Dispositional Learning Analytics to Investigate Students Use of Learning Strategies

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Abstract: What can we learn from dispositional learning analytics about how first-year business and economics students approach their introductory math and stats course? This study aims to understand how students engage with learning tasks, tools, and materials in their academic pursuits. It uses trace data, initial assessments of students' learning attitudes, and survey responses from the Study of Learning Questionnaire (SLQ) to analyse their preferred learning strategies. An innovative aspect of this research is its focus on clarifying how learning attitudes influence and potentially predict the adoption of specific learning strategies. The data is examined to detect clusters that represent typical patterns of preferred strategies, and relate these profiles to students' learning dispositions. Information is collected from two cohorts of students, totalling 2400 first-year students. A pivotal conclusion drawn from our research underscores the importance of adaptability, which involves the capacity to modify preferred learning strategies based on the learning context. While it is crucial to educate our students in deep learning strategies and foster adaptive learning mindsets and autonomous regulation of learning, it is equally important to acknowledge scenarios where surface strategies and controlled regulation may offer greater effectiveness.

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1 INTRODUCTION

In today's technology-driven and ever-changing landscape, the acquisition of skills conducive to adaptability is imperative. Self-regulated learning (SRL), highlighted as essential by various sources (Ciarli et al., 2021), is vital for continuous learning and development in the dynamic digital age. SRL encompasses a set of skills that facilitate learning processes and lead to positive academic outcomes, such as improved performance and continuous progress (Haron et al., 2015; Panadero and Alonso Tapia, 2014). Specifically, SRL involves (meta-) cognitive and motivational learning strategies that shape a dynamic and cyclical process enabling students to guide their own learning (Zimmerman, 1986). While there exist six different models of SRL (Panadero, 2017), most of them have the cyclical process comprising three phases in common: preparatory, performance, and appraisal. Despite the abundance of scientific literature on SRL and its promotion in educational settings, teachers and students often encounter challenges in fostering these skills, even within pedagogical approaches like PBL, where self-regulation is more integrated (Loyens et al., 2013).

Educational technology presents an opportunity to promote students' SRL. However, while some educators successfully foster SRL using technology, others struggle (Timotheou et al., 2023). This discrepancy may stem from variations in technology features and student engagement with technology, which influence its impact on learning and performance (Lawrence and Tar, 2018; Zamborova and Klimova, 2023). Recent advancements in educational research, particularly in learning

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analytics, notably dispositional learning analytics, offer valuable insights into SRL in technology-enhanced learning (Pardo et al., 2016, 2017; Tempelaar et al., 2015, 2017).

Recent years have witnessed a significant expansion in learning analytics research, providing novel insights into how students engage with online educational tools and content. Dispositional learning analytics, a methodological approach focused on understanding learners' inherent characteristics and tendencies, has emerged as a significant development (Buckingham Shum and Deakin Crick, 2012). By combining dispositional data with objective trace data, researchers can potentially derive predictive and actionable insights, aiding in understanding student behavior, learning strategies, and enabling a more tailored educational experience (Han et al., 2020; Tempelaar et al., 2015, 2017).

The current study investigates the learning strategies of first-year business and economics students enrolled in an introductory mathematics and statistics course. This context is of interest due to the challenges and opportunities presented by the subject matter, which requires both conceptual understanding and practical application and is often perceived as difficult by students. Our focus on this group aims to illuminate how students engage with complex quantitative content, thereby contributing to enhancing academic success. Our primary objective is to explore and understand the range of learning strategies preferred by these students. To achieve this, we employ a dual approach: analyzing trace data, which provides digital footprints of students' interactions with learning tools and materials, combined with dispositional data such as learning related mindsets and learning strategies. This analysis aims not only to identify prevalent learning strategies but also to discern their correlation with students' engagement with digital learning tools. This understanding is pivotal for informing more effective pedagogical approaches and targeted interventions to enhance student learning outcomes (Han et al., 2020).

This study introduces several innovative aspects to the field of dispositional learning analytics. Firstly, it emphasizes the importance of linking initial learning dispositions, measured at the beginning of the course, with subsequent learning strategies. By identifying profiles in this data, we aim to uncover how initial dispositions may predict the adoption of specific learning strategies. This approach represents a significant departure from traditional methods, which often focus solely on outcomes, to a more nuanced understanding that encompasses the origins and evolution of learning behaviors. Moreover, we leave the traditional variable-centred method of analysis, in favour of a person-centred analysis.

The insights derived from this study offer potential benefits to various stakeholders in education. For educational scientists and designers, our findings provide critical data to inform the development of more effective curriculum designs and learning tools. Teachers can leverage this information to better understand their students' learning processes, potentially identifying those employing less beneficial strategies. This understanding is crucial for developing targeted interventions that can significantly enhance student learning outcomes and promote more effective self-regulation in the learning process.

2 BACKGROUND

Self-regulated learning (SRL) stands as a key educational strategy essential for navigating today's dynamic academic environment. Defined by a repertoire of skills enabling learners to effectively manage and oversee their own learning processes, SRL has been extensively studied for its pivotal role in achieving favourable academic outcomes, such as improved performance and ongoing advancement (Haron et al., 2015; Panadero and Alonso-Tapia, 2014). At the core of SRL lies a cyclical and dynamic process encompassing cognitive, metacognitive, and motivational strategies (Zimmerman, 1986). Despite the extensive literature on SRL, its practical implementation, particularly in cultivating these skills within diverse pedagogical contexts, remains a significant challenge for educators and learners alike.

This challenge extends to student-centred pedagogical approaches like Problem-Based Learning (PBL), which inherently complements and supports the principles of SRL (Hmelo-Silver, 2004; Schmidt et al., 2007). PBL, centred on real-world problem-solving, encourages learners to actively participate in their learning journey, fostering critical thinking and self-regulated learning skills. In a program based on PBL principles, learners are continually required to self-regulate as they collaboratively and individually navigate through problems, apply knowledge, and adjust strategies based on feedback and reflection. However, research shows mixed results regarding student learning approaches. A comprehensive literature review on the adoption of deep versus surface learning approaches in PBL revealed a small positive effect size concerning the adoption of deep learning approaches (Dolmans et al., 2016), yet some studies report a tendency to adopt surface learning approaches across the studied population (Loyens et al., 2013).

The affordances of educational technology have been recognized as a potent means to promote SRL (Persico and Steffens, 2017). However, despite the unparalleled developments in digitization in (higher) education, technology alone is not a cure-all for delivering high-quality technology-enhanced education, especially considering the emergency remote learning implementations (Mou, 2023). Educational research indicates that while some teachers succeed in fostering SRL in their students through technology-enhanced learning means, others do not (Timotheou et al., 2023). Several factors could underlie this finding, including teacher attitudes and behaviours regarding technology, the features of technology, and student engagement with the technology (e.g., Lawrence and Tar, 2018; Zamborova and Klimova, 2023). In technology-enhanced learning environments that promote self-regulated learning through scaffolding, dispositional factors have been found to influence student engagement (Tempelaar et al., 2017, 2020). Advances in the development of dispositional learning analytics show promise in aiding the understanding of SRL in technology-enhanced learning contexts (e.g., Pardo eta al., 2016, 2017; Tempelaar et al., 2017, 2020).

2.1 Dispositional Learning Analytics

In the ever-evolving realm of educational research, Learning Analytics (LA) emerges as a crucial tool, providing a thorough examination of educational data to extract actionable insights for learners, educators, and policymakers (Hwang et al., 2018). Initially, LA research primarily centred on constructing predictive models using data from institutional and digital learning platforms. However, these early efforts mainly demonstrated the descriptive capabilities of LA, confined to aggregating and analysing learner data within existing educational infrastructures (Viberg et al., 2018; Siemens and Gašević, 2012). Acknowledging the limitations imposed by the static nature of such data, Buckingham Shum and Deakin Crick (2012) introduced the concept of Dispositional Learning Analytics (DLA), proposing an innovative framework that intertwines traditional learning metrics with deeper insights into learners' dispositions, attitudes, and values.

By incorporating learner dispositions into the analytic process, DLA aims to enhance the precision and applicability of feedback provided to educational stakeholders, thereby refining the effectiveness of educational interventions (Gašević et al., 2015; Tempelaar et al., 2017). The concept of 'actionable feedback,' as conceptualized by Gašević et al. (2015), emphasizes the transformative potential of DLA in fostering a more nuanced approach to educational support, moving beyond generic advisories to deliver tailored, context-sensitive guidance.

Despite the recognized value of LA in identifying at-risk students, the challenge of translating analytic insights into effective pedagogical action remains significant, as evidenced by studies such as Herodotou et al. (2020). DLA seeks to address this gap by incorporating a multidimensional analysis of learning dispositions, thereby offering a richer, more holistic understanding of learners' engagement and potential barriers to their success.

For instance, the simple directive to 'catch up' may prove insufficient for students consistently falling behind in their learning process. A deeper exploration into their learning dispositions through Dispositional Learning Analytics (DLA) might reveal specific barriers to their academic engagement, such as a lack of motivation or suboptimal self-regulation strategies, enabling more precise interventions (Tempelaar et al., 2021).

A notable utility of DLA lies in the nuanced integration of motivational elements and learning regulation tactics within the broader LA framework. Our previous research indicates that, although a high degree of self-regulation is often praised, striking a balance between self-directed and externally guided regulation is essential (Tempelaar et al., 2021a, b). Identifying students predisposed to either excessive self-reliance or significant disengagement allows for the design of tailored interventions that resonate with their unique learning styles. For individuals inclined towards overemphasis on self-regulation, feedback may highlight the benefits of external inputs and adherence to the prescribed curriculum framework. Conversely, for those displaying disengagement, strategies may focus on igniting intrinsic motivation and fostering active participation in the learning process.

2.2 Research Objective and Questions

In this current investigation, we aim to delve deeper into how DLA can enhance both the predictive and intervention capabilities of LA. Expanding upon prior research conducted by scholars such as Han et al. (2020), Pardo et al. (2016, 2017), and Tempelaar et al. (2021a, b), we pivot our focus in this study to learning strategies. The research questions arising from this research objective involve examining whether and how dispositional learning analytics can help us better understand how learning attitudes influence and potentially predict the adoption of specific learning strategies within a student-centred teaching approach.

3 METHOD

3.1 Context and Setting

This research was conducted within the framework of a mandatory introductory mathematics and statistics module tailored for first-year undergraduate students. This module constitutes an essential component of a business and economics program at a medium-sized university in The Netherlands, with data collection spanning academic years 22/23 and 23/24. The module extends over an eight-week period, requiring a weekly commitment of 20 hours. Many students, especially those with limited mathematical skills, perceive this module as a significant hurdle.

The instructional approach adopted involves a flipped classroom design, primarily emphasizing face-to-face Problem-Based Learning (PBL) sessions. These sessions, conducted in tutorial groups of up to 15 students, are led by content expert tutors. Each week, students participate in two such tutorial groups, each lasting two hours. Fundamental concepts are introduced through lectures delivered weekly. Additionally, students are expected to allocate 14 hours per week to self-study, utilizing textbooks and engaging with two interactive online tutoring systems: Sowiso (https://sowiso.nl/) and MyStatLab (Nguyen et al., 2016; Rienties et al., 2019; Tempelaar et al., 2015, 2017, 2020).

A primary goal of the PBL approach is to cultivate Self-Regulated Learning (SRL) skills among students, emphasizing their responsibility for making informed learning choices (Schmidt et al., 2007). Collaborative learning through shared cognitions is another objective. To achieve these aims, feedback from the tutoring systems is shared with both students and tutors. Tutors utilize this feedback to guide students when necessary, initiating discussions on feedback implications and suggesting improvement strategies. These interactions take place within the tutorial sessions and are not observed.

The student learning process unfolds in three phases. The first phase involves preparation for the weekly tutorials, during which students engage in self-study to tackle "advanced" mathematical and statistical problems. While not formally assessed, this phase is crucial for active participation in the tutorials. The second phase centres on quiz sessions held at the end of each week (excluding the first). These quizzes, designed to be formative, provide feedback on students' mastery of the subject. With 12.5% of the total score based on quiz performance, students are motivated to extensively utilize the resources available, particularly those with limited prior knowledge. The third and final phase is dedicated to exam preparation during the last week of the module, involving graded assessments.

3.2 Participants

In total, data from 2406 first-year students enrolled in academic years 2022/2023 and 2023/2024 were utilized in this study. All of these students had engaged with at least one online learning platform. Among these students, 37% identified as female, while 63% identified as male. Regarding educational background, 16% possessed a Dutch high school diploma, while the majority, comprising 84%, were international students. The international student cohort predominantly hailed from European countries, with a notable representation of German (33%) and Belgian (18%) nationalities. Additionally, 7% of students originated from outside Europe.

The approach to teaching mathematics and statistics varies considerably across high school systems, with the Dutch system placing a greater emphasis on statistics compared to many other countries. However, across all countries, math education is typically categorized into different levels based on its application in sciences, social sciences, or humanities. In our business program, a prerequisite for admission is prior mathematics education tailored towards social sciences. Within our study cohort, 37% of students pursued the highest track in high school, contributing to a diverse range of prior knowledge. Therefore, it was essential for the module to accommodate these students by offering flexibility and accommodating individual learning paths, alongside providing regular interactive feedback on their learning strategies and tasks.

In addition to a final written exam, student assessment included a project where students statistically analysed personal learning disposition data. To facilitate this, students completed various individual disposition questionnaires to measure affective, behavioural, and cognitive aspects of aptitudes, including a learning strategies questionnaire at the outset of the module. Subsequently, they received personalized datasets for their project work.

3.3 e-Tutorial Trace Data

Trace data were collected from both online tutoring systems and the Canvas LMS, which provided general course information and links to Sowiso and MyStatLab. Both Sowiso and MyStatLab employ mastery learning as their instructional method (Tempelaar et al., 2017). However, they differ significantly in their capabilities for collecting trace data. MyStatLab offers students and instructors several dashboards summarizing student progress in mastering individual exercises and chapters but lacks time-stamped usage data. Conversely, Sowiso provides time stamps for every individual event initiated by the student, along with mastery data, enabling the full integration of temporality in the design of learning models. Previous studies (Tempelaar et al., 2021a, 2023) focused solely on the rich combination of process and product trace data from Sowiso. In this study, we incorporate both trace data of product type, taken from both e-tutorials, as well as trace data of process type from Sowiso only. The mastery achieved by students in each week as preparation for their quiz sessions constitutes the product type data. Mastery data represent the proportion of assignments students are able to solve without using any digital help, in every week of the course.

The main type of process data, available for the mathematical e-tutorial Sowiso, is the number of attempts students undertake to solve the weekly assignments. Following previous research (Tempelaar et al., 2023), we delineated three distinct learning phases based on the timing of learning activities. In phase 1, students engaged in preparation for the tutorial session of the week. During these face-to-face tutorial sessions, students discussed solving 'advanced' mathematical and statistical problems, necessitating prior self-study to facilitate active participation in discussions. Phase 2 learning involved preparing for the quiz session at the conclusion of each module week. Phase 3 encompassed preparation for the final exam, scheduled for the eighth week of the module. Consequently, students made timing decisions regarding the extent of their preparation across each of the three phases.

3.4 Instruments

3.4.1 Study of Learning Questionnaire

The learning strategies questionnaire (see Table 1) was adapted from the questionnaire employed by Rovers et al. (2018), which in turn was adjusted from the questionnaire developed by Hartwig and Dunlosky (2012) to suit a Problem-Based Learning (PBL) environment. To customize it for the specific course, supplementary items regarding the utilization of online learning platforms were integrated. All items were assessed on a Likert scale ranging from 1 (never) to 7 (often). The survey was administered midway through the course to ensure participants' familiarity with the included learning strategies. It is apparent that the initial items predominantly focus on passive learning strategies, which are generally deemed less effective compared to the subsequent items that emphasize more active strategies like self-testing (Dunlosky et al., 2013; Hartwig and Dunlosky, 2012).

Table 1: Learning Strategy Questionnaire Items.

Item	Learning strategy engagement
LrnApp01	Rereading textbook and reader
LrnApp02	Making summaries
LrnApp03	Underlining/marking text
LrnApp04	Explaining to myself what I am reading
LrnApp05	Remembering keywords
LrnApp06	Trying to form a mental image (an image in my head) of what I am reading
LrnApp07	Testing myself by doing Sowiso exercises
LrnApp08	Testing myself by doing MyStatLab exercises
LrnApp09	Testing myself with self-made test questions
LrnApp10	Studying worked-out examples in Sowiso
LrnApp11	Studying worked-out examples in MyStatLab
LrnApp12	Asking someone else to test me
LrnApp13	Asking questions to other students (outside of the tutorial group)
LrnApp14	Studying with friends/other students
LrnApp15	Visiting lectures

3.4.2 Mindset Measures: Self-Theories of Intelligence, Effort-Beliefs and Goals

Self-theories of intelligence measures encompass both entity and incremental types, originating from Dweck's Theories of Intelligence Scale – Self Form for Adults (2006). This scale comprises eight items: four statements reflecting Entity Theory and four reflecting Incremental Theory. Effort-belief measures were sourced from two references: Dweck (2006) and Blackwell (2002). Dweck offers example statements illustrating effort as either negative—EffortNegative, where exerting effort implies low ability—or positive—EffortPositive, where exerting effort is seen as enhancing one's ability. The former serves as the introductory item on both subscales of these statement sets (see Dweck, 2006). Furthermore, Blackwell's comprehensive sets of Effort beliefs (Blackwell et al., 2007) were utilized, consisting of five positively formulated and five negatively formulated items.

To identify goal setting behaviour, we have applied the Grant and Dweck (2003) instrument, which distinguishes the two learning goals Challenge-Mastery and Learning, as well as four types of performance goals—two of appearance nature: Outcome and Ability Goals, and two of normative nature: Normative Outcome and Normative Ability Goals.

3.4.3 Learning Processes and Regulation Strategies

We employed Vermunt's (1996) Inventory of Learning Styles (ILS) tool to assess learning processing and regulation strategies, which are fundamental aspects of Self-Regulated Learning (SRL). Our investigation specifically targeted cognitive processing strategies and metacognitive regulation strategies.

The cognitive processing strategies align with the SAL research framework (see Han et al., 2020) and are organized along a continuum from deep to surface approaches to learning. In the deep approach, students strive for comprehension, while in the surface approach, they focus on reproducing material for assessments without necessarily understanding the underlying concepts:

- Deep processing: forming independent opinions during learning, seeking connections and creating diagrams.
- Stepwise (surface) processing: investigating step by step, learning by rote.
- Concrete Processing: focus on making new knowledge tangible and applicable.

The metacognitive regulation strategies shed light on how students oversee their learning processes and facilitate categorizing students along a spectrum that spans from self-regulation as the predominant mechanism to external regulation. These scales encompass:

- Self-regulation: self-regulation of learning processes and learning content.
- External regulation: external regulation of learning processes and learning outcomes.
- Lack Regulation: absence of regulation.

The instrument was administered at the onset of the academic study, indicating that the typical learning patterns observed in students are those developed during high school education.

3.4.4 Academic Motivations

The Academic Motivation Scale (AMS, Vallerand, et al., 1992) is rooted in the framework of self-determination theory, which discerns between autonomous and controlled motivation. Consisting of 28 items, the AMS prompts individuals to answer the question "Why are you attending college?" The scale encompasses seven subscales, with four categorized under the Autonomous motivation scale, representing the inclination to learn stemming from intrinsic satisfaction and enjoyment of the learning process itself. Furthermore, two subscales are part of the Controlled motivation scale, indicating learning pursued as a means to an external outcome rather than for its inherent value. The last scale, A-motivation, denotes the absence of regulation.

3.5 Statistical Analyses

Drawing from the framework of person-centred modelling approaches (Malcom-Piqueux, 2015) and employing cluster analysis methodologies to identify unique and shared learner profiles based on their learning strategy data, this study utilized *k*-means cluster analysis (Pastor, 2010). The input data consisted of fifteen responses to the Study of Learning Questionnaire (SLQ) instrument. Although trace data and other disposition data could have been included in the cluster analysis, the decision was made to focus solely on profiles derived from SLQ data. By categorizing students into clusters based solely on perceived learning strategies, the study gains the advantage of distinguishing and exploring relationships between self-reported aptitudes and those manifested in learning activities, as well as other aptitude measures (Han et al., 2020). An alternative approach, as seen in previous studies by the authors (Tempelaar et al., 2020), could have combined behavioural and dispositional measures for clustering, resulting in profiles representing a mix of actual learning activities and self-perceived learning dispositions. Another potential approach could have focused exclusively on trace data for clustering, examining differences in learning behaviours among clusters, as demonstrated by Tempelaar et al. (2023). However, due to the absence of process-type trace data for the MyStaLab e-tutorial, this approach was not considered viable for this study.

The determination of the number of clusters aimed to maximize profile variability while ensuring that clusters were not overly small (comprising less than 5% of students). Ultimately, a five-cluster solution was selected, revealing five clearly distinct profiles. Solutions with higher dimensions did not significantly alter cluster characteristics and posed challenges in interpretation. Subsequently, differences between profiles in E-tutorial use, mindsets, learning patterns, academic motivations and course performance were explored through variable-centred analysis using ANOVA. Since due to large sample size, nearly all profile differences are strongly significantly different beyond the .0005 level, reporting is focussing on effect sizes.

4 RESULTS

4.1 Student Learning Strategy Profiles

The optimal characterization of students' learning strategy profiles emerged through a five-cluster solution. This selection was predominantly driven by the preference for solutions that offer a straightforward and intuitive interpretation of the profiles, prioritizing parsimony. The five-cluster solution proves to be the best fit, delineating distinct profiles of learning approaches within the clusters. The clusters are presented in Figure 1.

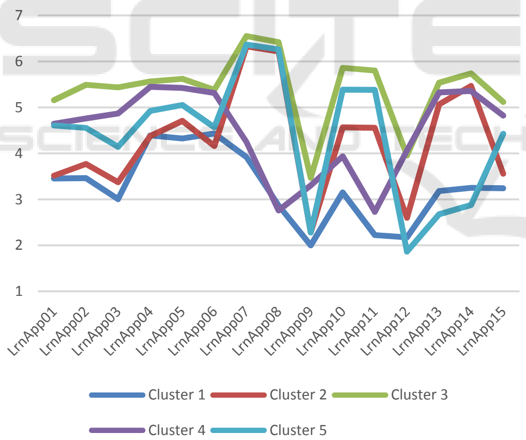

Figure 1: Clusters Based On Learning Strategy Data.

The largest profile with 693 students is given by Cluster 3, encompassing students who achieved “all high” scores across all learning strategy items, resulting in a relatively uniform and less diverse learning strategy pattern compared to other clusters. Conversely, Cluster 1, 297 students, serves as its counterpart in many aspects, with “all low” scores for most learning strategies. Cluster 4, 340 students, is the profile of "non-tool users". These students apply passive learning strategies such as rereading, marking, and attending lectures, and trust on the collaboration with peers. The two remaining profiles are characterized by a strong focus on self-testing. Cluster 5 students (505) are the intensive “tool-users”: they utilize the e-tutorials not only for self-testing but also for accessing worked-out examples. Cluster 2 students (571) combine the focus on using tools to self-test with the tendency to collaborate with peers in learning.

4.2 Profile Differences in e-Tutorial Use

Figure 2 illustrates the average e-tutorial mastery scores for the weekly topics. On the left side are the seven mathematical topics covered over seven weeks, while on the right side are the mastery scores for the seven weekly statistical topics.

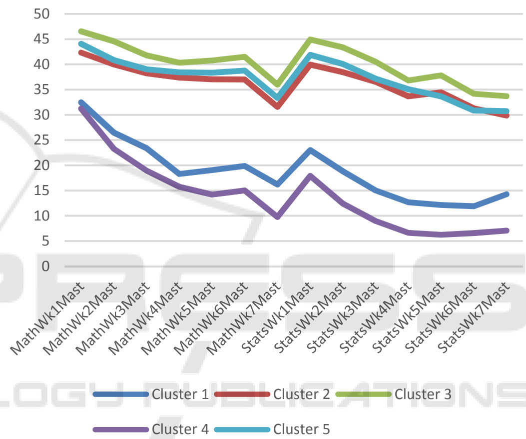

Figure 2: Profile Differences in Weekly Mastery Scores.

The five profiles are categorized into two patterns, emphasizing notable distinctions between the two profiles characterized by consistently low scores ("all low") and those identified as "non-tool users," which also attain low mastery scores. Conversely, the "all high" profile, along with the two "self-testing" directed profiles, are positioned on the opposite end of the spectrum. Across all profiles, there is an observable decline in mastery scores over time, with the most significant decrease observed in the profiles starting with relatively low mastery levels.

Process-type trace data, represented by Attempt data for each of the weekly mathematics topics across the three learning phases (preparing for tutorial sessions, quizzes, and exams), exhibit a similar declining pattern over the weeks. Furthermore, they indicate that students predominantly focus on the second learning phase, the preparation of quizzes, elucidating the saw tooth gradient in Figure 3. At the

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lower end of the saw tooth, the "all low" and "non-tool users" profiles reappear. However, notably, the gap between these two profiles and the other three profiles is much narrower compared to the mastery data. Evidently, extensive utilization of e-tutorials coincides with less efficient usage.

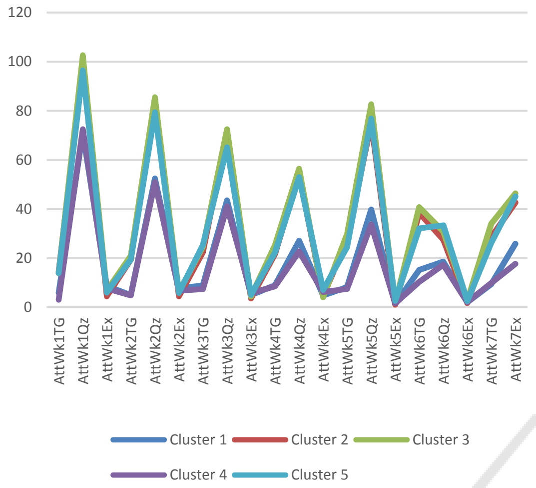

Figure 3: Profile Differences in Weekly Attempts, by Learning Phase.

4.3 Profile Differences in Mindsets, Effort Beliefs and Goals

Different mindsets, whether it's the entity theory implying a fixed intelligence belief or the incremental theory suggesting intelligence is adaptable, show minimal distinctions in their profiles. The most notable variances are found in the incremental theory, accounting for a 3.4% eta squared effect size. This effect is magnified when paired with positive effort beliefs, resulting in a doubled effect size of eta squared 6.8%, whereas differences in negative effort beliefs are ignorable.

When examining students' goal-setting behaviours across the five profiles, variations emerge, particularly in outcome goals (8.5% eta squared effect size), learning goals (9.2% eta squared effect size), and challenge-mastery goals (4.8% eta squared effect size). Among these more pronounced profile distinctions, students in “all high” Cluster 3, characterized by consistently high attributes, tend to align with adaptive behaviours, while those in “all low” Cluster 1, with consistently low attributes, tend to lean towards maladaptive behaviours. However, no consistent patterns are observed in the remaining three clusters: see Figure 4.

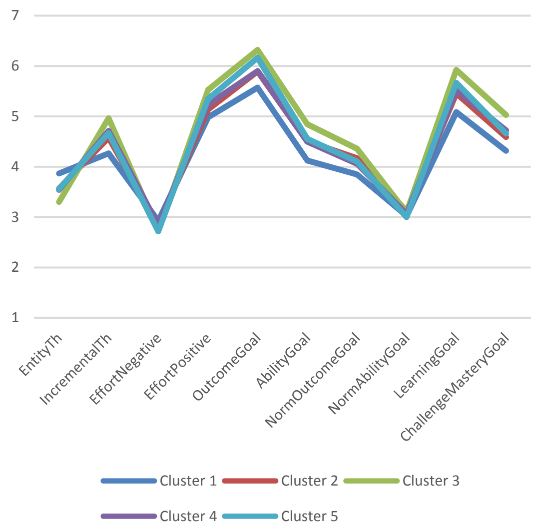

Figure 4: Profile Differences in Mindsets, Effort Beliefs and Achievement Goals.

4.4 Profile Differences in Learning Patterns

The most prominent and consistent disparities across all learning dispositions are observed in the instrument that assesses cognitive learning processing and metacognitive learning regulation. Consistency is defined by consistently scoring either high or low on processing and regulation strategies, regardless of their type (except for the maladaptive lack of regulation strategy). Cluster 3 students, identified as exhibiting "all high" tendencies in employing various learning strategies, demonstrate this characteristic consistently in both processing and regulation. Their propensity for deep learning, as well as surface (stepwise) and concrete (strategic) learning, surpasses that of any other cluster. Moreover, their application of self-regulation and external regulation of learning exceeds that of all other clusters. Conversely, Cluster 1 students, labelled as "all low" in terms of learning strategies, exhibit uniformly low scores across all learning processing strategies and both adaptive learning regulation strategies. For the students in Cluster 2, their emphasis on self-testing and collaborative learning translates into a relatively modest intensity in applying processing or regulation strategies. However, a clear pattern is absent in the profile differences between the remaining two clusters, the "tool users" and "non-tool users" of Clusters 4 and 5. Effect sizes vary from 7% for external regulation to 13.2% for stepwise processing, as depicted in Figure 5.

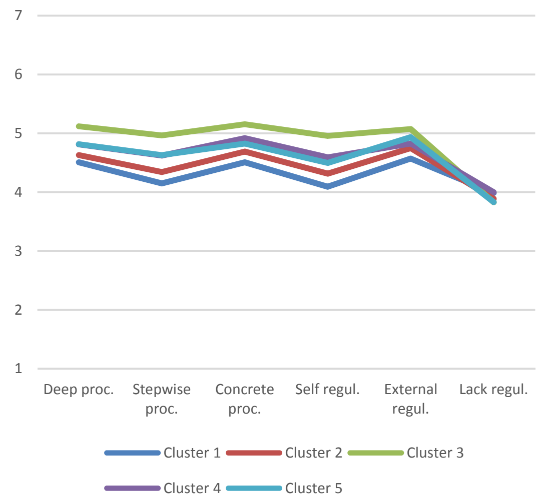

Figure 5: Profile Differences in Learning Processing and Learning Regulation.

4.5 Profile Differences in Academic Motivations

In line with the outcomes discussed in the previous section, distinct and consistent disparities among clusters emerge in Autonomous and Controlled Motivation. However, the only substantial effect size is associated with Autonomous Motivation, reaching 13.8% eta squared, as shown in Figure 6.

Cluster 3 students, characterized as "all high," demonstrate the highest levels of both autonomous and controlled motivation, while Cluster 1 students, identified as "all low," exhibit the lowest levels of motivation across both dimensions. This observation challenges the assumptions of self-determination theory, which suggest the prevalence of one dimension of motivation over the other. Profile variances among Clusters 2, 4, and 5 are minimal and lack a similarly consistent pattern.

4.6 Profile Differences in Course Performance

The true gauge of achievement lies in performance, specifically in how students perform in the course. Performance metrics including ExamMath, ExamStats, QuizMath, and QuizStats reveal variations among profiles, with effect sizes ranging from 3.9% to 7.3%. The most notable effect size is found in both quiz scores, where the eta squared effect size reaches 7.3%.

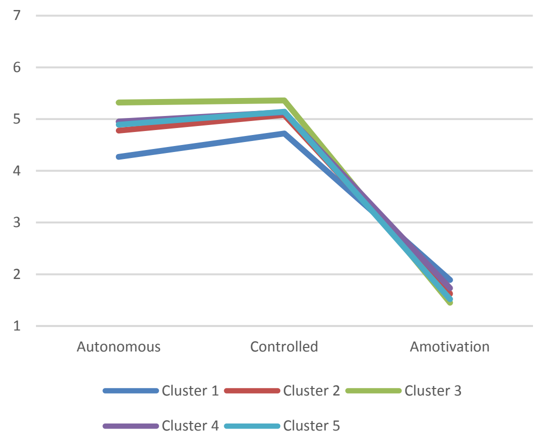

Figure 6: Profile Differences in Academic Motivations.

Somewhat smaller, be it better visible in Figure 7, are the profile differences in performance scores: quiz scores (with range 0…4) and exam scores (with range 0…20).

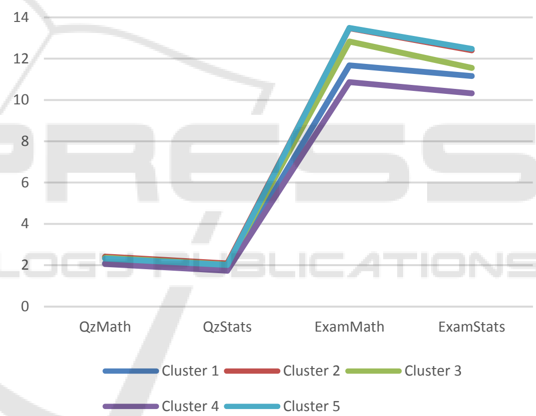

Figure 7: Profile Differences in Course Performance.

Two clusters stand out as top performers: the two clusters characterized by extensive "tool usage," namely Clusters 2 and 5. Despite being the most adaptable learners, students in Cluster 1, the "all high" cluster, achieve intermediate levels of performance. On the other hand, Cluster 1, consisting of "all low" students, and Cluster 4, comprising "non-tool users," exhibit lower performance levels.

5 DISCUSSION & CONCLUSIONS

In our research, we examined students' preferences for learning strategies through self-report surveys. In a PBL curriculum, where students have access to

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various learning strategies both within and outside of technology-enhanced learning environments, this is the only way to identify how learning takes place. However, if all learning occurs within digital confines, the identification of learning strategies is not limited to self-report methods but can also be achieved behaviourally, through the analysis of traces of learning activities. An illustrative example of such behavioural identification of learning strategies is provided by Fan et al. (2022), who investigated learning within a MOOC environment. Fan and colleagues identified two successful learning strategies, called intensive and balanced, which were positively associated with course performance. Interestingly, these characteristics closely align with our "all high" profile of preferred learning strategies identified through self-reports.

Going back to the most salient finding of Rovers et al.'s (2018) investigation of learning strategies within a PBL-based program: again, it were the students who employ a diverse range of learning approaches who tend to excel. This diversity includes strategies traditionally viewed as suboptimal, such as surface-level learning methods. The key factor for effective learning seems to be adaptability. Rovers et al. (2018) conclude that students who reported utilizing various strategies, including some traditionally considered "ineffective" (like highlighting, rereading, etc.), but in ways that suited their learning context, appear being the most adaptive students.

Our study expands upon the application of diverse instructional methods. Even within a standard PBL curriculum, students have access to abundant learning resources. By integrating blended learning into our investigation, we further diversify the available resources, compelling students to select from an even broader array of learning strategies. Despite significant shifts in learning environments, Rovers et al.'s (2018) primary finding remains more or less consistent: one of the effective learning approaches, as indicated by course performance, involves integrating all available learning strategies. This includes employing deep learning whenever possible but transitioning to surface-level approaches when necessary. Students are encouraged to use autonomous regulation when suitable but should not hesitate to employ controlled regulation in challenging circumstances.

Two additional profiles indicative of effective learning methods concerning course performance were observed among students who prioritize self-testing. While the significance of self-assessment in self-regulated learning is widely recognized (Panadero et al., 2019), it's essential to exercise caution in generalizing this finding beyond our specific context, which involves two e-tutorials grounded in mastery learning within a test-oriented learning environment. It is evident that within a learning environment offering ample opportunities for self-assessment, students inclined towards self-assessment tend to excel, even achieving the highest course performance. However, the question arises whether this pattern persists in contexts where self-assessment isn't as robustly supported as in our particular learning environment.

When assessing performance as a measure of learning effectiveness, we identify two learning strategy profiles that exhibit below-average performance relative to others, albeit with modest performance differences. Cluster 1 students primarily rely on non-digital resources and employ surface-level learning strategies such as highlighting, underlining, and rereading. Cluster 2 students also depend on non-digital resources, focus on memorizing keywords, utilize self-explanation, and heavily rely on peer collaboration for learning. The rigorous nature of our course (mathematics and statistics, which may not align with the preferences of many business and economics students) could contribute to the limitations associated with these two learning strategy profiles. Conversely, students who incorporate testing as a significant component of their learning strategies demonstrate above-average performance, underscoring its importance.

Importantly, previous mathematics education does not account for variations in learning strategy preferences, whereas gender does. Female students are overrepresented among those who adopt effective learning strategies compared to their male counterparts.

Addressing challenges related to fostering SRL in higher education, particularly in student-centred learning approaches like PBL, is complex. The current study offers additional insight into how SRL can be understood through DLA, aligning with findings from previous research indicating that employing DLA aids in understanding learners' motivations, attitudes, and learning strategies, thereby facilitating the development of more personalized and effective educational interventions (Pardo et al., 2016, 2017; Persico & Steffens, 2017; Tempelaar et al., 2017, 2020). For practical implementation, DLA could be integrated into the development of learning analytics dashboards to inform both students and instructors about learning progress (e.g., Matcha et al., 2019). However, it is crucial to consider that interpreting results would require some level of instruction to enhance understanding and implementation of SRL strategies within various learning and teaching contexts, as well as how to interpret DLA data accordingly.

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