

# The Mediating Role of Learning Analytics: Insights into Student Approaches to Learning and Academic Achievement in Latin America

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## Abstract

Researchers in learning analytics have created indicators with learners' trace data as a proxy for studying learner behaviour in a college course. Student Approaches to Learning (SAL) is one of the theories used to explain these behaviours, distinguishing between deep, surface, and organized study. In Latin America, researchers have demonstrated that organized approaches to learning could be more effective in higher education, leading to better performance and course approval. However, further analysis of student behavioural data is needed to understand this relationship and inform interventions targeting study habits and academic performance. In this study, we analyzed the relationship between student approaches to learning and their final grade in six college courses, using behavioural trace data as a mediator variable. Specifically, we conducted a quantitative study in two Latin American institutions where data of different granularity was collected from their Learning Management Systems. We observed that most learning analytics indicators do not mediate the effect between approaches to learning and course performance. However, there was evidence for fine-grained indicators acting as total mediators. Implications are discussed at methodological and pedagogical levels, aiming to inform the advancement of learning analytics in the region and its use for supporting student learning.

## Notes for Practice

- Coarse-grained indicators were not found to be mediators of student approaches to learning, while fine-grained data, such as session counts, were significant predictors of final grade.
- Session count acts as a mediator between student approaches to learning and their final grades, with surface learners engaging less and achieving lower grades.
- Fine-grained data and self-reported metrics could be leveraged to create a varied range of learning analytics indicators to feed different support tools for students, teachers, and managers.
- Efforts are needed to address challenges in generalizability and limited data availability in Latin American (LATAM) universities, emphasizing the need for enhanced data infrastructures and further research on contextual factors and additional learning analytics indicators.

## Keywords

Student approaches to learning (SAL), mediation analysis, learning analytics (LA), Latin America

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## 1. Introduction

Over the past few years, learning analytics (LA) has emerged as a field focused on understanding and enhancing learning in the environments where it occurs (Siemens & Gašević, 2012). This means gathering educational data from different sources, such as demographic data (e.g., gender, age), administrative data (e.g., course enrolment, class attendance), and traces of student behaviour (e.g., student log data from Learning Management Systems [LMSs]). These traces are often summarized in indicators that quantify some aspect of student engagement (e.g., activity level or study regularity; see Jovanović et al., 2021), being used as a proxy of their behaviour at a course level. Although several studies have found correlations between these indicators and academic performance (Wang & Mousavi, 2023), there is still much debate on what these indicators are actually measuring (e.g., motivation or self-regulation; Conijn et al., 2017) since indicators generated from interactions with the LMS do not necessarily represent learning or ways to acquire knowledge or develop skills (Guzmán-Valenzuela et al., 2021). Furthermore, recent papers have shown that students' internal conditions (e.g., student motivations and perceptions) are a better predictor of student performance than LMS indicators (Jovanović et al., 2021). This suggests the need for further connections to learning theories to unveil learner behaviour from LA indicators (Guzmán-Valenzuela et al., 2021).

Student Approaches to Learning (SAL) is one of the theories used as a framework to explain learner behaviour. SAL research has focused on investigating how students carried out academic tasks by adopting a learning orientation to understand or reproduce the content of their courses (Biggs, 1993), discerning among deep, surface, and organized study regarding how students acquire new knowledge in academic settings. According to previous studies, SAL has proven to be a good predictor of learner performance on a course. In particular, students who self-report having deeper and more organized approaches tend to have better outcomes, while learners with more surface approaches have lower learning outcomes (Postareff et al., 2017; Tuononen et al., 2020). Furthermore, several studies indicate that student learning approaches could be reflected in their learning behaviour in the LMS and detected with LA methods (López-Pernas & Saqr, 2021).

To analyze student log data from traces in the LMS of the course, it is common to create indicators related to different aspects of student engagement with the online material, such as the student activity level and regularity of study (Wang & Mousavi, 2023; Jovanović et al., 2021). Indicators can have different levels of temporal granularity, such as focusing on weekly and daily behaviour or even focusing on actions performed during more specific time periods, defined as learning sessions (Jovanović et al., 2021). A recent review by Wang and Mousavi (2023) analyzed which indicators are significantly influential in predicting student achievement across 88 studies. While some indicators tended to be significant across studies, such as regularity of session duration and the number of online sessions, most results varied significantly across contexts. Furthermore, the generalizability of results has been a common challenge when translating LA results across different contexts (Matcha et al., 2020).

Although prior studies have illustrated the potential benefits of using LMS data to understand study habits and academic performance, there is a gap to be filled in this line of work. As aforementioned, numerous studies, including Wang and Mousavi (2023), show the correlation between specific indicators with academic performance. However, fewer efforts have been invested in understanding how indicators based on LMS trace data resonate with constructs from learning theory (Khalil et al., 2023). This lack of clarity hampers the development of targeted interventions, as educators and researchers face challenges in understanding and interpreting the theoretical underpinnings of these indicators and their impact on academic performance (Guzmán-Valenzuela et al., 2021). More research is crucial to bridge the gap between observed correlations and a nuanced understanding of the psychological and educational constructs measured by these indicators.

Latin America provides a convenient study context to evaluate the nature of LMS-based indicators. In this region, prior research has indicated that LA could become a valuable strategy to boost learning outcomes and improve retention rates (Hilliger et al., 2020a). While LMS data has been shown to be effective in providing timely feedback and delivering early warning systems in developed world regions, work on LA in other contexts is scarce (Guzmán-Valenzuela et al., 2021). Neglecting the unique needs of developing regions, such as Latin America, perpetuates a North–South imbalance in studying learning outcomes, potentially reinforcing inequalities (Guzmán-Valenzuela et al., 2021; Hilliger et al., 2020a). Evaluating LMS-based indicators offers an opportunity to rectify this imbalance, enabling more inclusive and tailored educational interventions in Latin America.

Considering the need for theory in LA research, particularly in developing regions, we performed a study in six higher education courses of two large, selective Latin American universities that use different LMSs. Our focus was to examine the effectiveness of indicators with different levels of granularity in mediating the impact of student approaches to learning on their final course grades. This comparison can offer valuable insights into the learning process to enable practices that can enhance student success. Also, this can inform and convince regional higher education leaders about the potential benefits of having the infrastructure and regulations to use LMS fine-grained data at an institutional level. Although this effort might not be generalizable to a broader context, it aims to contribute to gradually increasing the regional understanding of the potential benefits of LA, such as meeting student needs for timely support during their learning process (Hilliger et al., 2020a).

## 2. Related Works

### 2.1. SAL Research in Learning Analytics

Student Approaches to Learning (SAL) refers to how students learn, differentiating between surface memorization and more profound comprehension of the new knowledge (Richardson et al., 2012). Students applying deeper approaches intend to develop an understanding of the fundamental aspects of the content presented, relating ideas and integrating them into a coherent whole. On the contrary, students applying a surface approach tend to focus on fragmented pieces of information that must be memorized to pass assessment demands. In this manner, they relate unreflectively with the contents without understanding or integrating them (Fryer & Vermunt, 2018). The third approach, organized studying, matches the intention of strategically arranging time and resources to obtain the best marks possible. Deep-organized students tend to obtain better learning outcomes than surface learners (Postareff et al., 2017). However, some learning environments tend to hinder deeper approaches to learning by promoting memorization of factual content, making workloads unmanageable, or not setting clear course goals (Parpala et al., 2010; Xie et al., 2022).

Previous studies in LA have focused mainly on interpreting student behaviour through the lens of SAL by categorizing or clustering student data logs traced by the LMS based on their learning approaches (López-Pernas & Saqr, 2021; Han et al., 2020). The resulting clusters are then interpreted through the lens of SAL. For instance, López-Pernas and Saqr (2021) effectively employed clustering methods to categorize learners in a programming course, revealing different learning tactics based on log data analysis from the Moodle LMS and an automated assessment tool. Some works also combine these clustering methods with self-report questionnaires developed to operationalize learning theory constructs (Han et al., 2020). In SAL research, some of the most employed questionnaires are LEARN (deep, surface, and organized study constructs; Parpala & Lindblom-Ylänne, 2012) and the Study Process Questionnaire (SPQ; deep and surface motives and strategies constructs; Biggs et al., 2001). These questionnaires make SAL-framed data readily available to be combined with data captured by the LMS and analyzed through LA techniques. For example, Han et al. (2020) employed the SPQ and clustering approaches to understand student learning processes in engineering courses. Han et al. (2020) identified significant associations in a blended learning course between clusters formed from self-reported methods and those derived from trace data. These works suggest a connection between students' self-reported approaches to learning and their actual behaviour throughout the course. However, while clustering approaches provide valuable overviews, they can result in generalized categorizations that potentially overlook finer details of individual student behaviours, which are crucial for targeted educational interventions (Jovanović et al., 2021).

Metrics generated from student behaviour are helpful to inform different interventions that might help improve student learning. These metrics, when processed into specific indicators, have the potential to guide actions that positively impact learners, as discussed by Guzmán-Valenzuela et al. (2021). The work by Chan et al. (2021) and Han and Ellis (2021) study the relationship between students' self-reported approaches to learning and the indicators of frequency of access to learning resources. Han and Ellis (2021) found that those who self-reported deep approaches to learning and positive perceptions of the integrated learning environment also presented higher engagement with online learning. Conversely, Chan et al. (2021), who analyzed interactions with videos and quizzes in a clinical course in dentistry, found no correlations between the approach to learning and accessing e-learning resources. This finding suggests that LMS interactions do not necessarily relate to student performance in every condition explored, highlighting the need for further research to understand the actual value of LMS data in providing adequate remedial support.

In this study, we built upon this prior work to combine data about students' self-reported SAL strategies and their trace data registered by the LMS of different quality and granularity to understand how indicators mediate the effect of student approaches to learning. Furthermore, we build upon prior work by utilizing the indicators compiled by Jovanović et al. (2021). These indicators, focusing on different aspects of student engagement in blended learning, mainly measure the level of student activity and the regularity of their study habits. This opens up possibilities for a more comprehensive understanding of the indirect effects of learning approaches on student outcomes and whether these effects can be captured through LMS data.

### 2.2. SAL Research in Latin American Higher Education

In Latin America (LATAM), several studies employ the SAL framework. Among the questionnaires that have been developed within this research tradition, many have been validated with Latin American populations, such as the SPQ (Freiberg Hoffmann & Fernández Liporace, 2016), LEARN (Lopez González, 2022), and the Approaches and Study Skills Inventory for Students, better known as ASSIST (Freiberg Hoffmann & Romero Medina, 2019). These validation efforts have mostly shown appropriate construct validity and acceptable-to-excellent levels of internal consistency, reporting empirical evidence for ASSIST and LEARN that has been consistent with the three-factors structure (deep, surface, and strategic [ASSIST]/organized study [LEARN]). So far, findings tend to confirm the positive association between self-reported deeper approaches to learning and better academic achievement established by prior literature. To complement questionnaire data, researchers have started to analyze LMS trace data over the past years (Celis et al., 2019). However, these efforts still need to be expanded to a specific

university setting, given the difficulties in accessing and analyzing data at scale. Although many higher education institutions around the world are offering online or blended learning, those located in developed countries have better technological infrastructures to facilitate these types of learning strategies, which in turn generates more possibilities for trace data collection and analysis (Guzmán-Valenzuela et al., 2021). Whereas LATAM universities have to deal with several challenges related to using LMS data: the lack of data infrastructure, LA experts, and data protection regulations (Hilliger et al., 2020b), in addition to technical issues related to data integration. Consequently, LMS trace data is rarely used to examine student behaviours and study habits to inform LA-based research or practice.

Since SAL is not an inherent characteristic of each student, more work is required to understand learning approaches in light of LMS trace data, as these approaches are influenced by the teaching-learning environment (Parpala et al., 2010). Considering that SAL may vary across contexts (Yin et al., 2018), it is also crucial to understand how SAL relates to different LMSs and institutional contexts. Across LATAM, nations have implemented policies and strategies to expand and diversify universities by increasing access, but institutional efforts are still incipient to meet student expectations and needs (Santelices & Celis, 2022). According to a systematic literature review led by Guzmán-Valenzuela et al. (2020), only 8% of the papers published between 2000 and 2017 regarding student learning experiences in LATAM higher education are actually about SAL, despite the increasing interest and data availability to inform further understanding of learning processes (Celis et al., 2019). To expand the current knowledge about SAL in LATAM, this study examines how self-reported learning approaches relate to student academic performance using LMS trace data as a mediator variable.

### 3. Methods

The purpose of this paper is to investigate how student learning approaches impact their course performance and how LA indicators of different natures play a role in mediating this effect. From this main goal, we derive the following research questions:

**RQ1.** What trace-based behaviour indicators (with different granularity levels) explain students' final grades in multiple HE courses?

**RQ2.** What approaches to learning (deep, surface, or organized) explain students' final grades in multiple HE courses?

**RQ3.** What trace-based behaviour indicators (with different granularity levels) mediate the effect between students' approach to learning and their final grades in multiple HE courses?

#### 3.1. Research Design and Study Context

In this work, we implemented a quantitative study. Based on a literature review conducted by Leitner et al. (2017) about learning analytics in higher education, we refer to LA quantitative studies as the analysis and interpretation of quantitative data for decision-making from a statistical perspective, aiming to detect student behaviours and predict student performance. Different literature reviews indicate that LA research is primarily quantitative in nature (Guzmán-Valenzuela et al., 2021), not only deploying varied types of approaches for data collection, organization, and analysis but also for formulating mathematical models to derive meaningful findings. Although this predominant quantitative orientation of LA has been criticized due to requiring time-consuming management of large data sets — often including irrelevant or biased attributes (Guzmán-Valenzuela et al., 2021), it has also been celebrated due to its capability of capturing learning processes moment-by-moment (Molenaar et al., 2021). This paper benefits from this quantitative orientation to provide better insights into student approaches to learning and how their interactions with the LMS system mediate their final grades.

We collected and analyzed data from two Latin American universities: U1 and U2. Although both institutions are comparable in size and prestige, they differ in administration and data-related practices. On the one hand, U1 is a private and confessional institution that uses a paid version of Canvas as its LMS. On the other hand, U2 is a public institution that uses an in-house LMS for its courses. This implies student interaction data with different characteristics in terms of both LMS features and granularity. In U1, student log data can be accessed through the Canvas Data API. This log data includes clickstream data about student interaction with the different resources in the course, accompanied by a timestamp. In contrast, in U2, student trace data can be exported to a CSV file that includes aggregated data about student interactions with the LMS. More precisely, U2's data includes mainly the number of actions performed per student per day, so data collected from U1 is more granular than from U2. Thus, this study compares findings regarding student approaches to learning in these two contrasting contexts, leveraging LA techniques to analyze behaviours according to different data granularity as we analyze the relationship between student performance and their self-reported learning approaches.

Data collected from each institution also differ. In U1, data was collected from four courses with different types of learning and teaching methods (see Table 1). The courses included were these: 1) an education course that emphasizes critical reading and discussions; 2) a project-based course in engineering design; 3) a computer science course that uses traditional lecturing, testing, and homework; and 4) an active learning course that is part of the core university curriculum. In U2, data was collected from two courses with a strong presence of physics science, mathematics, and engineering sciences. These U2 courses also



differ in their instructional design, including a junior-level project-based course in engineering and a first-year physics course using traditional lecturing, testing, and homework.

**Table 1.** Courses Included in this Study

University	Field	Course Name	Course Enrolment	Accepted Informed Consent
U1	Education	Education and Society	35	23
	Engineering Design	Anthro-Design	16	15
	Computer Science	Artificial Intelligence	101	33
	Institutional Core Curriculum	In Search of Well-Being	156	23
U2	Engineering	Leadership and Social Innovation	26	23
	Physics	Introduction to Modern Physics	52	50

**3.2. Data Sources**

**3.2.1. Self-reported SAL measures**

Self-reported data on SAL was collected at the beginning of each course using the LEARN questionnaire scales (Parpala & Lindblom-Ylänne, 2012). The instrument was previously validated with a population of approximately 2,500 students from eight institutions that fairly represented the diversity of the Chilean higher education system. Each construct (deep, superficial, and organized learning) had four associated questions. For each question, students answered on a Likert scale that went from 1 to 4. The score of each construct was computed by taking the mean of the responses to define the learning approach for each student. Internal consistency was measured using Cronbach’s alpha, yielding values acceptable to good: deep approach = 0.700; surface approach = 0.721; and organized study = 0.842. More information about its validation can be found in the report by Lopez González (2022).

**3.2.2. Indicators of learning behaviour**

For running the mediation analysis using student trace data, we calculated a set of fine-grained and coarse-grained indicators using as a reference the work by Jovanović et al. (2021). In this work, the authors compiled a comprehensive list of indicators commonly used to measure student level of activity and regularity of study in different blended learning courses (refer to Table 2). We took this proposal as a basis for generating the indicators from the data obtained from the institutional LMSs of U1 and U2.

Although both universities used different systems, both LMSs allowed us to collect data regarding student actions to see uploaded files, perform evaluations, and access administrative announcements. Thus, we obtained coarse-grained indicators from aggregating data regarding these types of student actions during an “active day” or an “active week.” An *active day* is defined as a day with at least one learning action of any type. Thus, an *active day* is a way of measuring student presence in the LMS environment of the course. An *active week* is defined by calculating the average of active days per week for all students along the course and classifying as *active weeks* those in which the number of active days is equal to or above this average. This classification allows measuring the student engagement in the courses considering a weekly periodicity.

The list provided by Jovanović et al. (2021) also proposes fine-grained indicators for representing student interactions during a learning session. Taking this as a basis, we also calculated our fine-grained indicators from unaggregated data; that is, data collecting student actions with a timestamp. A learning session is calculated as a continuous sequence of learning actions where the time gap between any two consecutive actions is below a chosen threshold of 30 minutes, which has been commonly used in prior work (Jovanović et al., 2017). To address the variability among the six courses, both coarse-grained and fine-grained were normalized by dividing them by the highest value of the indicator in their course.

**Table 2.** Indicators Used in This Study  
(Following classification and naming convention of Jovanović et al., 2021)

Category	Label	Description	Granularity	
			Coarse-grained	Fine-grained
Overall Level of Activity (OLA)	OLA_1	Session count, normalized		X
	OLA_2	Total session length (in seconds), normalized		X
	OLA_3	Average session length, normalized		X
	OLA_4	Average number of learning actions per session, normalized		X
	OLA_5	Proportion of active days	X	
	OLA_6	Average number of active days per week	X	
	OLA_7	Average time distance between two consecutive active days	X	
	OLA_8	Proportion of active weeks	X	
Learning Action-specific Level of Activity (LALA)	LALA_1 - LALA_3	Proportion of active days per learning action type  Three indicators in total, one for each learning action type: (1) <i>evaluation</i> , (2) <i>file</i> , and (3) <i>administrative</i>	X	
	LALA_4 - LALA_6	Proportion of active weeks per learning action type. One indicator for each learning action type	X	
Overall Regularity of Study (ORS)	ORS_1	Entropy of learning action counts per session		X
	ORS_2	Entropy of learning session length		X
	ORS_3	Proportion of weeks the student was active on the first day of the week	X	
	ORS_4	Proportion of learning actions on the first day of the week	X	
	ORS_5	Entropy of learning action counts per day	X	
	ORS_6	Proportion of weeks the student was active on the weekend	X	
	ORS_7	Proportion of learning actions on the weekend	X	
Learning Action-specific Regularity of Study (LARS)	LARS_1 - LARS_3	Entropy of daily action counts per learning action type (one indicator for each learning action type)	X	
	LARS_4 - LARS_6	Entropy of weekly action counts per learning action type (one indicator for each learning action type)	X	

Finally, we also computed an action-specific set, which refers to student interaction with particular functionalities of the LMS. Action-specific types of interactions analyzed from the recorded data from both LMSs included student access to 1) evaluations, 2) learning resources, and 3) administrative announcements. Then, we computed indicators of student level of activity and regularity that refer to these three learning actions. Student level of activity refers to indicators that measure student engagement with the online portion of the courses. Student regularity refers to indicators that measure the distribution of efforts done in the LMS over the course.

### 3.3. Analytical Approach

Once the LA indicators were defined, we conducted a correlational analysis to determine how these indicators relate to students' final course grades (see Figure 1). For the correlational analysis, we aggregated all data from courses in the same institution. Although each course follows a different instructional design, all courses in the same institution use the same LMS. However, given the difference in context and sample size, we decided to keep the analysis of both institutions separate and cross-analyze the findings to answer the research questions addressed. To answer RQ1, we computed a set of uncorrelated LA indicators and analyzed their significance in explaining the final course grade. To answer RQ2, we analyzed the significance of different approaches to learning in explaining the final course grade. Finally, to answer RQ3, we analyzed whether the LA indicators mediate the effects of student approaches to learning and their final grades.

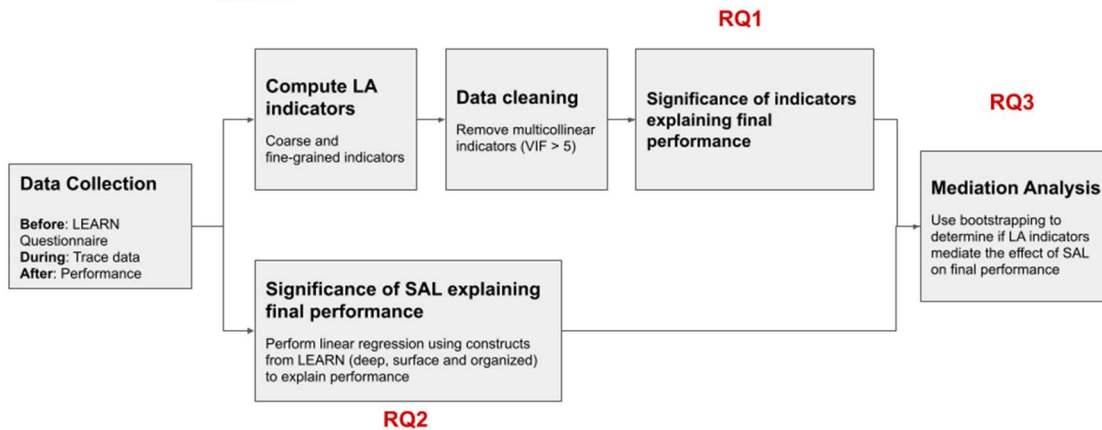


Figure 1. Pipeline of analytical approach to answer research questions.

### 3.3.1. Analyzing LA indicators to explain final course grades

As explained in section 3.2.2, the LA indicators created in this study were based on the list provided by Jovanović et al. (2021; see Table 2). To avoid problems with multicollinearity when analyzing their relationship with the final course grade, we removed indicators with a Variance Inflation Ratio (VIF) above 5 (James et al., 2013). As proposed by Jovanović et al. (2021), we also transformed the outcome variable using a nonparanormal transformation of the huge R package (Zhao et al., 2012) to address issues with the linearity of the dependent variable across different courses. Finally, we performed a linear regression between the set of uncorrelated LA indicators and the normalized final grade of the students. To control for differences across courses, we added the course belonging as a covariate in the regression.

### 3.3.2. Analyzing SAL to explain course performance

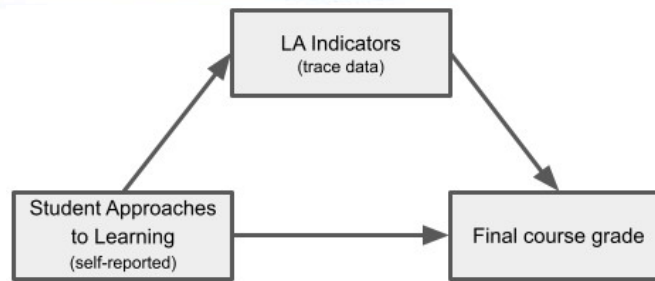
To understand the significance of SAL on the students' final grades, we analyzed the construct extracted from the LEARN questionnaire (deep, superficial, and organized). This construct was obtained by calculating the average score regarding four items whose answers ranged from 1 to 4. Since the average is a continuous variable, we could perform a linear regression to understand how each learning approach is related to the student's final grade. We also added the course belonging as a covariate in the linear regression to control for the instructional design differences among courses.

### 3.3.3. Mediation analysis

To understand if LA indicators explain the relationship between SAL and course performance, we performed a mediation analysis. This statistical method is used to determine if the relationship between an independent variable X and a dependent variable Y ( $X \rightarrow Y$ ) can be explained by the effects of X when there is a mediator variable M and the effects of M on Y ( $X \rightarrow M \rightarrow Y$ ; Fiedler et al., 2011). In our study, the independent variable X was the student score on the SAL constructs in LEARN, the mediator variable M was the set of LA indicators chosen in Section 3.2.1, and the dependent variable Y was the final grade. Our final goal was to study whether the LA indicators could explain the effect of student approaches to learning on their final grades. If so, LA indicators can serve as an “observable” representation of student behaviour in a course related to final grades (see Figure 2). Consequently, mediation analysis could only be applied in cases with a significant relationship between student approaches to learning and their final grades (see Section 3.2.2).

To understand whether LA indicators act as mediators, we computed the indirect effect of SAL on final grades per indicator. This **indirect effect** measures how a change in X affects M and, in turn, affects Y. A common approach to compute this effect is using bootstrapping (Preacher & Hayes, 2004). The effects were computed using 5,000 samples for bootstrapping. The **direct effect** is then the effect that X has on Y when controlling for M. Finally, the **total effect** is the sum of all direct and indirect effects to explain how much X affects Y. All of these effects were computed using the Pingouin-0.5.3 Python library (Vallat, 2018).

The mediation analysis is justified in our study since the theoretical background established that SAL impacts how students behave on a course and their learning outcomes (Han et al., 2020). We use the LA indicators as a proxy of observable and traceable student behaviour in the course. As such, there is a temporal precedence of student declarations of study intentions towards the course captured through the LEARN self-reported questionnaire to their behaviour in the course and, consequently, their final grades.



**Figure 2.** Proposed mediation model. The approach to learning can be either deep, surface, or organized, while the performance is the final grade obtained in the course. (Indicators based on the list provided by Jovanović et al., 2021)

## 4. Results

### 4.1. RQ1 — LA Indicators That Explain Final Course Grades

First, it is worth noting that we observed a high level of multicollinearity in the indicators. As such, we only analyzed as possible mediators those indicators resulting by filtering correlated features. Six out of 21 course-grained and two out of six fine-grained indicators were considered for U1, and three out of 21 coarse indicators for U2. Our findings show that none of the coarse-grained indicators explains student performance in either U1 or U2 (Table 3). The only feature close to significance was OLA 7 (average time distance between two active days) in U1 (Table 4). Concerning fine-grained indicators, only session count (indicator OLA\_1-Session count, normalized) was found to be significant in explaining student final performance.

**Table 3.** Course-Grained Indicators as Predictors  
No significant results found

Institution	Indicator Name	Coef.	Sd. Err.	p-val
U1	OLA_7 — Average time distance between two consecutive active days	-0.1193	0.070	0.0940
	LALA_4 — Proportion of active weeks (evaluation)	-0.0873	1.828	0.9620
	LALA_6 — Proportion of active weeks (administrative)	3.4040	8.389	0.6859
	ORS_4 — Proportion of learning actions on the first day of the week	-0.1343	1.230	0.9133
	ORS_7 — Proportion of learning actions on the weekend	0.4120	2.826	0.8844
	LARS_1 — Entropy of daily action counts (evaluation)	0.1368	0.283	0.6304
U2	OLA_7 — Average time distance between two consecutive active days	-0.0024	0.786	0.9975
	LALA_4 — Proportion of active weeks (evaluation)	0.1319	1.530	0.9316
	LALA_5 — Proportion of active weeks (files)	1.4175	1.177	0.2326

**Table 4.** Fine-Grained Indicators as Predictors  
Significant results bolded (p-val < 0.05)

Institution	Indicator Name	Coef.	Sd. Err.	p-val
U1	<b>OLA_1 — Session count, normalized</b>	<b>2.7248</b>	<b>0.5136</b>	<b>&lt;0.0001</b>
	OLA_4 — Average number of learning actions per session, normalized	-0.4653	0.5362	0.3875

### 4.2. RQ2 — SAL That Explain Final Course Performance

We found similar results in both institutions with respect to the influence of student approaches to learning (SAL) in final course grades (see Table 5). As shown in prior work (Tuononen et al., 2020), surface learning was correlated with lower overall final course grades, suggesting that surface approaches to learning can be detrimental to students’ final grades. Still, this



relation was significant only in U1 (coef.=−0.3430, p-val=0.0016) but not in U2 (coef.=−0.1946, p-value=0.1939). The organized learning approach was also significantly correlated with higher overall performance in U1 (coef.=0.3132, p-val=0.0034) but not significant in U2 (coef.=0.1827, p-val=0.1586). Finally, a deep learning approach was not significantly related to final grades in either institution.

**Table 5.** SAL as Predictor of Performance  
Significant results bolded (p-val < 0.05)

Institution	SAL	Coef.	Sd. Err.	p-val
U1	Deep	0.0119	0.1180	0.9198
	<b>Surface</b>	<b>−0.3430</b>	<b>0.1055</b>	<b>0.0016</b>
	<b>Organized</b>	<b>0.3132</b>	<b>0.1046</b>	<b>0.0034</b>
U2	Deep	−0.0251	0.1467	0.8649
	Surface	−0.1946	0.1483	0.1939
	Organized	0.1827	0.1281	0.1586

**4.3. RQ3 — LA Indicators as Mediators**

Since we did not find significant correlations between any approach to learning and student grades in U2, we did not consider the data from this institution for the mediation analysis since this is a condition for this type of analysis. Similarly, we did not pursue the mediation analysis of the deep learning approach with data from U1 since this approach was not found to be significantly related to the final performance. Therefore, our analysis was conducted with respect to the surface and organized approaches to learning data from U1. The mediation analysis results show that none of the coarse-grained indicators was found to be a significant mediator of the effect of SAL in the final grade (Table 6). This was probably because none of the indicators were significant predictors of the student’s final grades on their own. On the other hand, the fine-grained indicator corresponding to session count was found to be a total mediator of surface approaches in U1 (Table 7). This means that, after controlling for the effect of session counts, the direct effect that a surface approach had on final course grade was no longer significant. Therefore, the total effect of a surface approach on final grade is mainly explained by its indirect effect on the number of learning sessions and the subsequent impact on final grades. Specifically, students who adopted a superficial approach to learning engaged in fewer learning sessions, leading to poorer performance in the course.

Although there is prior empirical evidence of the indicator of session count mediating for organized learning approaches (Postareff et al., 2017; Tuononen et al., 2020), these effects were not significant in this study. While we found that students with a more organized approach performed significantly more learning sessions, the bootstrapping analysis did not give significant results for session count being a mediator for this type of approach (p-val=0.0508). Nonetheless, this result does not necessarily rule out a potential link between organized learning approaches and performing more learning sessions during a course.

**Table 6.** Results of Mediation Analysis Using Coarse-Grained Indicators  
Significant results bolded (p-val < 0.05)

	Direct Effect			Indicator Name	Indirect Effect			Total Effect			
	SAL	Coef.	Sd. Err.		p-val	Coef.	Sd. Err.	p-val	Coef.	Sd. Err.	p-val
U1	Surface	<b>-0.3627</b>	<b>0.120</b>	<b>0.0033</b>	OLA_7 — Average time distance between two consecutive active days	-0.0214	0.037	0.4832	<b>-0.3408</b>	<b>0.110</b>	<b>0.0026</b>
					LALA_4 — Proportion of active weeks (evaluation)	0.0028	0.040	0.8528			
					LALA_6 — Proportion of active weeks (administrative)	0.0650	0.082	0.3448			
					ORS_4 — Proportion of learning actions on the first day of the week	0.0022	0.017	0.9084			
					ORS_7 — Proportion of learning actions on the weekend	0.0066	0.035	0.9496			
					LARS_1 — Entropy of daily action counts (evaluation)	-0.0333	0.046	0.362			
	Organized	<b>0.2426</b>	<b>0.115</b>	<b>0.0382</b>	OLA_7	0.0295	0.040	0.4328	<b>0.2778</b>	<b>0.109</b>	<b>0.0127</b>
					LALA_4	-0.0001	0.036	0.9956			
					LALA_6	0.0000	0.022	0.9464			
					ORS_4	-0.0001	0.026	0.8808			
					ORS_7	-0.0031	0.045	0.7492			
					LARS_1	0.0091	0.036	0.8424			

**Table 7.** Results of Mediation Analysis Using Fine-Grained Indicators  
Significant results bolded (p-val < 0.05)

	Direct Effect			Indicator name	Indirect Effect			Total Effect			
	SAL	Coef.	Sd. Err.		p-val	Coef.	Sd. Err.	p-val	Coef.	Sd. Err.	p-val
U1	Surface	-0.2050	0.105	0.0542	<b>OLA_1 — Session count, normalized</b>	<b>-0.1152</b>	<b>0.052</b>	<b>0.0200</b>	<b>-0.3300</b>	<b>0.109</b>	<b>0.0031</b>
					OLA_4 — Average number of learning actions per session, normalized	-0.0098	0.025	0.698			
	Organized	0.1767	0.100	0.0800	OLA_1	0.1236	0.062	0.0508	<b>0.3031</b>	<b>0.106</b>	<b>0.0050</b>
OLA_4					0.0029	0.012	0.8748				

## 5. Discussion

This study examined the relationship among LA indicators, student approaches to learning, and final course performance in two LATAM universities, illustrating the potential benefits and challenges of using LMS trace data for understanding and interpreting their learning process. Concerning RQ1 about trace-based behaviour indicators that better explain students’ final grades, the findings revealed that none of the coarse-grained indicators were significantly related to final course performance. In contrast, the “session count” fine-grained indicator significantly correlated with the final grades. This same result is aligned with prior work, which shows that the number of online learning sessions was one of the indicators significantly influential in predicting students’ final achievement across publications (Wang & Mousavi, 2023). Given the nature of the course sample in this work, daily and weekly indicators were probably irrelevant because most students followed the same predetermined course

schedule. Consequently, the differences in final course grades could have come from the amount of work students did while connected to the LMS rather than from how often they accessed the LMS.

Although this finding shows the importance of capturing learning processes moment-by-moment throughout LA strategies (Molenaar et al., 2021), it also corroborates that generalizability is a common challenge when translating LA results across different contexts (Matcha et al., 2020). In this study, the main challenge was to work with two LATAM universities with two different LMSs capturing trace data of different granularity. In U2, where trace data was aggregated daily, no significant relationship was found between session counts and student performance. This finding adds to the list of difficulties in implementing LA strategies in LATAM (Hilliger et al., 2020b), highlighting the need for fine-grained quality data in the region to facilitate conducting high-impact analytical research across institutions.

In relation to RQ2 about what approaches to learning explain students' final grades, this study found that the surface approach was associated with lower grades while the organized approach with higher ones. These results are aligned with previous research that shows that surface approaches are related to lower student grades (Tuononen et al., 2020) than organized approaches (Parpala et al., 2010). While these results were only statistically significant in U1, it was surprising not to find significant correlations between the deep approach and final grades in either of the two universities, as reported in other studies (Postareff et al., 2017). This result might be explained by the fact that SAL represents contextual responses since learning approaches vary according to the environment in which learning occurs. According to López et al. (2020), Chilean students tend to adopt organized approaches to learning by carefully planning their time and effort to focus on those courses they recognize as important for their professional future. Previous research shows that Chilean students reported being overwhelmed by their academic workloads (Yin et al., 2018). Still, and considering that none of the learning approaches were significantly correlated with performance in U2, further work is needed to consider other contextual aspects that might affect student approaches to learning, such as the course's instructional design.

Regarding RQ3 about the trace-based behaviour indicators mediating the effect between student approaches to learning and their final grades, results showed that the fine-grained indicator "session count" was a total mediator of surface approaches. This means that students reporting a surface approach engaged less with online materials and activities of a course — performing significantly fewer learning sessions, and students with fewer learning sessions obtained significantly lower grades. This result aligns with prior work, which shows that the number of learning sessions is a good predictor of final grades across several contexts (Wang & Mousavi, 2023). Furthermore, some studies have found correlations between self-reported surface approaches and LMS activity (Han et al., 2020). Our study extends these findings by demonstrating that session count not only predicts but also mediates the relationship between the learning approach and final grades. That is, the direct effect of the surface approach on final grades is no longer significant after introducing the mediator variable (i.e., session count indicator), suggesting that the number of learning sessions can directly explain final grades, even without having any information about student approaches to learning. Conversely, despite finding that an organized approach correlated with more online sessions and higher final grades, the mediation effect of all LA indicators was insignificant. This observation differs from previous studies (Postareff et al., 2017; Tuononen et al., 2020), which found session count as a mediator for organized learning approaches. Furthermore, we could not test for mediators of deep learning approaches, given that this learning approach was not associated with students' final grades. This differs from prior work, in which deep learning approaches engage more with online activities and obtain higher academic grades (Han et al., 2020; Celis et al., 2019).

It is important to acknowledge that, as our mediation analysis primarily relies on correlations, it has limitations in isolating a causal effect. For example, the "session count" indicator was highly correlated with the total time spent in the LMS. This strong correlation presents challenges in pinpointing the exact mediator impacting students' final grades. This situation exemplifies the broader methodological constraints in identifying precise causal pathways. Despite the need for cautious interpretation, these insights contribute meaningfully to understanding learning behaviours through LMS data.

## 6. Conclusions, Implications, and Limitations

### 6.1. Conclusions

This study explored the relationship between trace-based behaviour indicators, student approaches to learning, and their final grades in LATAM universities' higher education (HE) courses. The findings revealed that fine-grained indicators, particularly session count, were significantly associated with students' final grades, while no significant relationship was observed with coarse-grained indicators. Importantly, the study identified session count as a mediator between student approaches to learning and their final grades. In particular, students adopting a surface approach engaged significantly less with online materials and activities, resulting in lower grades.

The implications of this research suggest practical actions for educators and institutions. By leveraging trace data and self-reported metrics, instructors can gain valuable insights into student learning behaviours and adapt their teaching strategies accordingly. This can involve designing learning experiences that encourage active engagement, incorporating student-centered approaches, and aligning assessment tasks with desired learning outcomes.

The study underscored the challenges of generalizability across different contexts and the limited availability of detailed data in LATAM universities, emphasizing the need for enhanced data infrastructures. Moving forward, further research is required to investigate contextual factors and explore additional learning analytics indicators on a bigger scale. This will contribute to the ongoing efforts to advance educational practices and improve learning outcomes in the LATAM region and beyond.

## 6.2. Analytical Implications

From an analytical point of view, coarse-grained indicators were not found to be mediators of student approaches to learning. While it cannot be denied that student interactions with online learning environments and education technologies have generated increasing amounts of trace data, the extent to which these data can be used to improve student learning remains unclear (Guzmán-Valenzuela et al., 2021). This is particularly challenging for research conducted in LATAM, where advanced learning technologies and related data infrastructures have not been widely implemented as in other regions in the world (Guzmán-Valenzuela et al., 2021), therefore affecting the capacity of HE institutions to collect and analyze student data at different timescales (i.e., week, day, and moment to moment). This study illustrates the importance of collecting trace data for generating fine-grained indicators, such as session counts, since they could be significant mediators between surface or organized approaches to learning and final grades. This implies not only collecting trace data but also applying systematically validated questionnaires to collect information about student profiles to identify those who may be exhibiting surface approaches earlier during the academic period to propose early support measures. The availability of fine-grained data and self-reported metrics could be leveraged to create a varied range of LA indicators to feed different support tools for students, teachers, and managers, including online dashboards for course instructors and students to inform the teaching and learning process (Pérez-Sanagustín et al., 2022). This type of effort might not only expand the limited understanding of SAL in the region (Guzmán-Valenzuela et al., 2021) but also motivate further capacity building to leverage trace data of LMS data so that staff can reflect on their teaching based on student characteristics and behaviours (Hilliger et al., 2020a).

## 6.3. Pedagogical Implications

From a pedagogical standpoint, it is crucial to explore how instructional designs in HE courses in Latin America (LATAM) may promote organized or surface approaches to learning. As previously mentioned, an overwhelming workload within a subject can hinder the adoption of deeper learning approaches (Parpala et al., 2010). While learning approaches exhibit variability across disciplines (Parpala et al., 2010), this concern is particularly pronounced in STEM fields, where courses often rely on traditional lectures and exams, fostering the memorization of factual content (Parpala et al., 2010). Numerous studies within the STEM domain have explored the impact of curriculum elements on student perceptions of workload, encompassing disciplines such as business (Xerri et al., 2018), computer science (Tabuenca, 2022), architecture (Souto-Iglesias & Baeza Romero, 2018), and engineering (Hilliger et al., 2023; Souto-Iglesias & Baeza Romero, 2018). One influential factor affecting perceived workload is the clarity of learning goals, especially when the significance of their attainment is ambiguous for students (Xerri et al., 2018). When students encounter courses with identical credit weights but differing demands (Souto-Iglesias & Baeza Romero, 2018), they often use organized approaches to merely prioritize tasks. This becomes particularly stressful and frustrating when assessments for various subjects coincide in the same weeks (Hilliger et al., 2023), preventing them from achieving equivalent learning outcomes despite investing the same amount of effort. Even in the realm of social sciences, a study by Smith (2019) demonstrated how psychology students' survey responses linked perceived workload to stressors and coping mechanisms involving negation. In this study, findings underscore the significant role of the organized study approach in attaining higher grades, possibly reflecting students who adeptly organize their studies to cope with increasing academic demands rather than focusing on a profound understanding and integration of content across diverse courses. Considering that an organized study approach driven solely by the intention to perform under pressure does not necessarily translate into deeper learning, it becomes imperative to equip course instructors with analytical tools to enable them to identify surface learners and effectively manage student workload during the course design process.

Consequently, faculty development units must play a key role in supporting course instructors to learn how to promote deeper approaches to learning among their students. The literature suggests that deep-strategic approaches are the optimal combination for better learning outcomes (Postareff et al., 2017), and therefore, this approach should be encouraged in learning designs. A wide literature establishes that the constructive alignment of learning outcomes, learning activities, and assessment tasks could lead to deep-strategic approaches to learning, together with student-centred approaches to teaching (Parpala et al., 2010). Not only should these elements be taken into account in the instructional design of HE courses but also in the implementation of policies aimed at expanding and diversifying student bodies at universities (Santelices & Celis, 2022), aiming to enhance student learning experiences and, in this manner, advancing to meet their expectations from higher education.



#### 6.4. Limitations

The main limitation of our study is the small sample of courses. Given that our findings and prior research suggest that instructional course design plays a vital role in student engagement with the LMS, our findings may differ if more courses were included in the analysis. Additionally, we could not compare some of the results across institutions due to the nature of the data. In future work, examining how these findings can be applied to a larger sample size of courses and institutions is crucial.

Given the study's correlational nature, we are also limited to the causal claims that can be derived from the mediation analysis. While the model can be justified through the given theoretical underpinnings and prior literature, we did not control for other factors that could influence the relationships. Demographic variables such as gender or age could play a role in moderating the relationships between learning approaches and final grades observed in this study, changing the significance of the results. Finally, we only used the data of those students accepting participation in the study, which could have produced a self-selection bias from the beginning and only from one semester, which could also condition the results. Further studies should consider issues of stability of LMS indicators.

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#### References

- Biggs, J. (1993). What do inventories of students' learning processes really measure? A theoretical review and clarification. *British Journal of Educational Psychology*, 63(1), 3–19. <https://doi.org/10.1111/j.2044-8279.1993.tb01038.x>
- Biggs, J., Kember, D., & Leung, D. Y. P. (2001). The revised two-factor study process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology*, 71(1), 133–149. <https://doi.org/10.1348/000709901158433>
- Celis, S., López, D., & Silva, J. (2019, March). Analyzing the influence of online behaviors and learning approaches on academic performance in first year engineering. *Proceedings of the 2nd Latin American Workshop on Learning Analytics (LALA 2019)*, 18–19 March 2019, Valdivia, Chile (pp. 110–121). CEUR Workshop Proceedings. <https://ceur-ws.org/Vol-2425/paper21.pdf>
- Chan, A. K. M., Botelho, M. G., & Lam, O. L. T. (2021). The relation of online learning analytics, approaches to learning and academic achievement in a clinical skills course. *European Journal of Dental Education*, 25(3), 442–450. <https://doi.org/10.1111/eje.12619>
- Conijn, R., Snijders, C., Kleingeld, A., & Matzat, U. (2017). Predicting student performance from LMS data: A comparison of 17 blended courses using Moodle LMS. *IEEE Transactions on Learning Technologies*, 10(1), 17–29. <https://doi.org/10.1109/TLT.2016.2616312>
- Fiedler, K., Schott, M., & Meiser, T. (2011). What mediation analysis can (not) do. *Journal of Experimental Social Psychology*, 47(6), 1231–1236. <https://doi.org/10.1016/j.jesp.2011.05.007>
- Freiberg Hoffmann, A., & Fernández Liporace, M. M. (2016). Enfoques de aprendizaje en estudiantes universitarios argentinos según el R-SPQ-2F: Análisis de sus propiedades psicométricas [Learning approaches in Argentine university students according to the R-SPQ-2F: Analysis of its psychometric properties]. *Revista Colombiana de Psicología*, 25(2), 307–329. <https://doi.org/10.15446/rep.v25n2.51874>
- Freiberg Hoffmann, A., & Romero Medina, A. (2019). Validación del approaches and Study Skills Inventory for Students (ASSIST) en Universitarios de Buenos Aires, Argentina [Validation of approaches and Study Skills Inventory for Students (ASSIST) in undergraduates from Buenos Aires, Argentina]. *Acción Psicológica*, 16(2), 1–16. <https://dx.doi.org/10.5944/ap.16.2.23042>
- Fryer, L. K., & Vermunt, J. D. (2018). Regulating approaches to learning: Testing learning strategy convergences across a year at university. *British Journal of Educational Psychology*, 88(1), 21–41. <https://doi.org/10.1111/bjep.12169>
- Guzmán-Valenzuela, C., Rojas-Murphy Tagle, A., & Gómez-González, C. (2020). Polifonía epistémica de la investigación sobre las experiencias estudiantiles: El caso latinoamericano [Epistemic polyphony of research on student experiences: The Latin-American case]. *Education Policy Analysis Archives/Archivos Analíticos de Políticas Educativas*, 28(96). <https://doi.org/10.14507/epaa.28.4919>

- Guzmán-Valenzuela, C., Gómez-González, C., Rojas-Murphy Tagle, A., & Lorca-Vyhmeister, A. (2021). Learning analytics in higher education: A preponderance of analytics but very little learning? *International Journal of Educational Technology in Higher Education*, 18, 23. <https://doi.org/10.1186/s41239-021-00258-x>
- Han, F., Pardo, A., & Ellis, R. A. (2020). Students' self-report and observed learning orientations in blended university course design: How are they related to each other and to academic performance? *Journal of Computer Assisted Learning*, 36(6), 969–980. <https://doi.org/10.1111/jcal.12453>
- Han, F., & Ellis, R. A. (2021). Assessing the quality of university student experiences in blended course designs: An ecological perspective. *Higher Education Research & Development*, 40(5), 964–980. <https://doi.org/10.1080/07294360.2020.1800597>
- Hilliger, I., Ortiz-Rojas, M., Pesántez-Cabrera, P., Scheihing, E., Tsai, Y.-S., Muñoz-Merino, P. J., Broos, T., Whitelock-Wainright, A., & Pérez-Sanagustín, M. (2020a). Identifying needs for learning analytics adoption in Latin American universities: A mixed-methods approach. *Internet and Higher Education*, 45, 100726. <https://doi.org/10.1016/j.iheduc.2020.100726>
- Hilliger, I., Ortiz-Rojas, M., Pesántez-Cabrera, P., Scheihing, E., Tsai, Y.-S., Muñoz-Merino, P. J., Broos, T., Whitelock-Wainright, A., Gašević, D., & Pérez-Sanagustín, M. (2020b). Towards learning analytics adoption: A mixed methods study of data-related practices and policies in Latin American universities. *British Journal of Educational Technology*, 51(4), 915–937. <https://doi.org/10.1111/bjet.12933>
- Hilliger, I., Astudillo, G., & Baier, J. (2023). Lacking time: A case study of student and faculty perceptions of academic workload in the COVID-19 pandemic. *Journal of Engineering Education*, 112(3), 796–815. <https://doi.org/10.1002/jee.20525>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. Springer.
- Jovanović, J., Gašević, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *The Internet and Higher Education*, 33, 74–85. <https://doi.org/10.1016/j.iheduc.2017.02.001>
- Jovanović, J., Saqr, M., Joksimović, S., & Gašević, D. (2021). Students matter the most in learning analytics: The effects of internal and instructional conditions in predicting academic success. *Computers & Education*, 172, 104251. <https://doi.org/10.1016/j.compedu.2021.104251>
- Khalil, M., Prinsloo, P., & Slade, S. (2023). The use and application of learning theory in learning analytics: A scoping review. *Journal of Computing in Higher Education*, 35, 573–594. <https://doi.org/10.1007/s12528-022-09340-3>
- Leitner, P., Khalil, M., & Ebner, M. (2017). Learning analytics in higher education: A literature review. In A. Peña-Ayala (Ed.), *Learning analytics: Fundamentals, applications, and trends: A view of the current state of the art to enhance e-learning* (pp. 1–23). Springer, Cham. [https://dx.doi.org/10.1007/978-3-319-52977-6\\_1](https://dx.doi.org/10.1007/978-3-319-52977-6_1)
- López, M. J., Catalán, X., Ibáñez, A., González, C., López, D., Silva, J., & Celis, S. (2020). *Enfoques de aprendizaje: Uso de plataformas digitales y desempeño académico en la educación superior* [Approaches to learning: Use of digital platforms and academic performance in higher education]. Unpublished internal company document. <https://nmedsup.cl/wp-content/uploads/2021/06/PolicyBrief7-2.pdf>
- Lopez González, D. (2022). *Cuestionario VOCES: Vida, oportunidades y experiencias en la educación superior* [VOICES questionnaire: Life, opportunities and experiences in higher education]. [https://nmedsup.cl/wp-content/uploads/2022/07/INFORME\\_Final\\_VOCES.pdf](https://nmedsup.cl/wp-content/uploads/2022/07/INFORME_Final_VOCES.pdf)
- López-Pernas, S., & Saqr, M. (2021). Bringing synchrony and clarity to complex multi-channel data: A learning analytics study in programming education. *IEEE Access*, 9, 166531–166541. <https://doi.org/10.1109/access.2021.3134844>
- Matcha, W., Gašević, D., Ahmad Uzir, N., Jovanović, J., Pardo, A., Lim, L., Maldonado-Mahauad, J., Gentili, S., Pérez-Sanagustín, M., & Tsai, Y.-S. (2020). Analytics of learning strategies: Role of course design and delivery modality. *Journal of Learning Analytics*, 7(2), 45–71. <https://doi.org/10.18608/jla.2020.72.3>
- Molenaar, I., Horvers, A., & Baker, R. S. (2021). What can moment-by-moment learning curves tell about students' self-regulated learning? *Learning and Instruction*, 72, 101206. <https://doi.org/10.1016/j.learninstruc.2019.05.003>
- Pérez-Sanagustín, M., Pérez-Álvarez, R., Maldonado-Mahauad, J., Villalobos, E., & Sanza, C. (2022). Designing a Moodle plugin for promoting learners' self-regulated learning in blended learning. In I. Hilliger, P. J. Muñoz-Merino, T. De Laet, A. Ortega-Arranz, & T. Farrell (Eds.), *Educating for a new future: Making sense of technology-enhanced learning adoption* (pp. 324–339). Lecture Notes in Computer Science, vol. 13450 (EC-TEL 2022). Springer, Cham. [https://doi.org/10.1007/978-3-031-16290-9\\_24](https://doi.org/10.1007/978-3-031-16290-9_24)
- Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, 138(2), 353–387. <https://doi.org/10.1037/a0026838>
- Siemens, G., & Gašević, D. (2012). Guest editorial: Learning and knowledge analytics. *Journal of Educational Technology & Society*, 15(3), 1–2. [https://drive.google.com/file/d/1SJQZSFOrix9\\_WZTvBtzvUL70bsLa\\_eqQ/view](https://drive.google.com/file/d/1SJQZSFOrix9_WZTvBtzvUL70bsLa_eqQ/view)

- Smith, A. P. (2019). Student workload, well-being and academic attainment. In L. Longo & M. C. Leva (Eds.), *Human Mental Workload: Models and Applications: Proceedings of the Third International Symposium (H-WORKLOAD 2019)*, 14–15 March 2019, Rome, Italy (pp. 35–47). Springer, Cham. [https://doi.org/10.1007/978-3-030-32423-0\\_3](https://doi.org/10.1007/978-3-030-32423-0_3)
- Souto-Iglesias, A., & Baeza Romero, M. T. (2018). A probabilistic approach to student workload: Empirical distributions and ECTS. *Higher Education*, 76(6), 1007–1025. <https://www.jstor.org/stable/45116841>
- Parpala, A., & Lindblom-Ylänne, S. (2012). Using a research instrument for developing quality at the university. *Quality in Higher Education*, 18(3), 313–328. <https://doi.org/10.1080/13538322.2012.733493>
- Parpala, A., Lindblom-Ylänne, S., Komulainen, T., & Hirsto, L. (2010). Students' approaches to learning and their experiences of the teaching-learning environment in different disciplines. *British Journal of Educational Psychology*, 80(2), 269–282. <https://doi.org/10.1348/000709909X476946>
- Postareff, L., Mattsson, M., Lindblom-Ylänne, S., & Hailikari, T. (2017). The complex relationship between emotions, approaches to learning, study success and study progress during the transition to university. *Higher Education*, 73(3), 441–457. <https://doi.org/10.1007/s10734-016-0096-7>
- Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, 36(4), 717–731. <https://doi.org/10.3758/BF03206553>
- Santelices, M. V., & Celis, S. (2022). Introduction to the special issue: Student experience in Latin American higher education. *Education Policy Analysis Archives*, 30(59). <https://doi.org/10.14507/epaa.30.7549>
- Tabuenca, B., Greller, W., & Verpoorten, D. (2022). Mind the gap: Smoothing the transition to higher education fostering time management skills. *Universal Access in the Information Society*, 21(2), 367–379. <https://doi.org/10.1007/s10209-021-00833-z>
- Tuononen, T., Parpala, A., & Lindblom-Ylänne, S. (2020). Complex interrelations between academic competences and students' approaches to learning: Mixed-methods study. *Journal of Further and Higher Education*, 44(8), 1080–1097. <https://doi.org/10.1080/0309877X.2019.1648776>
- Vallat, R. (2018). Pingouin: Statistics in Python. *Journal of Open Source Software*, 3(31), 1026, <https://doi.org/10.21105/joss.01026>
- Wang, Q., & Mousavi, A. (2023). Which log variables significantly predict academic achievement? A systematic review and meta-analysis. *British Journal of Educational Technology*, 54(1), 142–191. <https://doi.org/10.1111/bjet.13282>
- Xerri, M. J., Radford, K., & Shacklock, K. (2018). Student engagement in academic activities: A social support perspective. *Higher Education*, 75(4), 589–605. <https://doi.org/10.1007/s10734-017-0162-9>
- Xie, Q., Xhang, L.-F., & King, R. B. (2022). Why do students change their learning approaches? A mixed-methods study. *Educational Psychology*, 42(9), 1089–1108. <https://doi.org/10.1080/01443410.2022.2049708>
- Yin, H., González, C., & Huang, S. (2018). Undergraduate students' approaches to studying and perceptions of learning context: A comparison between China and Chile. *Higher Education Research & Development*, 37(7), 1530–1544. <https://doi.org/10.1080/07294360.2018.1494142>
- Zhao, T., Liu, H., Roeder, K., Lafferty, J., & Wasserman, L. (2012). The huge package for high-dimensional undirected graph estimation in R. *Journal of Machine Learning Research*, 13(37), 1059–1062. <https://www.jmlr.org/papers/volume13/zhao12a/zhao12a.pdf>