



HAL
open science

Analyzing Learners' Perception of Indicators in Student-Facing Analytics: A Card Sorting Approach

Esteban Villalobos, Isabel Hilliger, Mar Pérez-Sanagustin, Carlos González, Sergio Celis, Julien Broisin

► **To cite this version:**

Esteban Villalobos, Isabel Hilliger, Mar Pérez-Sanagustin, Carlos González, Sergio Celis, et al.. Analyzing Learners' Perception of Indicators in Student-Facing Analytics: A Card Sorting Approach. 18th European Conference on Technology Enhanced Learning (ECTEL 2023), EATEL; Universidade de Aveiro, Sep 2023, Aveiro, Portugal. pp.430-445, 10.1007/978-3-031-42682-7_29 . hal-04224953

HAL Id: hal-04224953

<https://hal.science/hal-04224953>

Submitted on 2 Oct 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Analyzing Learners' Perception of Indicators in Student-Facing Analytics: A Card Sorting Approach

Esteban Villalobos¹[0000-0002-6026-3756], Isabel Hilliger²[0000-0001-5270-7655],
Mar Pérez-Sanagustín¹[0000-0001-9854-9963], Carlos González²[0000-0002-3154-
0777], Sergio Celis³[0000-0002-0502-5608], Julien Broisin¹[0000-0001-8713-6282]

¹IRIT, Université Toulouse III - Paul Sabatier, Toulouse, France

²Pontificia Universidad Católica de Chile, Santiago, Chile

³Universidad de Chile, Santiago, Chile

{esteban.villalobos, mar.perez-sanagustin,
julien.broisin}@irit.fr; {ihillige,cgonzalu}@uc.cl,
scelis@uchile.cl

Abstract. Many studies have explored using different indicators to support students' self-monitoring. This has motivated the development of student-facing analytics, such as dashboards and chatbots. However, there is a limited understanding of how learners interpret these indicators and act on that information. This study evaluates different indicators from a student perspective by adapting the card sorting technique, which is employed in Human-Centered Design. We chose eight indicators based on different comparative reference frames from the literature to create 16 cards to present both a visual and a text representation per indicator. Qualitative and quantitative data were collected from 21 students of three majors at two Latin American universities. According to the quantitative results, students' agreement level about the indicators' interpretability and actionability was relatively low. Nonetheless, the indicators that included temporality were found to be less interpretable but more actionable than those that did not. The analysis indicates that several students would use this information to improve their study habits only if their performance in the course is lower than expected. These findings might be used as a starting point to design student-facing analytics. Also, adapting the card sorting technique could be replicated to understand learners' use of indicators in other TEL contexts.

Keywords: Self-monitoring, Learning Analytics Dashboards, Indicators

1 Introduction

Researchers in the area of technology-enhanced learning (TEL) have proposed solutions to support students' self-monitoring based, mainly, on Learning Analytics Dashboards (LADs). LADs are "single displays that aggregate different indicators about learner(s), learning processes(es), and/or learning context(s) into one or multiple visualizations" [6] to help students interpret their learning strategies and produce effective changes for their learning [1]. However, to know how students make sense of dashboard

indicators is still a challenge for TEL designers and researchers [2], which might affect the appropriation of LADs and, therefore, their impact on learners' strategies. Recent literature stresses the importance of providing actionable (knowing how to use the information to adapt their behavior) and interpretable (being able to understand the information being presented) indicators for generating actual behavioral changes [3, 4]. This article aims to understand which indicators are interpretable and actionable to advance the support of autonomous learning strategies. Specifically, the following research question is addressed: What type of self-monitoring indicators are more actionable for higher education students and which way of delivery are more interpretable?

1.1 Challenges when Defining Indicators for Self-monitoring Learning Analytics Dashboards

Researchers have been studying indicators to guide students in their learning process. These indicators are computed from trace data and delivered as LADs [5]. LADs transform raw data into 'actionable insights', usually delivered through indicators, to produce student behavioral changes [3]. Several proposals using different indicators are found in the literature, especially for MOOC-based platforms [5]. However, the proposed indicators have not been shown to be very effective in activating students' behavioral changes. To be effective, indicators have to be interpretable and actionable to students, so they can use this information to adapt their behavior [3, 4].

According to Vytasek et al. [7], one of the main challenges in supporting students through Learning Analytics (LA) is selecting appropriate reference frames for the indicators. Reference frames are defined as the comparison point of an individual's engagement activities to some standard or benchmark when giving analytics to students [8]. Thus, careful selection of reference frames is crucial, as they act as mediators between analytics and students' motivation to enhance engagement [9].

To guide the selection of reference frames, Jivet et al. [10] describe three types that differ in when the anchor for comparison is set (past-, present- and future-directed). Past-directed indicators focus on the student's progress so far, anchoring the learner on a past state to evaluate their performance. Present-directed indicators focus on a social reference frame, as learners compare their current state to the performance levels of their peers at the same point in time. Future-directed indicators outline goals and a future state that learners aim for and how far they are from this goal. This classification highlights the importance of time as a key dimension in reference frames.

Molenaar and Wise [11] provide another framework that conceptualize temporal indicators regarding position, duration, rate, or frequency. They classified indicators as being expressed as an absolute value (e.g., "There were 3 planning actions") and relative terms (e.g., "Planning actions were 33% of all the actions taken"). In a similar line, Schwendimann et al. [6] classified indicators into six groups: action-related, learner-related, content-related, result-related, context-related, and social-related. A subsequent review by Pérez-Álvarez et al. [5] found that action-related indicators were the most commonly used to support students in online environments.

Regarding the representation of the indicators, Schwendimann et al. [6] found that the most common representation for indicators were, in descending order of usage, bar charts, line graphs, tables, pie charts, and scatterplots. Méndez et al. [12] suggested that

some representations to show the indicators are vaguer than others. For example, they found that textual representations, despite being considered more vague than other visualizations, were preferred by students.

Despite the existing approaches and frameworks proposed for providing indicators to learners, there is still a limited understanding of how learners interpret them and act on their information [3]. This work aims to understand how students make sense of different indicators and use them to change their behavior. We take as a basis the action-based indicators, proposed by Schwendimann et al. [16], and organize them according to the reference frames proposed by Jivet et al. [3] and Molenaar and Wise [20]. We then distinguish between absolute and relative indicators [20], and between indicators with social comparison or without it [3]. Finally, we also compare textual with visual representations of the data, in the line of Méndez et al. [12] studies.

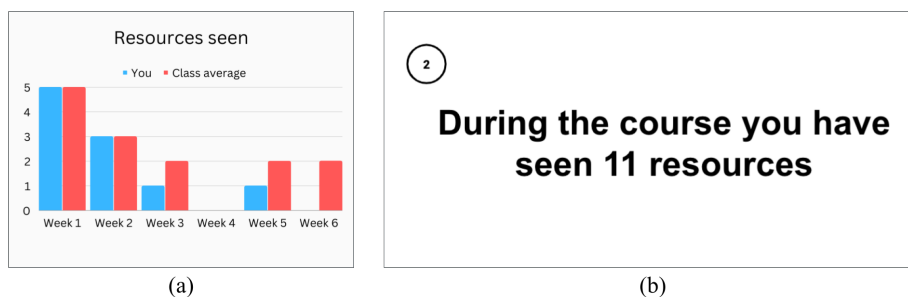


Fig. 1. (a) Example of a card with a visual representation of a self-monitoring indicator. (b) Example of a card with a text representation of a self-monitoring indicator.

2 Methods

A concurrent mixed-methods design was selected as the main methodological approach [13]. The aim was to collect quantitative and qualitative data to understand how higher education students interpret and act on different indicators. To design more effective indicators, some researchers are applying Human-Centered Design approaches to Learning Analytics (HCLA) [14, 15] to help stakeholders think about indicator design choices systematically. In the same line, we selected the card sorting technique to evaluate all indicators in parallel. This technique has been extensively used in Human-Computer Interaction (HCI) as a user-centered design method. It is an eliciting technique that explores how different items could be classified. It aims to identify consistent patterns in how people think about particular items [16]. We followed the suggestions by Spencer [16] for designing and implementing the card sorting sessions.

(1) Deciding what you want to learn. The aim of this study was to examine whether students could make sense of different indicators described in the literature for identifying patterns in students' perceptions about the interpretability and actionability of indicators to support changes in their learning strategies.

(2) Selecting the method. Students received a predetermined set of category names in individual cards made of paper so that they can manipulated (i.e., self-monitoring indicators), and they were asked to organize the individual cards according to their level of actionability and interpretability. We conducted in-person sessions that lasted one hour and thirty minutes, using laminated paper cards and bid sheets of paper to sort the cards according these two parameters. One researcher moderated the activity, while two research assistants took notes and pictures. All sessions were audio recorded.

(3) Choosing the cards' content. We chose action-related indicators as defined Schwendimann et al. [6], as these are the most commonly found in LADs for students [5]. Then, we took the comparative reference frame proposed by Jivet et al. [10] and Molenaar and Wise [11] (see details about these frameworks in Section 2) to organize and classify the indicators into three categories:

- Temporal versus non-temporal,
- Absolute versus relative,
- Social versus non-social.

We then proposed a textual and a visual representation for each indicator. We chose these two representations because, according to [12], students can prefer text-based indicators to receive feedback. The result was 16 cards to be used in the sessions with the students. Fig. 1 shows an example of how one of the indicators was presented as a text and visual graph, while Table 1 summarizes all the indicators considered in the study.

Table 1. Classification of self-monitoring indicators evaluated in this study.

	Non-temporal (do not use time as a frame of reference)	Temporal (use time as a frame of reference)
Absolute	Number of resources viewed	Number of resources viewed per week
Relative	Percentage of resources viewed of the total available	Percentage of resources viewed of the total available per week
Social absolute	Number of resources viewed compared to the rest of the class	Number of resources viewed per week compared to the rest of the class
Social relative	Percentage of resources viewed of the total available compared to the class	Percentage of resources viewed of the total available per week compared to the class
Absolute	Non-temporal (do not use time as a frame of reference)	Temporal (use time as a frame of reference)

(4) Choosing and inviting participants. Study participants were selected by using a convenience sampling method among students from two different universities: U1 and U2. U1 is a non-profit private university, while U2 is a public institution. Both universities are large and selective institutions in Latin America. They are part of a large research project that aims to analyze the experience of higher education students in post-pandemic learning environments. Out of these universities, we selected a purposive sample of students affiliated with different degrees. Purposive sampling is a non-probabilistic strategy widely used in social sciences, which consists of selecting study participants from a particular section of the population of interest who have different characteristics that you need in your sample [17, 18]. In this study, these characteristics consisted of exposure to different learning technologies and different learning experiences. Students affiliated with U1 use a different LMS than those affiliated with U2, exposing them to different LMS features and reporting. Within U1, students enrolled

in social science courses are exposed to different learning and teaching methods than those enrolled in STEM courses. Students within this sample received an email inviting them to participate in this study, and they voluntarily registered in the card sorting sessions through a form. 21 undergraduate students participated in the card sorting sessions (see Table 2), who signed a written consent form at the beginning of each session. As a compensation for their participation on the study, they opted to a gift card that was raffled among participants.

Table 2. Purposive sample of card sorting participants

Higher education degree	Course	Course enrollment	Card sorting participants
Education (U1)	Education and society	35	6
Physiotherapy (U1)	Research unit in physiotherapy	70	5
Engineering (U1)	Anthrodesign	16	2
Engineering (U2)	Leadership and social innovation	26	8

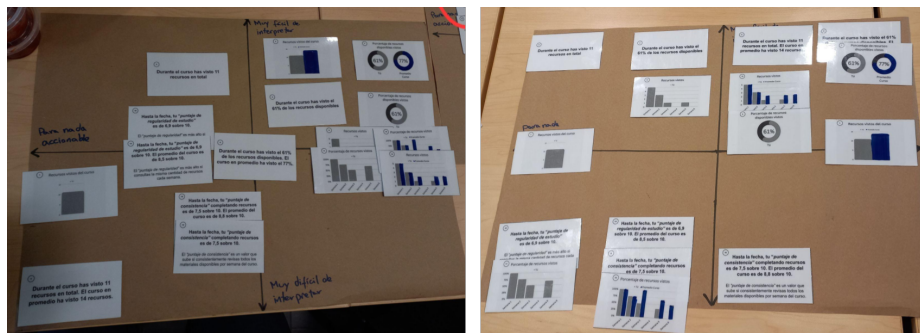


Fig. 2. Examples of how different students sorted different indicators according to their interpretability (horizontal axis) and their actionability (vertical axis).

(5) Running the card sorting and recording the data. Four card sorting sessions were held; one per higher education degree (see Table 2). Each session was organized into five phases, following steps suggested by Spencer [16].

a. Introducing the activity. Researchers in charge of moderating the card sorting sessions introduced the activity by exposing a fictional scenario:

“You are a student in a course of your degree, with 30 students and one professor. It is a course that has both face-to-face and online activities held synchronously and asynchronously, using the institutional LMS. Data can be captured from your behavior in the LMS, deriving different indicators to support your learning.”

b. Handing out the materials. After the introduction, researchers provided students with 16 paper cards with all the selected indicators (see Table 1). The moderator presented the materials to the students in the following way:

“You will be shown a series of cards, each card with an indicator based on your actions in the course. These indicators were obtained directly from the LMS data and could be updated whenever you click on a resource.”

c. Sorting the cards. After five minutes of reviewing the indicators, participants were required to rank them in a 2D grid. The horizontal axis went from “Not at all actionable” to “Very actionable,” and the vertical axis went from “Not at all interpretable” to “Very interpretable” (see Fig. 2).

d. Asking follow-up questions. After the card sorting, students asked to justify their decisions in a 10-minute discussion session: Could you explain why you ordered the indicators this way?

e. Recording the outcomes. Two research assistants were in charge of recording both qualitative and quantitative data (see subsection 3.2). Qualitative data gathering implied recording the session’s audio, which was later transcribed verbatim through a paid software and reviewed by the researcher in charge of moderating each card sorting session. For gathering quantitative data, pictures were taken for each one of the cards sorting grids (see examples in Fig. 2). Grids were analyzed by a researcher who translated the position of each card into rank scores from 1 (lowest preference) to 16 (highest preference).

(6) Analyzing outcomes. To analyze the qualitative outcomes (i.e., transcriptions of audio sessions), we conducted a thematic analysis as proposed by Nowell et al. [19]:

1. Getting familiarized with the data (the researcher and the two research assistants involved in the card sorting sessions read each transcript individually)
2. Generating initial categorical codes concerning the types of codes evaluated (see Table 1): (a) text vs visual, (b) absolute versus relative, (c) social versus non-social reference frames, and (d) temporal versus non temporal.
3. Searching for themes: the three researchers met to discuss potential themes based on the categorical codes established step (2).
4. Reviewing themes’ adequacy by extracting quotes from the raw data
5. Naming themes: (a) Actionability, (b) Interpretability, (c) Prioritized indicators, (d) Relationship between indicators and academic performance, and (e) Self-monitoring support interventions
6. Producing a report. The two research assistants wrote a 7-page manuscript with the principal findings for each theme, including the quotes extracted from sessions’ transcripts.

Regarding quantitative data, we analyzed the preferences elicited from students in their grids. We computed (1) which type of indicators were ranked higher on average, and (2) the level of agreement across students. We computed a score for each axis for each card based on where it was placed from 1 (ranked as the lowest preference) to 16 (ranked as the highest preference). Since students ranked preferences in a 2D grid, there was the possibility that some cards could tie on either axis. In these cases, the score assigned was the average rank of the group. To determine which type of indicators students preferred, we computed the mean score of its corresponding cards that we called the *rank score*. To compute the agreement between two students, we computed the Kendall Tau-b correlation coefficient [20]. The values for the Tau-b correlation can go from -1 (meaning perfectly inverted preferences) to 1 (perfectly aligned preferences). For all pairs of participants in the study, we computed their agreement regarding the interpretability and actionability of the indicators. Both qualitative and quantitative results were triangulated by contrasting findings to answer the research question.

3 Findings

Table 2 reports the three main findings obtained from the quantitative and qualitative analysis of card sorting information.

3.1 Results regarding the actionability of indicators

The quantitative analysis indicates that **Visual elements** (rank score=9.9/16) **were preferred over text elements** (rank score=7.1/16). According to the quantitative analysis, visual elements help some students understand the indicators, which leads them to plan and change their study habits. Most students agreed that the most actionable indicators were those that contain a visual element (e.g., bar chart or pie chart). As one of the students points out:

“I also found it (visual indicators) much easier to interpret and kind of actionable at the same time. Graphs and percentages tell you more than words. For example, you have seen 11 resources in total. doesn't tell you anything. It's nothing relevant because it doesn't even tell you a number.” [Physiotherapy Student, Female, U1].

Regarding **temporality, indicators with temporal information** (rank score=9.2/16) **were found to be more actionable than non temporal indicators** (rank score=7.8/16). The qualitative analysis indicates that students would like to know how they progress week by week to monitor their progress during the semester and visualize their failures, in order to set up a study plan for the following weeks:

“If this week I have a test, that week my bar will be very high and the following week it will be zero because I already had the test and I'm not going to study it... I'm interested in knowing, especially if I have a neurology test one week, the next week my bar will be high and the next week it's the other way around. So that kind of pays me back a bit, I direct my study according to the time I manage.” [Physiotherapy Student, Female, U1]

Regarding **relative indicators**, participants perceived **percentages to be much clearer and much more engaging**. According to the qualitative analysis, having a **relative or a social frame** of reference allows students to know how far they are regarding their studies concerning an upcoming evaluation. The frame of references indicate that something needs to be improved as indicated by the following student:

“The comparison with the course, I still find it good, because perhaps it makes you think, if your study is paying off, if you are doing well, because maybe you are not. Maybe I am not doing so well and I feel like I'm studying super well but I realize that studying for the course requires having required 80% of the resources, I'm 30 and there's the answer.” [Physiotherapy Student, Female, U1]

Some students said **they would be prompted to act only if their course performance was lower than expected**. For example, when asked about their preferences, one student answered:

“Personally, I wouldn't care. I mean, if I'm doing badly, I would mind. But if I'm doing well, even if I have already seen ten PDFs, if I have a good grade, then I wouldn't mind.” [Engineering Student, U2]

Table 3. Table 2. Main findings regarding the actionability and interpretability of self-monitoring indicators. For qualitative results, the rank score goes from 1 (ranked at the lowest preference) to 16 (ranked as the highest preference).

Findings	Quantitative results	Qualitative results
<p>F1. Students tend to find more actionable:</p> <ul style="list-style-type: none"> • Visual over text • Temporal over non temporal (but less interpretable) • With social comparison over no social comparison • Relative indicators over absolute indicators <p>Indicators that are less actionable require greater attention and effort for its understanding.</p>	<p>The rank score for actionability was <i>higher</i> for:</p> <ul style="list-style-type: none"> • Visual elements (9.9) over text elements (7.1) • Temporal indicators (9.2) over non temporal (7.8) • Elements with social comparison (9.1) over no comparison (7.9) • Relative indicators (9.4) over absolute indicators (7.6) 	<ul style="list-style-type: none"> • Visual elements were perceived to be more actionable • Temporal indicators allow students to review their progress and failures • Relative and social indicators were perceived to be more motivating
<p>F2. Students tend to find more interpretable:</p> <ul style="list-style-type: none"> • Visual over text • Non temporal over temporal (but could generate confusions) • With social comparison over no social comparison • Relative indicators over absolute indicators <p>Indicators that are less interpretable usually contain a greater amount of text and images.</p>	<p>The rank score for interpretability was <i>higher</i> for:</p> <ul style="list-style-type: none"> • Visual elements (10.5) over text elements (6.5) • Non temporal indicators (9.1) over temporal (7.9) • Elements with social comparison (8.8) over no comparison (8.2) • Relative indicators (8.8) over absolute indicators (8.2) 	<ul style="list-style-type: none"> • Visual elements were perceived to be easier to understand • Relative indicators provided students with a frame of reference, as well as social indicators.
<p>F3. Regarding self-monitoring interventions:</p> <ul style="list-style-type: none"> • Students emphasized the need for customization and being able to review the indicators whenever they wanted. • Students appreciated hints that were applicable to their courses. • Students who received mailing generally did not see it. • Students who received text messages valued their closeness. 	<ul style="list-style-type: none"> • The average level of agreement across pairs of students was overall weak for both actionability (0.14) and interpretability (0.16) • Several pairs of students reported inverted preferences for actionability (31.6%) and interpretability (26.46%) 	<p>Students like to have data about their progress using learning resources during the semester, but students report different preferences about images or nudges to improve their performance.</p>

Despite the observed trends, there was much variability in both qualitative and quantitative sources, and we observed a weak level of agreement between students. The mean correlation coefficient was 0.14, considered a weak level of agreement (see Fig. 3a). Furthermore, several pairs of students (31.62%) had inverted preferences, since they had a negative correlation. Concerning **text indicators**, some students claim that text can work as a motivator for their learning but as a complement to indicators that contain charts or images. Students also perceive that absolute indicators can work like

text indicators to complement relative indicators. Regarding **temporal indicators**, some students perceive them to be confusing to understand. In other words, these indicators might be less interpretable, making them less actionable. Finally, some students indicated that they do not like the comparison with the course average but rather compete with themselves, looking for other frames of reference, such as, for example, the total number of resources they viewed.

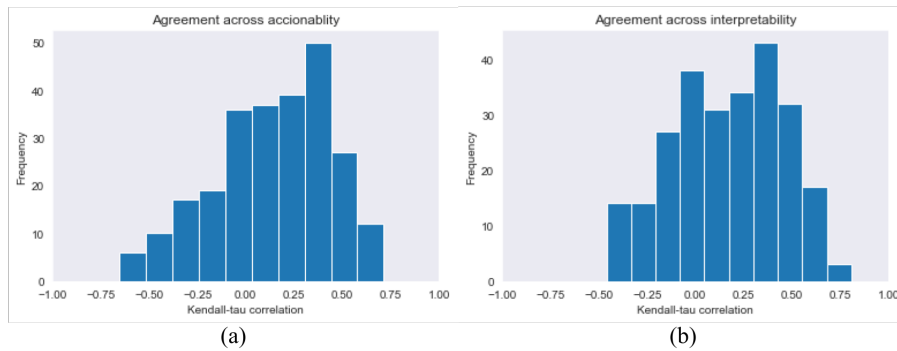


Fig. 3. Ranking correlation between pairs of students regarding (a) actionability and (b) interpretability. (-1 is perfectly inverted preferences, 1 is perfectly aligned preferences, and 0 is no correlation).

3.2 Results regarding the interpretability of indicators

Most students perceive **visual indicators** (rank score=10.5/16) **as easier to interpret than text-based ones** (rank score=6.5/16). Some students mentioned that cards with text took longer to understand, which turned out to be not very actionable, as described by the following students:

“Pure text, it really bothered me a lot. It is difficult to interpret and for the same reason, it is not actionable for me, because I can't take advantage of the mation” [Engineering Student, U2]

“I divided the cards between the most actionable side, what is proper and at least, what is actionable compared to the course, and what is easier to interpret is graphic ” [Physiotherapy Student, U1].

Regarding the use of **relative indicators**, some students indicated that the use of percentages was key for greater interpretability of the data because it gave them a frame of reference of the total (100%):

“The percentages are much easier to interpret and I also feel that they give you how, I don't know how to say it, just that one can, how to relate it to something.” [Physiotherapy Student, U1]

“Percentage of seen resources makes it clear to me that I have not seen the total. So it is much easier for me to interpret how today I have not reviewed the total, so I could organize myself better to see what resources I have reviewed.” [Engineering Student, U1]

Concerning **social comparisons**, students tend to consider those with social comparison more interpretable (rank score=8.8/16) than those without (rank score=8.2/16), because it gives them a standard to be achieved:

“The same as seeing the course average. I don't know whether it would help me, maybe because the competition would encourage me to do more as I did less than most of the course. Even so it makes it clear to me that I did not see all the course material.” [Engineering Student, Female, U1]

Regarding **temporality**, most students ranked **temporal indicators** (rank score=7.9/16) as **less interpretable than non temporal indicators** (rank score=9.1/16), as the former could lead to confusion. This is generated mainly by indicators that inform the number of resources seen during the week. During the card sorting sessions, participants indicated that each student plans their weeks differently. This is why some students may misunderstand these types of indicators, so it becomes confusing to plan the next steps in relation to that information:

“For example, you may have reviewed four additional resources than the average, but those resources can be like 5% of the total. So you may have a false idea that you are more advanced without having reviewed all the resources” [Education Student, U1]

"Because there are people who, I don't know, one week may study a lot because they don't like to study week by week, so information by week may not be found useful." [Kinesiology Student, U1].

As for what the students considered **less interpretable**, they tend to disregard indicators that contain more text than images and dismiss indicators that contain absolute numbers rather than percentages.

3.3 Results regarding self-monitoring

Students agreed that self-monitoring indicators tend to be more actionable when they have lower performance in their courses. By comparing with the rest of the course, students can evaluate whether they are performing above or below the average. Some students perceive that the most actionable and relevant indicators are those that inform the resources viewed week by week:

“It could be useful to see the comparison with the course, because I don't know if there was a test one day or one week and my classmates reviewed a specific resource a lot. (...) Maybe I could provide information on why I didn't do so well” [Physiotherapy Student, Female, U1]

Finally, we asked about how they would like to have access to this information. Students indicated that they would value the data to be directly accessible (for example, when entering a platform, they could see it in the home page) and during the whole semester, in the course's own platforms. Not so much through mail messaging, which would rather be complementary). In addition, in some cases, students note that they would like to customize these indicators. One education student mentioned:

"(...) if I could change the colors, customize it and, in my own case, I would really like to move things. In [the LMS] you can, I like that because you can move it around and I like things in alphabetical order" [Education student, Male, U1].

4 Discussion

This study contributes to the existing body of knowledge regarding the design of student-facing analytics by illustrating students' preferences on self-monitoring indicators. Both qualitative and quantitative findings obtained from the analysis of the card sorting outcomes indicate that students find more actionable: (1) visual indicators over text, (2) temporal indicators over non-temporal, (3) social comparisons rather than without them, and (4) relative indicators over absolute metrics. Regarding interpretability, some students found temporal indicators less interpretable, as they could lead to confusion. Still, our work suggests that there is a connection between the type of indicators and their interpretability and actionability, which have some implications at different levels.

4.1 Implications about the relationship between indicators and self-regulated learning

Prior research on LA identified self-regulated learning (SRL) as a primary focus of LADs. However, recent literature indicates that few analytical efforts are grounded in SRL theories [1]. Theories of learning play a key role in the development of these initiatives as they provide frameworks to understand students' actions better and, thus, adjust support. The findings of this study are discussed concerning these theories and highlight some hypotheses that could inspire future work.

First, indicators provided within a temporal frame could potentially promote metacognitive monitoring strategies. Our findings suggest that embedding indicators within a temporal frame are key to providing students with a reference for their progression in the course. This aligns with what some SRL models call the "performance phase" [21] or cognitive regulatory strategies [22], in which students perform metacognitive monitoring of their progress. These indicators could help students recognize their temporal evolution and change their behavior accordingly.

Second, indicators embedded within a social context are perceived as more actionable and, therefore, could promote self-reflection and more strategic learning strategies. Our findings show that students perceive the indicators as more actionable when provided with social comparisons with their course companions, especially if their course results are under their expectations. This relates to the forethought phase, as defined by Zimmerman [21], in which students reflect on their goals and evaluate their outcomes and expectations.

In summary, we observe potential relationships that should be further evaluated when analyzing our results concerning SRL theories. Future experimentations could be conducted to evaluate the analyzed indicators' potential to support learning strategies.

4.2 Implications in the design of LADs

This study illustrates how reference frames work as a mechanism to support the interpretation of indicators from the perspective of students. Students who participated in card sorting sessions justified their interpretation of indicators with a similar lens to the reference frames proposed by Jivet et al. [10]. Mainly, students viewed in-

dicators displaying weekly information to understand their prior progress (past-directed). For example, some students remarked that they would like to have this information to see if there were any changes they could make to their study habits. Non-temporal indicators, such as the percentage of total resources seen, tended to be associated with future-directed behavior. Students usually associated these indicators with the amount of work to be done. Our work suggests that students found past-directed indicators less interpretable but more actionable. In particular, past-directed indicators were seen valuable if they were unsatisfied with their performance.

Still, it is important to consider designing flexible LADs to embrace students' diversity and needs. Most students indicated that comparing the rest of the course would motivate them to take action. However, some students perceived comparisons as less actionable, as they put them in a situation of anxiety or demotivation because they were not at the same level as their classmates. As Vytasek et al. [7] note, using social comparison as a reference frame might be challenging, as it can promote negative emotions such as frustration or hopelessness, likely further disengaging struggling students. This partly explains why some students argue that, despite finding this reference frame interpretable and actionable, they would not like to have access to this information.

Some students said they would be prompted to act only if their course performance was lower than expected. This relation between student performance and the actionability of indicators can be linked to the goal-directed behavior of students. In particular, Jivet et al. [2] showed that students' goals could shape what reference frames students find relevant for their particular situation. They found that students that aim to master the subject prefer different indicators compared with those whose goal was just to pass the course. In our study, several students reported that their goal was to pass their courses. This could explain why students reported that they would act upon indicators only if they saw that they were at risk of having a bad performance in the course.

It is worth considering that although the students mentioned indicators that could be useful concerning their performance, this arose spontaneously and in a limited group of participants, so it was not possible to go deeper on the characteristics of such indicators. This would be interesting to be explored in future studies, especially considering the variability of the answers. New insights on this regard could lead to recommendations or information for students according to their performance to help them to take action and plan their study.

Regardless of identifying students' predominating preferences towards specific indicators, our findings also revealed variability in the general agreement across students' rankings. Prior research has already seen that students' preferences for indicators can vary across students depending on their goals [2]. The 'one-size-fits-all' design philosophy has already been under question, as numerous external and internal factors may affect the impact of an intervention [23, 24]. In line with previous HCLA efforts [14, 15], implementing a user-centered design method such as the card sorting technique was useful for collecting nuanced information about how students think about different types of indicators for different academic scenarios.

5 Conclusions and limitations

Our work provides insight into what types of indicators students find actionable and interpretable. The findings suggest that visual indicators, temporal indicators, social comparisons, and relative indicators are more actionable and interpretable. However, the study also highlights that no one-size-fits-all approach exists, and students' goals and individual factors can significantly impact their preferences. The card sorting method proved useful for understanding learners' use of indicators and could be replicated in other Technology-Enhanced Learning (TEL) contexts. These findings could be valuable for designers of student-facing analytics, as it provides insight into what indicators could effectively promote students' self-monitoring and academic success. Additionally, this research emphasizes the importance of a user-centered design approach and highlights the need to consider individual differences in the design of student-facing analytics.

The main limitation of this study is the use of non-probabilistic sampling, which can introduce potential self-selection bias. Jivet et al. [2], for example, show that there exists a relationship between SRL skills and students' preferences for some indicators. When selecting students, we did not control for SRL skills, which could have introduced bias in our result or explained the variability of the responses. Furthermore, while card sorting intends to go beyond self-reported by alluding to students' mental models, most findings still rely on prompts given by students based on their perception. This means that some students' preferences elicited in this study might not align with what they would be interested in during an entire course. These preferences could also change depending on the system used to access the information, the indicators' availability, and the course's instructional design.

Acknowledgments

This paper has been funded by the ANR LASER (156322) and the Chilean National Agency for Research and Development (ANID), under the 'Student Experience in Higher Education in Chile: Expectations and Realities' Millennium Nucleus. The authors acknowledge PROF-XXI, which is an Erasmus+ Capacity Building in the Field of Higher Education project funded by the European Commission (609767-EPP-1-2019-1- ES-EPPKA2-CBHE-JP). This publication reflects the views only of the authors and funders cannot be held responsible for any use which may be made of the information contained therein.

References

1. Matcha, W., Ahmad Uzir, N., Gasevic, D., Pardo, A.: A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective. *IEEE Trans. Learn. Technol.* PP, 1–1 (2019). <https://doi.org/10.1109/TLT.2019.2916802>.
2. Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., Drachler, H.: From students with love: An empirical study on learner goals, self-regulated learning and sense-making

- of learning analytics in higher education. *Internet High. Educ.* 47, 100758 (2020). <https://doi.org/10.1016/j.iheduc.2020.100758>.
3. Jørnø, R.L., Gynther, K.: What Constitutes an ‘Actionable Insight’ in Learning Analytics? *J. Learn. Anal.* 5, (2018). <https://doi.org/10.18608/jla.2018.53.13>.
 4. van Leeuwen, A., Teasley, S.D., Wise, A.F.: Teacher and student facing learning analytics. In: *Handbook of learning analytics*. p. 11 (2022).
 5. Pérez-Álvarez, R., Jivet, I., Perez-Sanagustin, M., Scheffel, M., Verbert, K.: Tools Designed to Support Self-Regulated Learning in Online Learning Environments: A Systematic Review. *IEEE Trans. Learn. Technol.* 15, 508–522 (2022). <https://doi.org/10.1109/TLT.2022.3193271>.
 6. Schwendimann, B.A., Rodríguez-Triana, M.J., Vozniuk, A., Prieto, L.P., Boroujeni, M.S., Holzer, A., Gillet, D., Dillenbourg, P.: Perceiving Learning at a Glance: A Systematic Literature Review of Learning Dashboard Research. *IEEE Trans. Learn. Technol.* 10, 30–41 (2017). <https://doi.org/10.1109/TLT.2016.2599522>.
 7. Vytasek, J.M., Patzak, A., Winne, P.H.: Analytics for Student Engagement. In: Virvou, M., Alepis, E., Tsihrintzis, G.A., and Jain, L.C. (eds.) *Machine Learning Paradigms: Advances in Learning Analytics*. pp. 23–48. Springer International Publishing, Cham (2020). https://doi.org/10.1007/978-3-030-13743-4_3.
 8. Wise, A.F.: Designing pedagogical interventions to support student use of learning analytics. In: *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge*. pp. 203–211. ACM, Indianapolis Indiana USA (2014). <https://doi.org/10.1145/2567574.2567588>.
 9. Lim, L., Dawson, S., Joksimovic, S., Gašević, D.: Exploring students’ sensemaking of learning analytics dashboards: Does frame of reference make a difference? In: *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*. pp. 250–259. ACM, Tempe AZ USA (2019). <https://doi.org/10.1145/3303772.3303804>.
 10. Jivet, I., Scheffel, M., Drachsler, H., Specht, M.: Awareness Is Not Enough: Pitfalls of Learning Analytics Dashboards in the Educational Practice. In: Lavoué, É., Drachsler, H., Verbert, K., Broisin, J., and Pérez-Sanagustín, M. (eds.) *Data Driven Approaches in Digital Education*. pp. 82–96. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-66610-5_7.
 11. Molenaar, I., Wise, A.F.: Temporal Aspects of Learning Analytics - Grounding Analyses in Concepts of Time. In: *Handbook of Learning Analytics*. p. 11 (2022).
 12. Mendez, G., Galárraga, L., Chiluíza, K.: Showing Academic Performance Predictions during Term Planning: Effects on Students’ Decisions, Behaviors, and Preferences. In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. pp. 1–17. ACM, Yokohama Japan (2021). <https://doi.org/10.1145/3411764.3445718>.
 13. Creswell, J., Guetterman, T.: *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research*, 6th Edition. (2018).
 14. Chatti, M.A., Muslim, A., Guesmi, M., Richtscheid, F., Nasimi, D., Shahin, A., Damera, R.: How to Design Effective Learning Analytics Indicators? A Human-Centered Design Approach. In: Alario-Hoyos, C., Rodríguez-Triana, M.J., Scheffel, M., Arnedillo-Sánchez, I., and Dennerlein, S.M. (eds.) *Addressing Global Challenges and Quality Education*. pp. 303–317. Springer International Publishing, Cham (2020). https://doi.org/10.1007/978-3-030-57717-9_22.
 15. Dimitriadis, Y., Martínez-Maldonado, R., Wiley, K.: Human-Centered Design Principles for Actionable Learning Analytics. In: Tsiatsos, T., Demetriadis, S., Mikropoulos, A., and Dagdilelis, V. (eds.) *Research on E-Learning and ICT in Education*. pp. 277–296. Springer International Publishing, Cham (2021). https://doi.org/10.1007/978-3-030-64363-8_15.

16. Spencer, D.: Card sorting: designing usable categories. Rosenfeld Media, Brooklyn, New York (2009).
17. Guarte, J.M., Barrios, E.B.: Estimation Under Purposive Sampling. *Commun. Stat. - Simul. Comput.* 35, 277–284 (2006). <https://doi.org/10.1080/03610910600591610>.
18. Purposive Sample. In: *Encyclopedia of Survey Research Methods*. Sage Publications, Inc., 2455 Teller Road, Thousand Oaks California 91320 United States of America (2008). <https://doi.org/10.4135/9781412963947.n419>.
19. Nowell, L.S., Norris, J.M., White, D.E., Moules, N.J.: Thematic Analysis: Striving to Meet the Trustworthiness Criteria. *Int. J. Qual. Methods.* 16, 160940691773384 (2017). <https://doi.org/10.1177/1609406917733847>.
20. Kendall, M.G.: The Treatment of Ties in Ranking Problems. *Biometrika.* 33, 239–251 (1945). <https://doi.org/10.2307/2332303>.
21. Zimmerman, B.J.: Attaining Self-Regulation. In: *Handbook of Self-Regulation*. pp. 13–39. Elsevier (2000). <https://doi.org/10.1016/B978-012109890-2/50031-7>.
22. Boekaerts, M.: Self-regulated Learning at the Junction of Cognition and Motivation. *Eur. Psychol.* 1, 100–112 (1996). <https://doi.org/10.1027/1016-9040.1.2.100>.
23. Teasley, S.D.: Student Facing Dashboards: One Size Fits All? *Technol. Knowl. Learn.* 22, 377–384 (2017). <https://doi.org/10.1007/s10758-017-9314-3>.
24. Jivet, I., Wong, J., Scheffel, M., Valle Torre, M., Specht, M., Drachsler, H.: Quantum of Choice: How learners’ feedback monitoring decisions, goals and self-regulated learning skills are related. In: *LAK21: 11th International Learning Analytics and Knowledge Conference*. pp. 416–427. ACM, Irvine CA USA (2021). <https://doi.org/10.1145/3448139.3448179>.