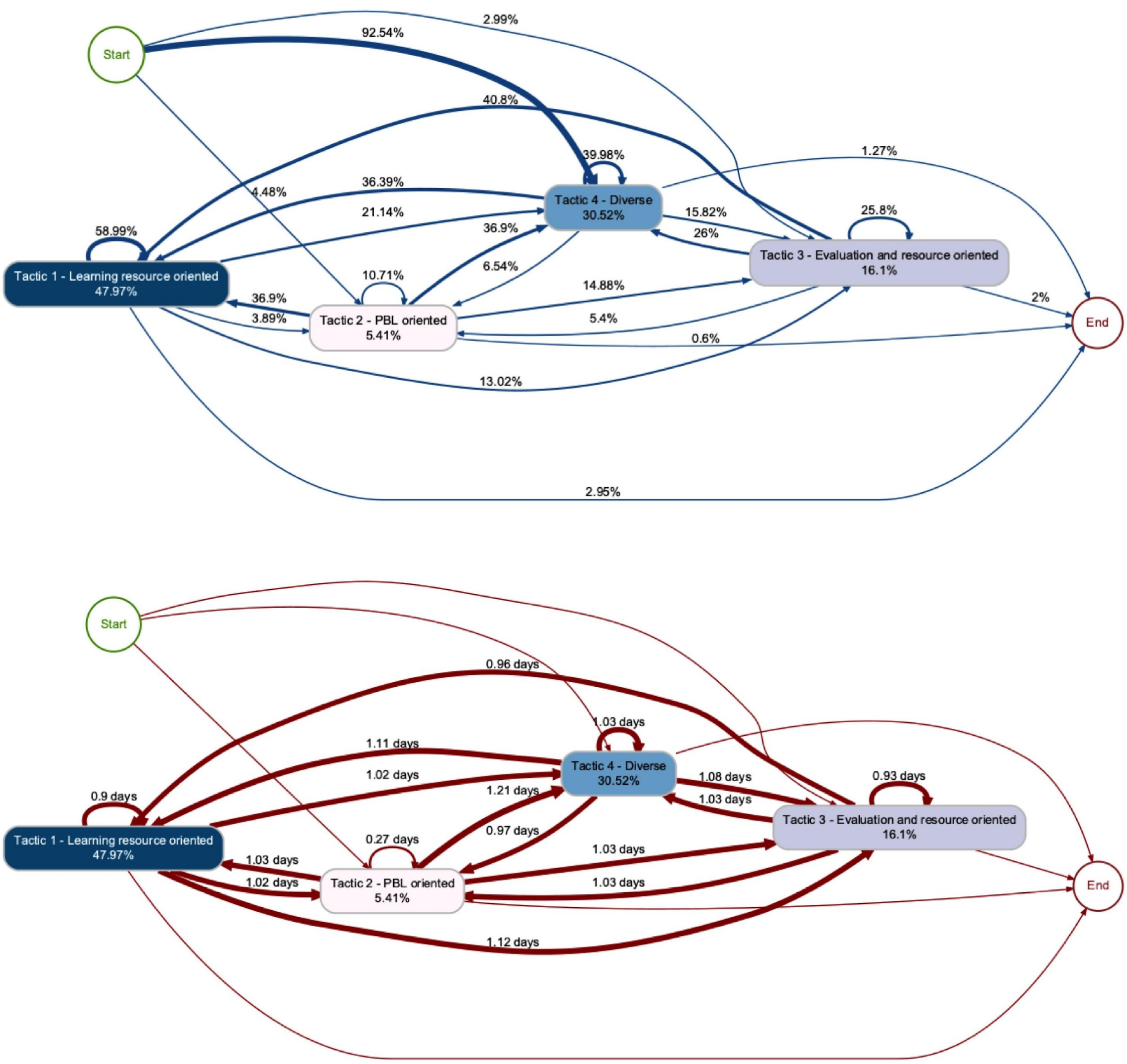

Figure 8. Process models for the learning processes of the *Resource oriented* strategy

It is worth noting that the only statistically significant transitions were (a) a more likely transition between *Intense diverse* and the *PBL intense* strategy (shown as blue shading in the mosaic plot in Figure 9) and (b) a less likely transition between the *Intense diverse* and the *Light diverse* (red shading in the mosaic plot).

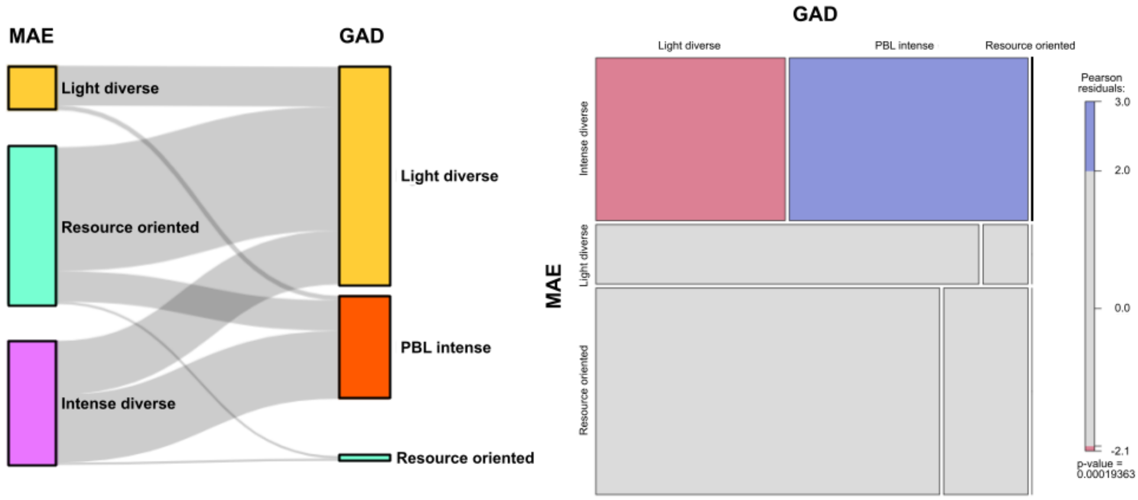

Figure 9. Transitions between strategies from one course to another (left), and mosaic plot showing the association between transitions (right). Blue shading indicates positive significant associations, red shading indicates negative significant associations and grey shading indicates non-significant associations.

Discussion

The aim of this research was to study how different course implementations are related to medical students' learning strategies, given the same course structure, design and student cohort as well as which strategies students adopted and which they adapted or carried to the next course and how the adoption of strategies was related to performance.

First, based on the log data collected from the students' online interactions, we identified four learning tactics. Each tactic is characterised by mutually similar sequences of learning actions that took place within the same learning sessions. The detected learning tactics were labelled after the dominant learning actions as those were considered to be the primary forms of the student engagement in the corresponding learning sessions. The four learning tactics consisted of *Learning resource oriented*, *PBL oriented*, *Evaluation and resource oriented* and *Diverse*. The characteristics of the tactics were aligned with course design.

When exploring the regulation of the identified tactics (i.e., learning strategies), we observed four distinct patterns that represented two different levels of engagement across the two courses: the deeper (*PBL intense*, *Intense diverse*) and the shallower (*Resource oriented* and *Light diverse*) engagement. These results are well aligned with the characteristics of approaches to learning (Biggs & Telfer, 1987) and with the literature that used methods similar to ours beyond medical education (Ahmad Uzir et al., 2020; Gašević et al., 2017; López-Pernas et al., 2021; López-Pernas & Saqr, 2021; Saqr & López-Pernas, 2021). For instance, using methods similar to ours, Matcha et al. (2019) identified three types of learning strategies in a flipped classroom, namely highly selective, strategic and intensive (related to deep learning). Other studies have also detected deep and surface strategies with different labels (e.g., Ahmad Uzir et al., 2020; Gašević et al., 2017; López-Pernas et al., 2021; López-Pernas & Saqr, 2021; Saqr & López-Pernas, 2021). Using learning analytics methods to detect and possibly monitor or support such learning strategies could offer educators a tool to proactively support students.

In our study, students who adopted deeper strategies were the ones who scored the highest grades (*Intense diverse* and *PBL intense* strategies) in each course. The students who adopted the less engaged strategy (*Light diverse*) scored the lowest scores in both courses. These results corroborate research highlighting the value of deep learning strategies and how they are associated with better performance (Ahmad Uzir et al., 2020; Broadbent & Poon, 2015; Gašević et al., 2017).

The results further reveal two factors that may have influenced students' choice of strategies. In the MAE course, where no scaffolding was offered, the students needed to self-regulate their learning strategies. According to Zimmerman and Kitsantas (2005), a key self-regulatory process is task analysis, identifying effective strategies and enacting such strategies. Students with effective self-regulating skills were able to adopt deep learning strategies and thus score better grades – the difference from other students has been significantly larger with large effect size. On the other hand, students' application of the *PBL intense* strategy in the GAD course was probably motivated by the instructors who interacted with the students. This reflects the role of scaffolding on the student's decision on how to proceed with the study. This is well aligned with the notion of self-regulated learning theory. As highlighted by Winne and Hadwin (2018), the task conditions, which refer to any external constraints to one's cognitive system, impact the decision to choose the learning tactics and strategies. Scaffolding, as one form of the instruction cues which is considered as the task condition, might have influenced the students' adoption of strategies. Furthermore, much research has highlighted that the learning success also depends on how well learners select and apply tactics and strategies that matched with the intended learning design/pedagogy (Fan et al., 2021; Hattie & Donoghue, 2016; Lust et al., 2013).

Next, our results seem to highlight an example of transferring strategies between courses. According to the learning strategies model by Hattie and Donoghue (2016), transfer strategies are a third type of learning strategies in addition to the commonly cited surface and deep strategies. Transfer strategies are concerned with how students transfer, adapt or adjust learning strategies in new contexts. Little research exists about transfer strategies or how students transition between courses or adapt to new contexts.

Our study showed that only a fraction (66%) of students were able to transfer deep strategies that are relevant to the new course requirements (from intense diverse, to PBL intense), and the rest resorted to surface strategies. The fact that some students with intense strategies used a light strategy in the next course highlights the need to help students adapt, adjust and transfer strategies between courses. We see that those students who successfully transferred their strategies scored the highest of all students. We also see that students who continued to use surface strategies were the least achieving of all students. Such findings provide empirical evidence for the need for more effective strategies, support or instruction to help students develop effective learning strategies within PBL curricula. PBL is assumed to encourage active, self-directed learning and enhance intrinsic motivation of medical students (Dolmans et al., 2016). However, our results show that technology-supported PBL needs more than just a mere online platform and instructions to be successful. Enacting technology-supported PBL requires essential ingredients, for example, using a structured process, having shared goals, monitoring and scaffolding, which corroborates research on collaborative learning (Beaumont et al., 2008; Gelan et al., 2018). Some studies seem to suggest that face-to-face PBL can be implemented without tutor support (Kaliyadan et al., 2012; Klegeris et al., 2013; McQuade et al., 2020). For instance, Klegeris et al. (2013) showed that tutor-less PBL has improved students' problem-solving skills in a large classroom compared to their tutored counterparts using blinded marking. Other researchers have shown the possibility of tutor-less PBL with comparable results to tutored groups (Hayashi et al., 2013; Kaliyadan et al., 2012; Klegeris et al., 2013; McQuade et al., 2020). An important distinction of our study is that it was based in an online setting. A systematic review by Dolmans et al. (2016) showed that PBL curricula may improve deep learning skills. However, their conclusions were that the effect size was small with curriculum implementations studies (studies examining full curriculum) and not conclusive when it comes to single course studies and therefore called for more longitudinal studies.

Research in medical education has mostly focused on studying students' strategies using self-reports. Our study shows the potential of data-informed methods in revealing students' strategies (Saqr, 2015). Although online data are far from perfect and have some limitations regarding scope and coverage, the collection of such data is unobtrusive, it can be automated and has shown reasonable results. Therefore, learning analytics can add to the methods of studying students' learning strategies in medical education, monitoring students' implementation of learning strategies and probably offering support (Jovanovic et al., 2017; López-Pernas & Saqr, 2021; Saqr & López-Pernas, 2021).

Limitations

Our data, analysis and interpretation are limited to the context of blended learning. Furthermore, since our data pertain to the online portion of the blended learning, we emphasise that the interpretation of the reported findings should be limited to online learning. Furthermore, online data are limited to the representation of students’ interactions with online learning resources and therefore, our results should be interpreted with this in mind. For example, students’ prior knowledge is one of internal factors that might have influenced the students' transfer of tactics and strategies. However, the prior knowledge levels in our sample were rather similar since these were the first two courses in the programme; therefore, all enrolled students had a GPA close to 90% in their secondary education (it was an entry requirement). Similarly, it could be argued that the teachers themselves might have been an important external factor. However, in PBL, teaching is distributed and therefore most teachers who taught the first course also taught the second course and there were around 20 teachers. Such a diversity of teachers and large overlap of teachers across the courses make this effect relatively small.

Conclusions and implications

Our study has tried to address the role of strategies and the transfer thereof within PBL context. We show that technology-supported PBL is not a spontaneous phenomenon and requires scaffolding and structuring to be successful. A strong link between the applied learning strategies and the role of instructional cues (i.e., scaffolding of the PBL) is shown by examining traces of students’ learning behaviours. Regarding learning strategies, our results have emphasised the relation of deep learning strategies to academic achievement but more importantly, demonstrated that data informed methods can be used to detect and monitor learning strategies. Our results also highlight the role of effective adjustment of deep learning strategies to new courses. Since medical students have to navigate several contexts that range from basic science courses, clinical rounds and practical sessions, the value of transferring or adjusting strategies between contexts is expected to be of central importance to students’ success. Given that medical students are future physicians who are supposed to have continuous medical education through life, the transfer of learning strategies cannot be more emphasised and requires due attention in curricula and training.

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