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Investigating students' use of self-assessments in higher education using learning analytics

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Abstract

Background: Formative assessments are vital for supporting learning and performance but are also considered to increase the workload of teachers. As self-assessments in higher education are increasingly facilitated via digital learning environments allowing to offer direct feedback and tracking students' digital learning behaviour these constraints might be reduced. Yet, learning analytics do not make sufficient use of data on assessments.

Aims: This exploratory case study uses learning analytics methods for investigating students' engagement with self-assessments and how this relates to performance in the final exam and self-reported self-testing strategies.

Materials & Methods: The research study has been conducted at a European university in a twelve-weeks course of a Bachelor's program in Economic and Business Education including $n_{\text{enroll}} = 159$ participants. During the semester, students were offered nine self-assessments each including three to eight tasks plus one mid-term and one exam-preparation self-assessment including all prior self-assessments tasks. The self-assessment interaction data for each student included: the results of the last self-assessment attempt, the number of processed self-assessment tasks, and the time spent on the last self-assessment attempt, the total self-assessment attempts, and the first as well as last access of each self-assessment. Data analytics included unsupervised machine learning and process mining approaches.

Results: Findings indicate that students use the self-assessments predominantly before summative assessments. Two distinct clusters based on engagement with self-assessments could be identified and engagement was positively related to performance in the final exam. The findings from learning analytics data were also indicated by students' self-reported use of self-testing strategies.

Discussion: With the help of multiple data from self-reports, formal exams, and a learning analytics system, the findings provided multiple perspectives on the use of self-assessments and their relationships with course performance. These findings call

Dirk Ifenthaler and Clara Schumacher contributed equally to this work and share the first authorship.

for applying assessment analytics and related frameworks in learning analytics as well as providing learners with related adaptive feedback.

Conclusion: Future research might investigate different (self-report) variables for clustering, other student cohorts or self-assessment forms.

KEYWORDS

assessment analytics, higher education, learning analytics, self-assessment, self-testing

1 | INTRODUCTION

The difficulties of characterizing differences and interrelationships between formative assessment and summative assessment have been much discussed in the literature (Bennett, 2011; Black & Wiliam, 2009). Summative assessment refers to an assessment of achievement or outcome at the end of the instructional defined period whereas formative assessment refers to ongoing assessment during the learning process for supporting learning (Pellegrino et al., 2001). Despite a shift to more formative assessments in higher education, the focus is still predominantly on the summative function (Pereira et al., 2021). This might also be due to resource constraints in higher education, as offering formative assessments and individual feedback are considered a resource as well as labour demanding (e.g. time, staff) (Broadbent et al., 2017; Graham Gibbs & Simpson, 2005). Therefore, formative self-assessments are increasingly facilitated through digital learning environments (Bayrak, 2021; Cukusic et al., 2014).

Digitally supported formative self-assessment occurs when learners take opportunities of (near) real-time information about their learning process and reflect on the findings to determine their strengths and shortcomings. This increasing implementation of educational technology in higher education and the related data produced might elude the above-mentioned constraints.

Accordingly, data and related analytics are considered valuable opportunities for realizing continuous and formative assessments (Williams, 2014). Even though current research begins to make use of data going beyond mere behavioural data, additional efforts are required to integrate assessment data such as assessment type, attempts, and results (Nouira et al., 2019), as well as to develop holistic learning analytics systems that incorporate elaborated frameworks related to theory on learning, assessment and feedback (Ifenthaler & Greiff, 2021; Schumacher, 2020). In addition, further research is required on how data on (self-)assessments can be integrated with learning analytics (Misiejuk & Wasson, 2017).

Hence, to promote research on the use of assessment data for learning analytics, this exploratory case study adopted learning analytics methods for analysing students' use of self-assessments during the semester, detecting different engagement, and learning behaviour and how this relates to final exam performance as well as self-report data.

1.1 | Self-assessment in higher education

Assessments can be formative or summative whereby the two functions are considered to be overlapping and dependent on how the inferences are used (Black & Wiliam, 2018). Taras (2005) states that every assessment starts with the summative function of judgement and by using this information for providing feedback for improving the function becomes formative. Hence, formative assessment helps students to understand standards and criteria of learning outcomes, supports their current state of learning, and guides them with feedback to take action to achieve their learning goals (Wiliam & Thompson, 2008).

Following Nieminen and Tuohilampi (2020), self-assessments can be formative or summative. Panadero et al. (2016) state that self-assessments are a good means to include students in the process of formative assessment. Self-assessments can be defined as 'a process during which students collect information about their own performance, evaluate and reflect on the quality of their learning process and outcomes according to select criteria to identify their own strengths and weaknesses' (Yan & Brown, 2017, p. 1248). Andrade and Valtcheva (2009, p. 12) note that 'the purposes of self-assessment are to identify areas of strength and weaknesses in one's work in order to make improvements and promote learning'. However, assessing and evaluating students can use a huge variety of mechanisms resulting in different understandings of the conceptualisation of self-assessments and different practices (Panadero et al., 2016). More precisely, self-assessments include four actions in which students (a) seek external feedback through monitoring; or (b) through inquiry; (c) seek internal feedback; or (d) engage in self-reflection (Yan, 2020). Panadero et al. (2016) investigated self-assessment typologies of which only a few considered comparable forms of self-assessments or self-tests as investigated in this study as a form of self-assessment. For example, Tan et al. (2010) claims that self-testing is rather a teacher- than student-involved practice including surface-level assessments that could be provided via a computer with a predominant summative function which the latter Panadero et al. (2016) consider as faulty implication. Given the various perspectives on self-assessments, it becomes obvious that self-assessments can be formative or summative, whereas the presented work focuses on the formative component of self-assessment.

In this paper, following the cyclic self-assessment framework for engaging students in self-assessment (Yan & Brown, 2017), the focus is on students' seeking external feedback from resources. This refers to students testing themselves using self-assessment tasks in a digital learning environment including at least some kind of feedback (e.g. correctness, template solution). Self-testing practices enable students to identify key concepts, and their gaps in learning and familiarize themselves with exam questions (Thomas et al., 2017). Thomas et al. (2017) found a positive relationship between students' final grades and the percentage of attempted self-tests in two health science courses. Similarly, Rodriguez et al. (2021) found a positive association between self-reported self-testing and students' final course grades in a biology course. In addition, research indicates that the use of instructor-generated self-tests has a higher positive impact on retention compared to rereading and a comparable (Weinstein et al., 2010) or higher effect than the use of self-generated questions (Lloyd et al., 2018). However, results might be different for other assessed learning outcomes except for retention (Weinstein et al., 2010). Generation of own questions demands students to perform higher cognitive processes to integrate knowledge by searching, creating, and synthesizing the learning materials which is particularly difficult for novices (Lloyd et al., 2018), and more time-consuming (Weinstein et al., 2010). This effect is referred to as the testing effect indicating that if students are tested on a certain material or learning content they remember it better than from restudying repeatedly (Butler & Roedinger, 2007; Karpicke et al., 2009).

Papamitsiou et al. (2021) investigated students' perceptions of an adaptive digital self-assessment tool and found that students were willing to use the tool and associated it with higher motivation to engage in self-assessments. Hence, such perceptions and the provision of tools easily accessible might also impact students' uptake of the learning support. Even though asking own questions and performing in more elaborated self-assessments might be a meaningful self-regulated learning strategy (Panadero et al., 2016) students often have difficulties engaging in suitable learning strategies and require further guidance. Hence, several studies focussing on learning engagement support the assumption that higher engagement of a learner corresponds with higher learning outcomes (Ifenthaler et al., 2020).

However, research also showed that students do not use self-testing sufficiently on their own in authentic educational settings (Karpicke et al., 2009) which might be among others due to lacking availability of self-test or students' perceptions that self-tests are similarly beneficiary for learning as rereading (Weinstein et al., 2010). Hence, students are not sufficiently aware of the beneficiary effects of self-testing for learning compared to the often chosen but less effective rereading (Karpicke et al., 2009). However, instructor-generated self-tests might still be a more efficient way for students to review learning materials and not demand too much time allocation (Lloyd et al., 2018), especially when facilitated in a digital learning environment enhanced with immediate feedback as investigated in this study. To enhance the research on students' usage of self-assessments and go beyond self-reported use of self-assessment practices as investigated by Rodriguez et al. (2021), learning analytics approaches are a suitable means as they offer additional insights into digital learning behaviour and engagement (Winne & Baker, 2013).

1.2 | Linking self-assessment with learning analytics

Learning analytics use static and dynamic information about learners and learning environments, assessing, eliciting, and analysing it for real-time modelling, prediction and support of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). Data- and analytics-driven insights are used to better understand and support student learning through personalization and feedback as well as predicting and enhancing study success (Ifenthaler & Yau, 2020). Wong and Wong and Li (2020) found in their systematic review that predominant learning analytics approaches include personalized recommendations, visualization of learning data and personalized reports on progress or performance.

Learning analytics indicators have been discussed widely (Richardson et al., 2012; Yau & Ifenthaler, 2020) and the inclusion of data on formative assessments have been found to be fruitful (Tempelaar et al., 2015). For example, Holmes (2018) investigated the use of low-stakes continuous weekly summative e-assessments concerning student engagement in a digital learning environment. Findings indicated that these assessments increased the overall engagement of students within the digital learning environment. Gašević et al. (2017) found four different behavioural patterns in which students focused either on formative assessments, summative assessments, reading course materials or combining videos with assessments. Students engaging in assessments showed better performance in the final exam. Jovanovic et al. (2017) clustered students in a flipped learning scenario based on their digital learning actions and identified five clusters of learners that used different learning strategies. They found that students' strategy use changed over time as they abandoned self-testing with formative self-assessments and engaged more in summative assessments and video watching plus reading which the authors considered less-effective strategies. Tempelaar (2020) clustered students in a blended-learning scenario based on their self-reported learning strategies and found that a cluster of students named adaptive learning approach had the highest learning time in the digital learning environment, the highest number of attempts and worked-out examples plus correctly solved problems compared to three other clusters. Learning analytics studies currently focus on the usage of resources with only a few investigating learning processes through understanding learning pathways or students' learning progress (Vieira et al., 2018). Fan et al. (2021) used process maps to analyse study tactics based on trace data and found that higher-performing learners used more content and assessment-related tactics and used different study tactics more adaptively over the entire time of the course. In a study on students' expectations of learning analytics, students rated a feature in a digital learning environment offering self-assessments for self-testing including immediate feedback as the most supportive for learning (Schumacher & Ifenthaler, 2018).

Accordingly, research on linking self-assessment with learning analytics has been of growing interest. Still, research on pedagogical-driven perspectives on self-assessments associated with learning analytics approaches are scarce.

1.3 | The current study

Tormey et al. (2020) highlight that even though learning analytics might support students' self-assessment and related feedback, this might currently not be satisfactorily realized. To date, learning analytics do make not sufficiently use of assessment data (Ifenthaler et al., 2018), and the two lines of research are not adequately linked (Misiejuk & Wasson, 2017; Schumacher, 2020; Tormey et al., 2020). Hence, this exploratory case study aims to address this research gap by investigating students' engagement with self-assessments using learning analytics approaches in a productive higher education learning environment.

First, Carless (2007) suggests allocating self-assessment tasks over an entire course period to facilitate learning. Furthermore, Holmes (2018) found that the use of continuous summative assessments counting 20% of the final course grade increased students' interaction in a digital learning environment. Accordingly, we assume that students use the provided formative self-assessments over the entire period of the semester (Hypothesis 1).

Further, learning engagement is a multifaceted construct that refers to a learner's ability to interact with learning artefacts in a continuous learning process on a behavioural, cognitive, emotional and motivational level (Wolters & Taylor, 2012). Following this broad assumption, engagement with self-assessments is considered to be beneficiary and positively related to academic achievement (Yan, 2020). However, learners differ in their reasons for engaging in learning tasks and these inter-individual differences require personalized support while learning (Schunk & Zimmerman, 1994). Therefore, we assume that distinctive groups of learners can be identified that engage with the self-assessments differently (Hypothesis 2a) and that these groups also show differences in their navigation behaviour in the digital learning environment (Hypothesis 2b). And if there are any distinct groups of learners regarding self-assessment engagement, we assume that learners with higher engagement in self-assessments outperform less engaged learners with self-assessments in the final exam performance (Hypothesis 2c).

Last, as self-report data on actual learning processes are considered to be limited, the combination with trace data for investigating how learners engage with certain resources such as self-assessments is considered to be more accurate (Fincham et al., 2019; Zhou & Winne, 2012). Thus, we assume that learners showing different engagement with self-assessments also differ with regard to their self-reported use of self-testing strategies (Hypothesis 3).

2 | METHOD

2.1 | Context and materials

The research study has been conducted at a European university in a 12-weeks (11 lectures) course of a Bachelor's program in Economic and Business Education with an expected semester workload of four ECTS (European Credit Transfer System; approximately 120 h of learning). The course focused on research methodologies (e.g. research process cycle, hypothesis testing, research ethics, research reporting) and utilized a blended-learning concept including 11 face-to-face lectures every week as well as extensive learning materials provided through the digital learning platform ILIAS (Integriertes Lern-, Informations- und Arbeitskooperations-System; www.ilias.de). For each lecture, students were provided with lecture recordings (slides and audio, made available after each lecture), suitable additional external resources such as texts or websites, and self-assessments enhanced with a general discussion forum. During the semester, students were offered nine self-assessments each including three to eight tasks plus one mid-term (31 tasks) and one exam-preparation self-assessment including all prior self-assessments tasks (48 tasks). The self-assessments were embedded in the LMS, had a formative function (i.e. being available during the semester anytime), and task types included multiple- and single-choice tasks, fill-in-the-blank texts, correlation problems, short texts or identification of mistakes. The self-assessments predominantly assessed declarative knowledge and knowledge transfer. Sample tasks are: 'Please complete the subsequent definition of measurement' asking students to fill in blanks. 'Which statement on statistical hypotheses is correct?' asking students to check the single correct answer. 'Please describe for what linear regression can be used: (a) Which types of hypotheses can be investigated using linear regression analysis?; (b) What is the basic assumption of linear regression analysis?; (c) Which requirements do variables need to meet?' asking students to write a text. Feedback to students included points achieved, simple right or wrong information, the solution, and explanations related to individual lectures. The final exam written either in week 16 or 23 of the semester included nine tasks with a maximum of 60 points assessing declarative knowledge and knowledge transfer. The two exam dates are specific for the higher education institution this case study has been situated. Students can either choose one of the exam dates, however, there are no more classes between the two dates. The tasks in the final exam did not repeat any of the self-assessment tasks, rather they were focused on cases. For example: 'Your task in a research project is to operationalise "leadership skill" including three dimensions with three elements each. Derive for each element an item which can be measured on an ordinal scale'.

2.2 | Participants

A total of $n_{enroll} = 159$ students were enrolled, $n_{exam} = 139$ took the exam, $n_{study} = 114$ participated in the study and $n_{trace} = 158$ agreed on collecting their digital learning behaviour. Depending on the research question and data used only the respective subsamples are analysed. Students participating in the survey study were on average 22.97 years old ($SD = 2.92$) and have on average studied for 5.50 semesters ($SD = 1.6$). The participants received one study credit for participating in the study.

2.3 | Learning analytics data

The Learning Management System (LMS) was enhanced with the learning analytics plugin LeAP (Learning Analytics Profiles) which allowed for tracking students' digital learning behaviour. The data were extracted from the database, cleaned, and pre-processed for analysis. The LMS enhanced with the LeAP plugin provides two sources of students' behaviour data: the traces of participants' interaction with the self-assessments; and the log of students' interaction with the course resource types.

The self-assessment interaction data for each student included: the results of the last self-assessment attempt, the number of processed self-assessment tasks, the time spent on the last self-assessment attempt, the total self-assessment attempts, and the first as well as last access of each self-assessment. For this paper, the following indicators were created and used:

- ratio $r_{a_i}^{rel}(s_j)$ of the result of the last self-assessment attempt r_{a_i} of student s_j of self-assessment a_i, compared to the maximum self-assessment result $r_{a_i}^{max}$ possible: $r_{a_i}^{rel}(s_j) = \frac{r_{a_i}(s_j)}{r_{a_i}^{max}}$.
- the ratio $n_{a_i}^{rel}(s_j)$ of the number of processed tasks n_{a_i} by student s_j of each self-assessment a_i compared to maximum number tasks $n_{a_i}^{max}$ available for the self-assessment a_i: $n_{a_i}^{rel}(s_j) = \frac{n_{a_i}(s_j)}{n_{a_i}^{max}}$
- number of student attempts per each self-assessment
- student processing time of each self-assessment.

Students' interaction with all course resource types (e.g. course entrance, files, sessions, folders, forum, tests, videos) in form of a click-stream log file were used for the construction of the process maps. Trace data was only considered until the official end of the term.

2.4 | Self-report data

Students were asked to answer a questionnaire on study-related constructs, such as their study interest (FSI; Schiefele et al., 1993), meta-cognitive awareness (MAI; Schraw & Dennison, 1994); learning goal orientations (SELLMO; Spinath et al., 2012), learning and study strategies (LASSI; Weinstein et al., 2016). For analyses in this paper, we focus on a sub-scale of the LASSI investigating students' self-reported use of self-testing strategies (6 items; 5-point Likert scale: 1 = not true at all to 5 = very true; Cronbach's alpha = 0.80; e.g.: *To check my understanding of the material in a course, I make up possible test questions and try to answer them.*). Students furthermore reported demographic information such as age, gender, semester and current GPA.

2.5 | Data analysis

2.5.1 | Clustering

Clustering is the unsupervised machine learning method for uncovering the patterns in the dataset via similarity between samples. In this study *k*-means algorithm (Murphy, 2012) has been used to cluster students' engagement with self-assessments to uncover students with similar self-assessment interaction patterns. For determining the optimal number of clusters (groups of students) two clustering quality measures have been used: with-cluster sum of squares *WCSS* (Thorndike, 1953); and the average silhouette measure (Kaufman & Rousseeuw, 2009).

The clustering has been applied on the dataset containing measures of students' self-assessment activity (see Section 2.3 for details). This leads to the dataset containing a total of 44 variables (4 for each of 11 self-assessments).

2.5.2 | Process mining

Process mining represents a set of methods from the field of data mining (Romero et al., 2010), which works on the notion of so-called process models to identify, confirm, or extend them based on the event data. The process model or process map is constructed from the event log, which records activities in the (educational) process (Bannert et al., 2014; Reimann & Yacef, 2013). Every process execution constitutes a case and produces a sequence of activity occurrences called a trace (Leno et al., 2018). Those occurrences form the sequences of events and they can be directly used for the construction of the directly following graph, which is called a process map. Nodes correspond to the activities, arcs represent the relations, and every node and arc is annotated with its corresponding frequency. For the construction of the process map, the method implemented in the Business Process Analysis R package (Jannssenswillen et al., 2019) has been used. For the construction of the process maps within the described research, we employed data from the LMS click-stream log, where each student represents the case and activity are the resource types available within the LMS. This enabled us to represent the overall activity of the students in the course and compare it to the activity of students divided into groups based on the self-assessment activities.

3 | RESULTS

3.1 | Use of self-assessments during the semester

For analysing students' usage of the self-assessments over the course period (Hypothesis 1), all clicks on each of the 11 available self-assessments per week were considered. Figure 1 (top) shows the absolute number of clicks of students per week for each self-assessment. As indicated, there is a peak of students' engagement in the week before (week 15) and in the week of the final exam (week 16). Further peaks are in weeks 22 and 23 before the second date of the final exam (week 23). As further indicated in Figure 1 (bottom), the mid-term assessment (week 11) and the exam preparation (weeks 13–16; weeks 19–23) encompass a great proportion of students' engagement with the self-assessments compared to each lecture-related self-assessments. Accordingly, the use of self-assessments during the semester is rather limited compared to the weeks close to the two final exam dates. Therefore, we reject Hypothesis 1.

3.2 | Cluster of engagement with self-assessments

To investigate whether there are distinct groups (clusters) of students regarding engagement with the self-assessments (Hypothesis 2a), a

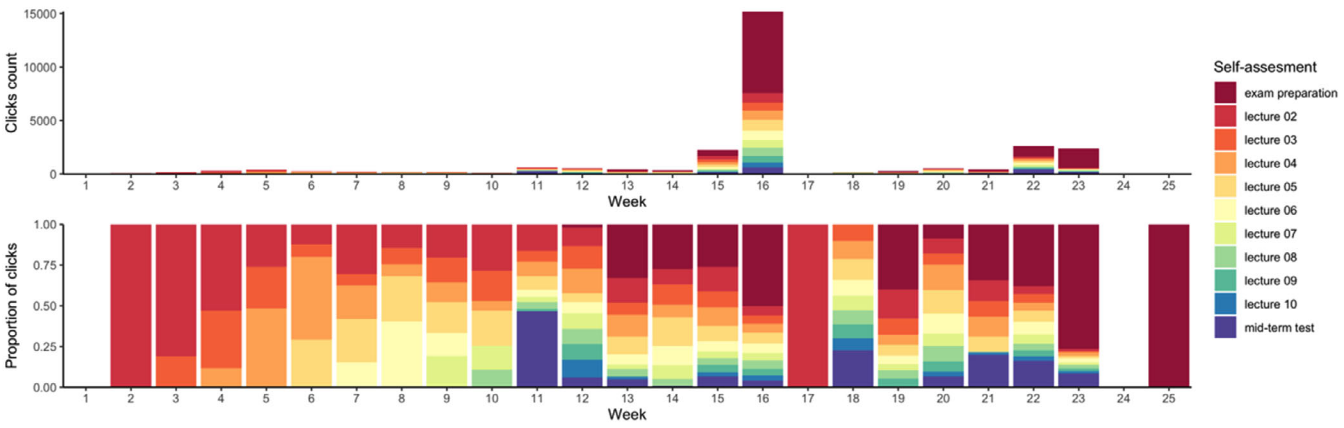

FIGURE 1 Usage of each self-assessment in total numbers (top) and the proportion of each self-assessment compared to all self-assessments (bottom)

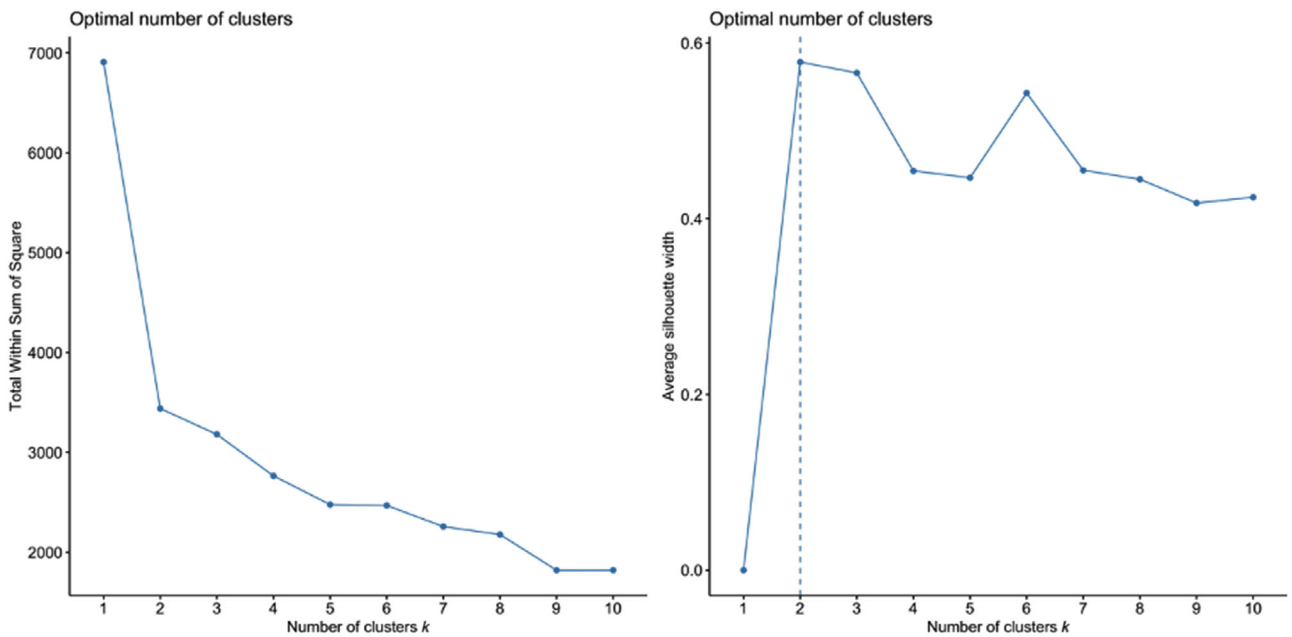

FIGURE 2 Values of measures for determining the optimal number of clusters (left: WCSS measure (elbow method); right: Average silhouette method)

cluster analysis was used. Indicators for self-assessments as described in Section 2.3 were used and *z*-standardized (Larsen & Marx, 2005). As described above, *k*-means clustering was employed for the clustering. For the selection of the optimal number *k* of clusters, the elbow method (Thorndike, 1953) and average silhouette method (Kaufman & Rousseeuw, 2009) were applied. The resulting values of clustering 'quality' for the range $k = \{1, 2, \ldots, 10\}$ are depicted in Figure 2. The results for *WCSS* measure (elbow method) show the steepest change in the value between the $k = 1$ and $k = 2$. It can be also observed that the direction of the change with the increasing number of *k* is more 'horizontal' making the typical elbow shape visible for $k = 2$. The result of the average silhouette method (Figure 2, right) indicated the highest value also for the $k = 2$, which suggests that the two clusters produced by the *k*-means algorithm are the most compact. Both methods indicated that a 2-cluster solution is the best representation of the data.

The clustering resulted in two distinct clusters of students. Cluster 1 can be described as the 'high engaged' cluster ($n_{c1} = 51$) and cluster 2 as the 'low engaged' cluster ($n_{c2} = 107$). Cluster 1 had higher numbers of self-assessment attempts, spent more time on each self-assessment, processed more of the available self-assessment tasks and obtained higher results (see Table 1 for descriptive statistics). Further, the cluster centre can be used as a representative sample. It represents the 'average' student in sense of self-assessment activity.

Figure 3 shows the comparison of the cluster centres using spiderweb plots. It can be observed that there exists a clear distinction between students in cluster 1 and students in cluster 2. There exist several outliers in the data, still, they can be assigned with the

TABLE 1 Descriptive statistics for variables used for each self-assessment per cluster

	Nrun				Ptime				res2max				ptask2ntask			
	Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Exam	1.65	0.96	0.65	0.83	3829.94	2527.8	1809.36	3556.18	0.69	0.31	0.17	0.29	0.79	0.33	0.23	0.35
Mid	0.73	0.85	0.33	1.34	632.51	1242.24	224.66	1166.41	0.15	0.30	0.04	0.16	0.18	0.36	0.05	0.20
t1	2.73	1.79	0.26	0.73	1041.33	896.85	99.85	252.3	0.69	0.34	0.09	0.25	0.87	0.32	0.14	0.34
t2	2.08	1.51	0.11	0.35	954.12	1150.04	37.8	141.43	0.81	0.29	0.07	0.23	0.86	0.28	0.08	0.26
t3	2.76	4.65	0.07	0.28	1485.16	1849.51	14.15	68.06	0.71	0.24	0.01	0.07	0.92	0.2	0.03	0.14
t4	1.73	1.15	0.03	0.17	916.16	884.18	5.79	35.44	0.66	0.24	0.01	0.08	0.82	0.26	0.02	0.12
t5	1.69	1.12	0.02	0.14	690.65	517.59	3.81	36.1	0.81	0.23	0.00	0.05	0.92	0.20	0.01	0.08
t6	1.59	1.65	0.04	0.23	717.82	566.56	5.37	42.37	0.64	0.33	0.01	0.10	0.87	0.31	0.01	0.10
t7	1.69	1.75	0.01	0.1	631.49	566.14	0	0	0.41	0.24	0	0	0.69	0.32	0.00	0.00
t8	1.04	0.82	0.01	0.1	354.16	336.82	1.02	10.54	0.57	0.4	0.01	0.05	0.63	0.44	0.01	0.06
t9	1.24	0.76	0.04	0.19	418.71	501.81	2.04	19.31	0.72	0.37	0.01	0.09	0.8	0.38	0.01	0.10

corresponding cluster making it possible to proceed with the detailed analysis.

Each spider web plot represents the normalized values of one of four variables used for the clustering for each self-assessment. The values represent the centre of the cluster, which can be considered a typical representative of students within the group. It can be observed that the students in the high-engaging cluster engage in general with all self-assessments more. Interestingly, there is minimal difference between the engagement for the mid-term test. Therefore, we consider the identified two distinct and different performing groups as supporting Hypothesis 2a.

3.3 | Differences in navigation behaviour

To analyse whether students in the two clusters showed different navigation behaviour in the digital learning environment (Hypothesis 2b), process maps for students' interactions with each resource type in the LMS (e.g. course entrance, lecture recordings, lecture slides, self-assessments) were built for each cluster (see Table 2 for descriptive statistics).

The process map is a directed graph, which consists of nodes and edges. Each node represents interaction of a student with a resource type and each edge represents a transition between activities. The percentage in the node (below its name) represents the relative number of instances (entries in the LMS log data) corresponding to the selected resource type. The percentage next to the edge represents the frequency of transitions between starting and ending node (resource type). For a better visualization, only the predominant events were displayed (a threshold of 80% was used). Resulting in displaying the following resource types: course homepage (crs), the self-assessments (tst) and the lecture recordings (xvid). Figure 4 shows the navigation transitions of all students, Figure 5 those of cluster 1, and Figure 6 shows the navigation transitions of cluster 2.

The graphs (Figures 5 and 6) indicate that cluster 1 was more active in the self-assessments but used the videos less than the students in cluster 2. Students in cluster 1 showed a higher transition probability from course entrance to self-assessments. Both clusters do not show high transitions from self-assessments to lecture recordings or vice versa. However, students might have used the path over the course entrance again. Cluster 2 only navigates via the course entrance whereas cluster 1 might have also used direct links to videos or tests. Due to the chosen threshold resources such as slides, external resources, the forum, or sessions (subfolder for each session) are not displayed here as they only represent a limited proportion of students' clicks in the LMS. Therefore, we accept Hypothesis 2b.

3.4 | Differences in final exam performance

To test for Hypothesis 2c, whether students engaging more in self-assessment practices (cluster 1) outperform students with less engagement in self-assessment practices (cluster 2) in the final exam performance, a *t*-test was used. Results indicated a significant

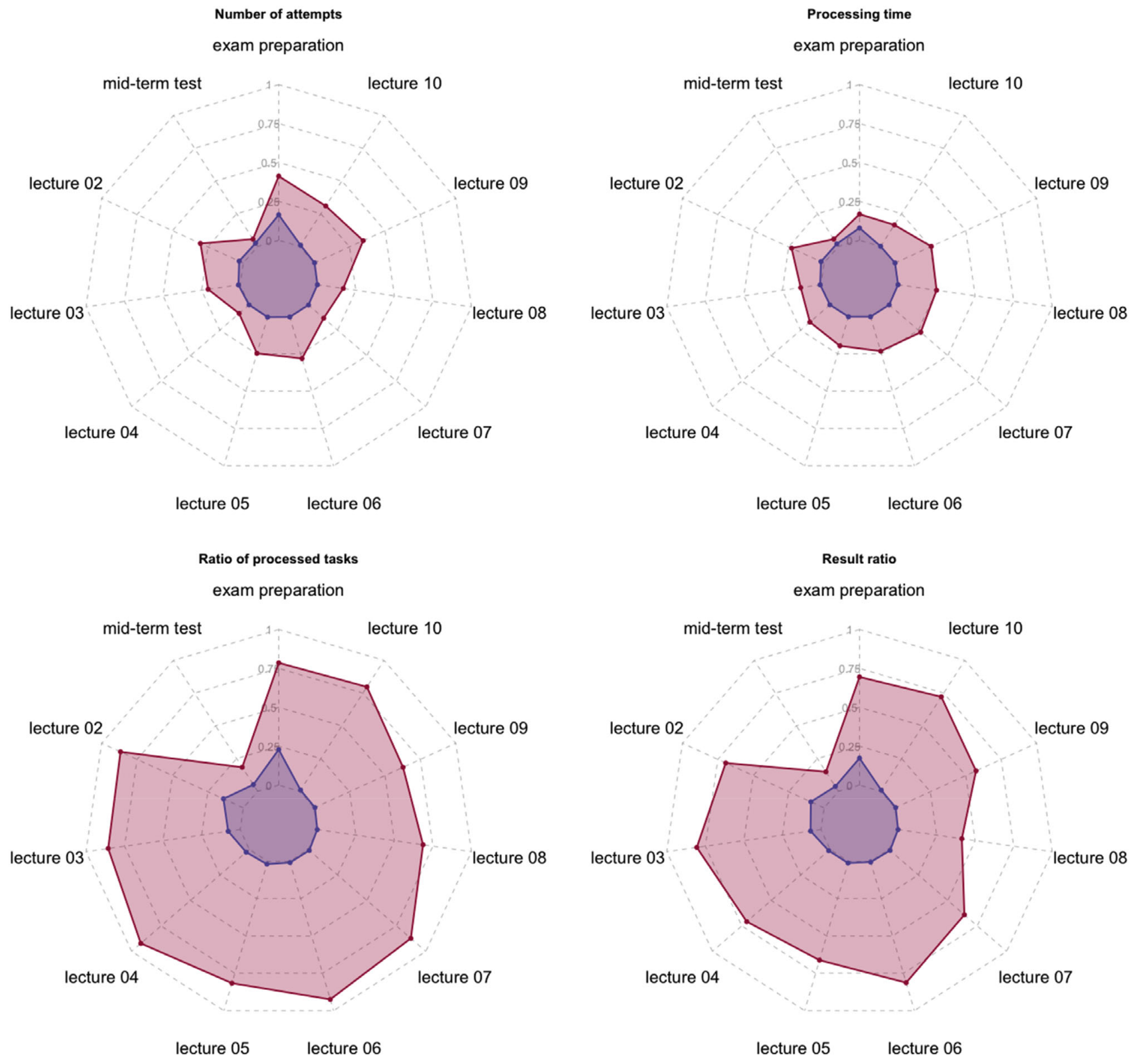

FIGURE 3 Visualization of clustering results via spiderweb plots (red = 'high engaged' cluster 1; blue = 'low engaged' cluster 2)

TABLE 2 Overall interaction with resource types

Resource type	Clicks on resource type	
	M	*SD*
xvid (lecture recordings)	611.39	566.44
tst (self-assessments)	218.24	176.38
crs (course homepage)	89.13	62.23
sess (session)	51.76	47.87
fold (folder)	51.73	27.79
file (file)	41.33	24.8
webr (webresource)	12.66	14.24
frm (forum)	12.21	11.35
grp (group)	6.14	5.45

difference between the two clusters (see Figure 7 for box plots of exam results) regarding their final exam performance $t(156) = 4.792$, $p < 0.001$, $d = 0.930$ with cluster 1 ($M = 50.11$; $SD = 5.417$) outperforming cluster 2 ($M = 37.39$; $SD = 18.562$) (respecting unbalanced sample size of the groups). Therefore, we accept Hypothesis 2c.

3.5 | Self-reported self-testing strategies

To investigate whether results indicated by the learning analytics data that students showed different patterns of engagement with the self-assessments are in line with students' self-reported use of self-testing strategies, a *t*-test for independent samples was used (Hypothesis 3). Results indicated that students in cluster 1 ($M = 3.425$, $SD = 0.531$)

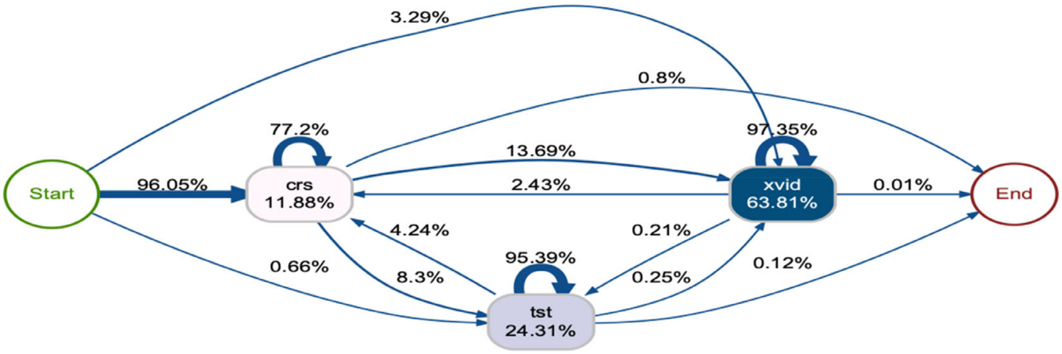

FIGURE 4 Most common navigation transitions of all students

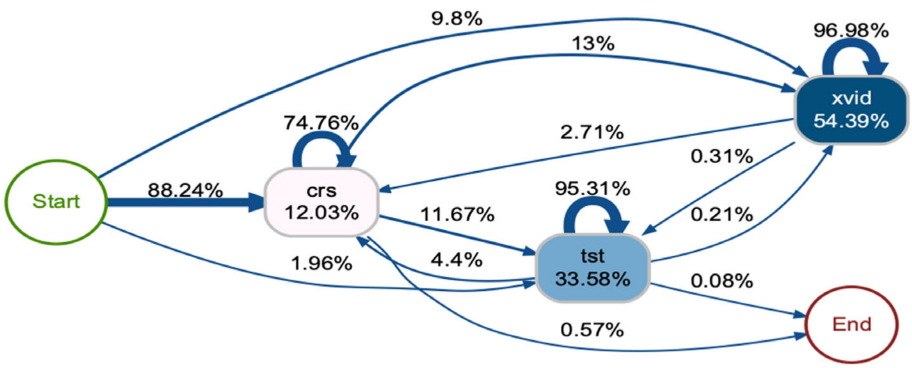

FIGURE 5 Most common navigation transitions of cluster 1 (high engagement in self-assessments and high-performing students)

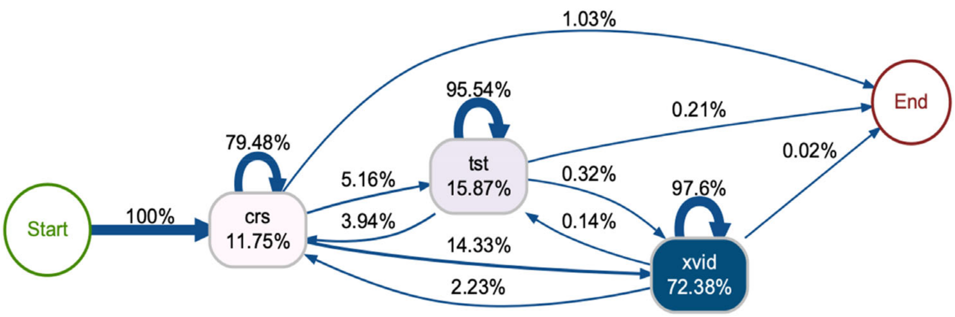

FIGURE 6 Most common navigation transitions of cluster 2 (low engagement in self-assessments and low-performing students)

reported a significant higher use of self-testing strategies than students in cluster 2 (M = 3.108, SD = 0.696), $t(82.64) = 2.384$, $p = 0.019$, $d = 0.506$. Accordingly, findings from both data sources can be considered as being aligned. Therefore, we accept Hypothesis 3.

4 | DISCUSSION

This exploratory case study aimed to investigate students' use of self-assessments in a productive higher education learning environment. Previous studies identified the opportunities of self-assessments for learners to continuously test themselves and receive informative feedback enabling them to identify key concepts and their gaps in learning (Thomas et al., 2017). Further, it was suggested that learning-oriented self-assessments may be distributed throughout the course of a semester (Carless, 2007). With the help of multiple data from self-reports, formal exams, and a learning analytics system, the findings provided multiple perspectives on the use of self-assessments and their relationships with course performance. The findings indicate (a) that the use of self-assessments is limited to specific periods in the semester, (b) that distinct groups of learners engage differently with self-assessments, (c) that these distinct groups of learners show differences in their navigation behaviour in the digital learning environment, (d) that learners engaging more in self-assessments outperform less engaged learners in the course performance, and (e) that data from self-reports and from the learning analytics systems are aligned. In the following sub-sections, we discuss the findings of each hypothesis and critically reflect on them with previous research.

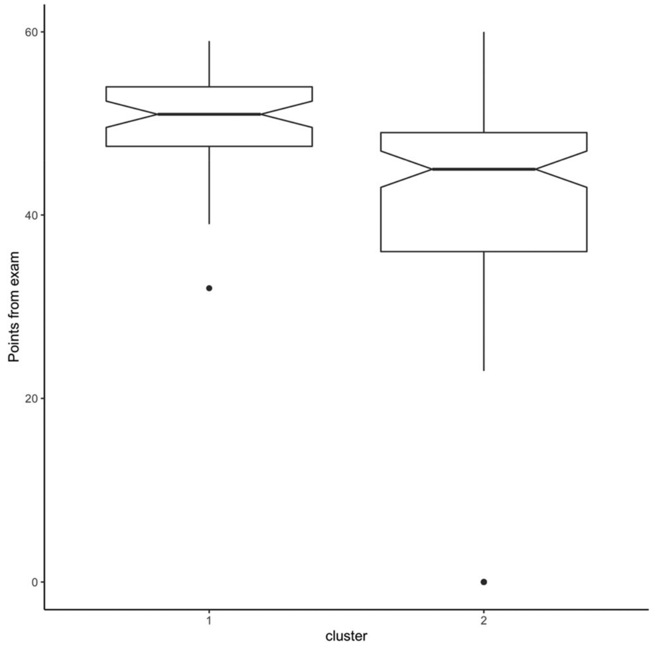

FIGURE 7 Box plots for exam results of cluster 1 (high engaged) and cluster 2 (low engaged)

4.1 | Use of self-assessments during the semester

We had to reject Hypothesis 1 as our findings indicate that students do not allocate their self-assessment practices over the whole period of the semester as suggested in research on self-assessments (Carless, 2007). More specifically, the learning analytics data identified peaks in students' engagement with self-assessments in the weeks before the exams. These findings are in line with previous studies based on self-report data (Yan, 2020), indicating that students use self-assessments instrumentally to get higher grades in their assignments when using it in the preparation and performance phases. Thus, student engagement in digital learning environments seems to be highly impacted by the function of the assessments (i.e. self-assessment vs. graded assessment). The detailed insights from learning analytics data emphasize the need for supporting students in their engagement in self-assessment practices (Gibbs & Simpson, 2005; Holmes, 2018). Students may benefit from learning analytics data through adaptive prompts which may support their self-regulated learning strategies (Schumacher & Ifenthaler, 2021; Weinstein et al., 2010; Wirth, 2009) and better facilitate their learning processes (Gašević et al., 2015). Making the learning analytics data available to facilitators could support (near) real-time interventions and a critical pedagogical reflection of assessment and course designs (Liu et al., 2018).

4.2 | Distinct engagement clusters

Concerning Hypothesis 2, we observed different clusters of engagement. Students belonging to Cluster 1 ('high engaged') used the self-assessments more frequently and spent more time with them. These students also processed more self-assessment tasks and achieved higher outcomes. In contrast, students belonging to Cluster 2 ('low engaged') showed less frequent use of self-assessments, spending less time with it and achieving lower outcomes. Students in these two distinct clusters also showed different navigation behaviour in the digital learning environment. The clustering approach appears to be a robust analytics strategy for obtaining meaningful insights into the frequent navigation behaviour (Poon et al., 2017). Making wider use of such learning analytics data through interactive dashboards may assist facilitators in their pedagogical decision-making throughout the semester (Arthars et al., 2019; Kaliisa et al., 2021). As students in both clusters did not show high transitions from self-assessments and lecture recordings and vice versa, adaptive recommendations on related learning material and suggested next steps after having taken a self-assessment or after having watched the lecture recordings may be beneficiary (Bodily et al., 2018) and could be further investigated.

A further analysis focussed on the distinct clusters of engagement with the self-assessments in relation to the final exam performance. Our findings show that students in the 'high engaged' cluster outperformed students in the 'low engaged' cluster in the final exam performance. The findings are in line with previous research suggesting that self-testing has a positive impact on learning outcomes (e.g. Lloyd et al., 2018; Rodriguez et al., 2021; Thomas et al., 2017; Weinstein et al., 2010). Hence, due to its positive impact on learning performance (e.g. Rodriguez et al., 2021; Thomas et al., 2017), opportunities for supporting students' engagement with self-assessments and learning materials, in general, could be further increased. This could be realized through student-facing learning analytics dashboards, highlighting details about self-assessment usage, learning processes and performance (Bodily et al., 2018; Sahin & Ifenthaler, 2021). However, as previous research on assessment and feedback indicated, this should be enhanced with recommendations on how to improve (e.g. Hattie & Timperley, 2007; Nicol & Macfarlane-Dick, 2006). However, learning analytics to date are predominantly focusing on representations of so-called check-point analytics of behaviour or performance indicators (Lockyer et al., 2013). Only presenting performance indicators to learners with the hope that they deduce relevant behavioural changes is not sufficient (Jivet et al., 2017; Kitto et al., 2017). Learning analytics dashboards for students are expected to offer more meaningful process-oriented feedback on how to improve learning strategies (Sedrakyan et al., 2020).

The findings require further critical reflections concerning the multifaceted nature of learning engagement, that is the construct refers to a learner's ability to interact with learning artefacts in a continuous learning process on a behavioural, cognitive, emotional, and motivational level. Therefore, the findings may be influenced by other constructs such as study interest or metacognitive awareness. While the design of our exploratory case study included self-report instruments focussing on such individual characteristics, we found no influence of the assessed characteristics on their engagement. Ascertain for possible influences in our uncontrolled classroom setting appears to be challenging, hence, quasi-experimental follow-up studies are required for generalizing our recent findings.

4.3 | Relation between self-report data and learning analytics data

By accepting Hypothesis 3, our findings show an alignment between self-reported data about self-testing strategies and the behavioural data collected in our learning analytics system. Specifically, students who belonged to the cluster with higher engagement in self-assessments also self-reported a higher use of self-testing strategies. Accordingly, combining different sources of data about learning processes and learning outcomes may validate analytics results. It may also help students as well as facilitators to understand or critically reflect analytics results in more detail. For example, Ellis et al. (2017) showed that the combination of students' self-reported data and behavioural explained a significantly higher variation in learning outcomes. However, data-driven approaches may tempt to use all data available for detecting patterns or relations to achieve a good model fit without scrutinizing whether this is meaningful from a pedagogical perspective (Lerche & Kiel, 2018; Rosé et al., 2019), that is not all behavioural indicators are relevant (Holmes, 2018). Accordingly, the focus should not be on learning analytics data that are available or easy to capture and analyse, but on the data which are considered to be meaningful for supporting learning (Kitto et al., 2018).

4.4 | Limitations and perspectives for future research

This exploratory case study shows several limitations and indicates future research needs. As the course investigated was facilitated in a blended design the data collected is facing incompleteness and thus might limit its explanatory power. For example, only one of the assessed self-report variables was considered for this paper. Thus, in future analyses, self-report measures (e.g. study interest, metacognitive awareness) will be investigated further concerning how they can enhance and how they are related to digital learning behaviour and learning outcomes. In addition, the self-assessments used in this setting were related to each lecture and thus several learning objectives. However, they were not embedded in a holistic assessment framework for generating sufficient evidence on learners' competencies and their areas for improvement to provide learners with informative just-in-time feedback. Yet, the scope of the self-assessments was different to the final exam task. Given the distinguishing design of the assessment tasks, a 'teaching to the test effect' can be ruled out. Furthermore, the current data collection in the digital learning environment did not yet allow for investigating students' progression as self-assessment results were only available from the last attempt. Furthermore, only one cohort of students was investigated which were undergraduates in the fifth semester with only limited prior knowledge of the course subject. Thus, it might be of interest to conduct a similar study with graduate students or other study cohorts to investigate possible differences. As empirical evidence on the effects of different self-assessment types on learning processes and outcomes is still limited, it would be interesting to compare more student-centred forms of self-assessments as proposed by the typologies reviewed by Panadero et al. (2016) with the self-tests investigated in this study. Such self-assessments might elicit more beneficiary learning processes and outcomes but they are also more time-consuming and challenging especially for novices, and our findings already indicated that many students did not even engage in the self-tests, thus, investigating how students engage in such forms and how this relates to learning performance would be relevant.

5 | CONCLUSION

This exploratory case study was considered to be an initial step considering assumptions from an educational theory that assessments are a key component of learning, that is assessment for learning, and a relevant predictor of learning performance. Hence, calling for action to implement assessment analytics frameworks and to enhance the evidence of learning analytics related to assessment toward adaptive process-oriented feedback. In contrast to previous studies, the study design included self-reported data, exam data and data from a learning analytics system.

The findings shed light on students' use of self-assessments and how their engagement is related to the final exam performance. It is evident that students engage differently with available self-assessments with more frequent use close to the final exam. But higher engaged students in self-assessments outperformed less engaged students in the final exam. Post-hoc analysis of self-report data on individual characteristics, such as study interest, did not help to further explain the differences identified in the learning analytics data. Yet, the behavioural engagement data appears to be a robust predictor for supporting learning processes with the help of learning analytics systems.

In conclusion, the findings call for advanced models and tools for integrating (self-report) data on learners' online and offline learning activities to be included in holistic learning analytics systems for valid and robust analysis of individual learning processes and the best possible support whenever they need it. On the other side, such holistic learning analytics systems may harnesses formative (i.e. dynamic) and summative (i.e. static) data from learners and their contexts (e.g. learning environments) to facilitate learning processes in near real-time and help facilitators to improve pedagogical decision making on-the-fly. Therefore, an emphasis on pedagogical approaches rather than a focus on extended statistics of data from learners' interaction with digital learning environments seems to be the way forward.

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CONFLICT OF INTEREST

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Dirk Ifenthaler declares no conflict of interest. Clara Schumacher declares no conflict of interest. Jakub Kuzilek declares no conflict of interest.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/jcal.12744.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

INFORMED CONSENT

Informed consent was obtained from all individual participants included in the study. Additional informed consent was obtained from all individual participants for whom identifying information is included in this article.

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