MAKING SENSE OF E-LEARNING PLATFORM DATA TO INFORM TEACHING AND LEARNING PRACTICE

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ABSTRACT

Masses of data are gathered by learning platforms while students are interacting with them. The learning analytics and knowledge (LAK) and educational data mining (EDM) research communities analyse these data to extract useful information. This study aims to give an overview and possible explanations for the findings of these research communities regarding the relationships between student online interactions and success or failure in a course. The available EDM and LAK literature from 2010 onwards was reviewed. Significant direct and indirect relationships between success and a range of variables were reported. The characteristics of good teaching and learning, as identified by Cognitive Load Theory (CLT), Chickering and Gamson's Seven Principles for Good Practice in Undergraduate Education, and Anderson's Equivalence Theorem were then used as a framework to reflect on and attempt to explain the findings. For example, various studies found the number of logins to be negatively correlated with success. This may be an indication of poor study methods or a warning sign of a poorly designed site. Spending unexpectedly long periods on a task may indicate a poor match between the task's cognitive load and the student's level of readiness. Passively listening to recorded lectures as a study method is also linked to lower levels of success. These findings may inform the guidance given to students regarding studying successfully online and have some lessons for the design of online environments to promote successful learning. With the complementary use of EDM, LAK and pedagogical theory, the data generated by e-learning platforms provide useful pointers to improve online teaching and learning.

KEYWORDS

Learning analytics, learning analytics and knowledge, educational data mining, interactions, forecasting, e-learning, online behaviour, navigational pattern, risk prediction, good teaching practice, quality instruction, e-platforms

INTRODUCTION

The assumption of this study is that both student factors and the quality of the instruction that they receive are important in student achievement. The increase in the use of e-learning platforms in teaching and learning necessitates a reflection on what quality instruction is in an online environment. Even when attending face-to-face classroom sessions in physical learning spaces, the online components of blended delivery models are increasingly forming fundamental parts of courses. The advent of the Covid -19 pandemic pushed the boundaries further by necessitating the use of online classes.

This study aims to integrate the findings of the educational data mining (EDM) and learning analytics and knowledge (LAK, formerly learning analytics [LA]) research communities with the characteristics of quality instruction according to generally accepted pedagogical theories, namely, Cognitive Load Theory (CLT), Chickering and Gamson's Seven Principles for Good Practice in Undergraduate Education, and Anderson's Equivalence Theorem. It reviews the findings of numerous research studies (2010 onwards) reporting on possible relationships between student interactions with e-learning platforms and success or failure in courses.

Relevant literature from the LAK (LA) and EDM fields, e-learning and pedagogical theory is used to:

- Identify interactions that can serve as indicators of success or risk of failing.
- Explain the found interactions and educational outcomes in the light of generally accepted pedagogical principles of quality instruction.

Background information regarding data collection by e-platforms, the analysis thereof and some relevant pedagogical theories are discussed below.

BACKGROUND

E-learning platforms such as Blackboard, Moodle, Canvas, Sakai and Desire2Learn are systems that provide an "integrated set of interactive online services that provide teachers, learners, parents and others involved in education with information, tools, and resources to support and enhance educational delivery and management" (Hill, 2012, p. 1).

Different applications, such as learning management systems (LMSs, such as Canvas), learning content management systems (LCMSs, such as Moodle), virtual learning environments (VLEs, such as Blackboard) and course management systems (CMSs, such as Desire2Learn) are designed to facilitate e-learning by making content available while managing and tracking student progress and performance (Chang, 2019; Greenberg, 2013). Data about how frequently students log in and what they click on, when they study, how long they study and how well they learn are collected in the background while students interact with the online resources on these applications. The term 'e-learning platforms' is generally used in this article to refer to any of the afore-mentioned applications and systems.

Numerous research studies aimed at finding if and how the data around student use of e-learning platforms can be utilised to predict success and/or risk of failure were found, and will be reported in the section Findings from Research Communities.

In some studies, LAK and/or EDM researchers focus on the data generated by e-learning platforms only. Other studies combine the e-learning platform data with those gathered using other instruments, including written examination and/or test results, personality-, self-efficacy-, learning-style surveys, and questionnaires (Kotsiantis et al., 2013; Zha & Adams, 2015; Rienties et al., 2016; Jo et al., 2016; Monteiro & Leite, 2016).

Siemens and Baker (2012, pp. 1–2) describe LAK as an approach using "measurement, collection, analysis and reporting of data about learners and their context for purposes of understanding and optimising learning and the environments in which it occurs." The EDM research community looks for patterns in large educational data collections that are too voluminous to be analysed without computerised methods (Romero & Ventura, as cited in Papamitsiou & Economides, 2014).

These two research communities are complementary: LAK uses a holistic framework, whereas EDM adopts a "reductionist viewpoint by analyzing individual components, seeking for new patterns in data and modifying respective algorithms" (Siemens & Baker, 2012; Papamitsiou & Economides, 2014, p. 50).

The findings of both research communities can help teachers/designers to optimise, customise and diversify online learning environments. Teachers can gain a better understanding of the optimal pedagogical processes. Their understanding can be fed back to students and help to formulate recommendations for good practice in online studies.

PEDAGOGICAL THEORY: TEACHING AND LEARNING PRINCIPLES THAT CHARACTERISE QUALITY INSTRUCTION

The features of quality instruction as described by Anderson's Equivalency Theorem, CLT and Chickering and Gamson's Seven Principles for Good Practice in Undergraduate Education are described below.

Equivalency Theorem

Designers/teachers create learning environments where students interact with content, other students, and their teachers. A successful learning environment promotes a mix of these different interactions (Monteiro & Leite, 2016).

Anderson's (2003) Equivalency Theorem states that at least one of these interactions has to take place at a high level to ensure deep and meaningful learning. In a tutorial delivery mode with small classes, high levels of learning are achieved "through high levels of student–student and student–teacher interaction" (p. 4). In a lecture mode of delivery, both student–teacher and student–content interactions are at a medium level, with low levels of student–student interaction: a less than satisfactory situation. To improve the mix, an online high-level student–content interaction component (as possible in a blended environment) could be added.

Per definition, all interactions within a fully online course have to be addressed through online interactions (Kurt, 2018). Khan et al. (2017) state that the course features that would encourage online student–content interactions for undergraduates may be similar to those that actively engage students with the content in face-to-face courses, making the application of classic pedagogical theories in online environments valid. In their opinion, the big difference in pedagogy (between e-learning and face-to-face environments) lies in the methods that are used to encourage student–student and student–teacher communication and interaction.

Cognitive load theory

The aim of instructional design (Paas et al., 2003; Yen et al., 2015) is to keep the cognitive load of the resources within the student's Zone of Proximal Development (ZPD). The ZPD is defined as the zone "between the actual developmental level as determined by independent problem solving and the potential development as determined by problem solving under adult guidance or in collaboration with more capable peers" (Vygotsky, 1978, p 86). Keeping the resource demands within the ZPD (Figure 1) enables students to succeed through their own learning efforts. Little learning takes place if the cognitive load is too low (without some challenge) or too high and consequently overwhelming the student.

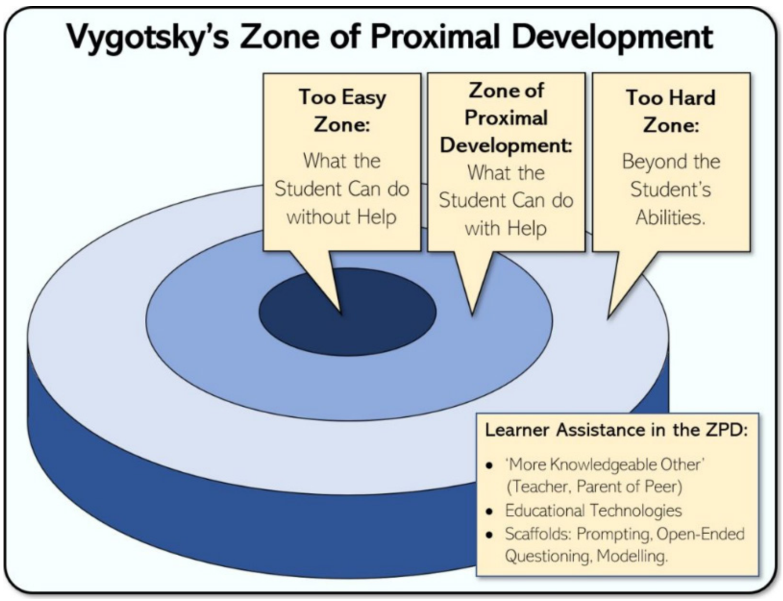

Figure 1. Vygotsky's Zone of Proximal Development (ZPD) (Drew, 2022).

Cognitive Load Theory identifies three types of cognitive load:

- Intrinsic cognitive load (ICL): a function of the inherent nature of the learning material and learners' prior knowledge. It can be assessed by content experts based on element interactivity, element complexity, the number of elements, the type of the content (procedures, concepts, facts, processes or principles), and the nature of the content (technical, theoretical, or practical).
- Extraneous cognitive load (ECL): determined by instructional design and the activities required of students.
- Germane cognitive load (GCL): the effort involved in relating prior knowledge to current instructional content to construct schemas stored in the long-term memory.

For the learning process to succeed, the global cognitive load (the sum of the three types [ICL + ECL + GCL]) should not exceed the student's cognitive resources (Yen et al., 2015; Pociask et al., 2013). As CLT provides a framework for analysing and evaluating learning and teaching resources (including online), it is a valuable tool for teachers/designers to optimise the learner experience and learning.

Principles of Good Practice

Chickering and Gamson's (1987) Seven Principles for Good Practice in Undergraduate Education is a summary of decades of research (Johnson, 2014). These principles form the basis of later guidelines, such as those from Ewell and Jones (1996), Macfadyen and Dawson (2012), Johnson (2014), Kontos (2015), and Crews and Wilkinson (2015). They link directly or indirectly with Anderson's (2003) Equivalency Theorem and CLT, as will be shown.

Quality instruction encourages active learning: it encourages learners to do things and think about what they are doing (Chickering & Gamson, 1999; Riley & Ward, 2017). Active learning represents high levels of student–content, student–student and student–teacher interaction (Anderson, 2003). It implies that students are engaged, motivated, participating (Salmon, 2013), self-directed, independent, taking responsibility for their learning with self-competence, have proficient reading and writing skills, time-management skills, and are inspired to learn (Kerr et al., 2006). Allen and Tanner (as cited in Khan et al., 2017) define active learning as "seeking new information, organizing it in a way that is meaningful, and having the chance to explain to others" (p. 108). Contrary to this, passive-recipient learning (such as simply listening to a lecture, representing low-level interaction), disregards the fact that students learn best when they get opportunities to use their skills. Assessments that require active demonstration of synthesis and application can play a role in promoting active learning (Ewell & Jones, 1996). Walsh et al. (2011) reiterate the aforementioned when describing an engaging pedagogical environment as one where learners "reflect on their own learning and become self-regulated and self-directed" (p. 3). Furthermore, Kintu et al. (2017) explain that self-regulation in learners, and intrinsic motivation that leads to persistence, are linked to knowledge construction.

In quality learning, the content is presented on suitable levels. This principle links directly with CLT and is under the control of the teacher/designer. To engage students and enable them to succeed through their efforts, Khan et al. (2017, p. 114), Kizilcec et al. (2013), and McLoughlin and Lee (2008) propose that course content must be simplified, follow micro-steps, and include cognitive tools (scaffolds) such as rubrics, carefully detailed guidelines, and examples to keep the cognitive load within the ZPD of the students by communicating clear expectations for student work. The content should augment thinking and cognition, and may include a wide variety of learner-generated resources accruing from students creating, sharing and revising ideas. Since student interests and levels of readiness differ, multiple means of instruction, engagement and assessment are needed for maximum engagement and learning. Audio, video, student group and individual work, reflections, demonstrations, presentations, diagrams, etc., should be included to make learning accessible for all students.

Good practice is also characterised by prompt and frequent feedback (Chickering & Gamson, 1999; Ewell & Jones, 1996) to students on their performance. Early assessment can provide teachers with indicators of students' readiness, and steps for remediation can be taken early. A quick turnaround of assessments is essential in this regard. In an online environment, much of the teaching consists of providing meaningful, constructive, individualised and actionable input and feedback on student work (Poll et al., 2014). An important consideration for going online is the speedy automatic feedback that students can get, especially with objective-type questions (such as teaching basic facts and scenario-based questions). Feedback has the ability to help students learn from their mistakes, guide them to be independent, take responsibility for their learning and become self-directed. This improves the quality of instruction through promotion of student–content and teacher–student interactions (Anderson, 2003) and provides support to bring the task's cognitive load within the students' ZPD. E-learning platforms provide students with powerful tools for self-study in their own time and in their own way. Newer developments include customised feedback models that automatically recommend the most relevant, suitable and personalised remedial sections in textbooks, in response to knowledge deficiencies exposed by online assessment outcomes (Thaker et al., 2020). These tools open up the scope of how further and deeper independent learning could be promoted by online platforms.

Quality instruction encourages student–student co-operation (Ewell & Jones, 1996; Chickering & Gamson, 1999). It provides opportunities for teamwork, which provides multiple feedback opportunities and increases involvement while modelling the world of work, where teamwork is often the norm. Kintu et al. (2017) found that face-to-face support is a predictor of learner satisfaction, and that social support among the learners predicts knowledge construction. An environment with a high degree of interactivity among learners (Anderson's [2003] student–student interaction), collaborative learning and interactive content is further ideal to engage disengaged students (Walsh et al., 2011). The ideal learning environment promotes different interactions between people, such as co-participation, communication and sharing (Monteiro & Leite, 2016). McLoughlin and Lee (2008) emphasise that students should be offered multiple opportunities for open, social, peer-to-peer and multi-faceted forms of communication with a network of peers and communities that then serve as their support. In an online environment, deliberately building a community through asynchronous and synchronous collaboration tools (forums, blogs, wikis, online discussions, student-led discussions, and small-group activities that could be followed up by large-group activities) is recommended to give students a sense of belonging, and for the exchange of ideas and information (Poll et al., 2014). Video-conferencing tools also make provision for group interaction in break-out rooms. Khan et al. (2017) state that engaging students in an online environment may be a challenge even for experienced online instructors. They advise against relying on physical, face-to-face interactions alone for student interaction in blended courses. Social aspects should be explicitly built into the online parts to increase engagement and motivation, deepen learning, make learning coherent and encourage students to interact with the online content.

Adequate time on task needs to be planned and communicated. Learning involves interacting with content and others, and these interactions need time. Research confirms that efficient learning requires a considerable investment in time, and being prepared to invest that time is important. Communication about expectations of how time should be utilised in a course can influence the learning quality significantly (Ewell & Jones, 1996). For example, the time expected to be spent after school hours (self-directed study) is usually part of the required study time in blended courses.

Out-of-class contact with teachers is important in engaging students (Ewell & Jones, 1996; Chickering & Gamson, 1999; McLoughlin & Lee, 2008; Walsh et al., 2011) and should be facilitated. Researchers agree on encouraging student–teacher contact (Equivalency Theorem's student–teacher interaction): Ewell and Jones (1996) explain that "contact between faculty and students is strongly associated with both program completion and effective learning" (p. 22). Students see teachers that they engage with as role models. This contact encourages them to think about their values and plans. To facilitate contact between students and teachers in an online course, Poll et al. (2014) stipulate that course information "should include instructor contact information and availability, course communication instructions and guidelines (like instructor email or message guidelines), and set appropriate standards for instructor responsiveness and availability (like response time, assignment feedback)" (p. 61).

The three pedagogical theories were used to create one simple framework (Figure 2) in which all the overlapping features are combined. Equivalency Theorem, CLT and the Seven Principles for Good Practice are described in

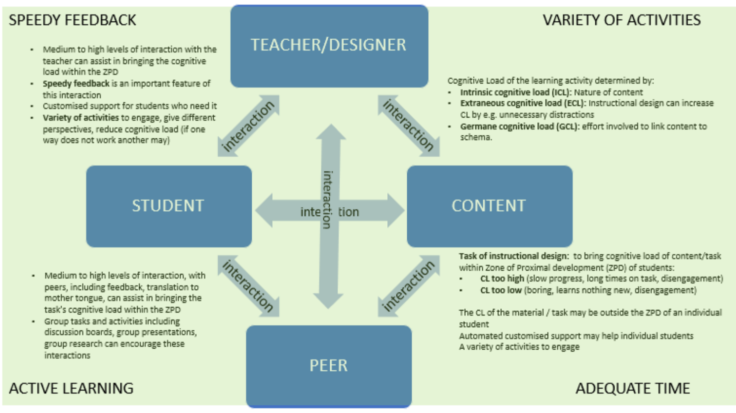

Figure 2. A framework based on Anderson's (2003) Equivalency Theorem combined with CLT (Paas et al., 2003) and the Seven Principles for Good Practice in Undergraduate Education (Chickering & Gamson, 1999).

terms of Anderson's three types of interactions (student–student, student–teacher and student–content). The three interactions are included in the Seven Principles for Good Practice – the remaining principles are characteristics that these three interactions should meet: the criteria of adequate time, active involvement, using a variety of activities to actively engage and support, and speedy feedback (Chickering & Gamson, 1999).

Cognitive Load Theory relates to all of these, since keeping the content within the student's zone of proximal development is fundamental in making the interactions successful and active learning possible. It provides the reason for adequate time, a variety of activities and timely feedback.

Looking at interactions includes looking at student–student, student–teacher/designer and student–content interactions, measurement of and platforms for interactions, and encouragement of interactions and co-operation.

Active learning includes encouraging active use of resources such as recorded lectures, a variety of types of tasks (multiple means of instruction) and suitable levels of the activities to keep the cognitive load within the ZPD. (There is the possibility that online activity types may be seen as active learning when they are not, and that the level of student–content interactions [Equivalency Theorem] or poorly designed online environments may increase the cognitive load without increasing active-learning opportunities).

Feedback includes the timing, frequency and the nature of the feedback.

Adequate time includes the communication of time demands, the consideration of timing, types of tasks, the cognitive load of the tasks and the avoidance of distracting time-consuming features.

METHOD

This study aims to identify from the literature the online behaviours and interactions that can serve as indicators of success or risk of failing, and then to evaluate these indicators using generally accepted pedagogical principles of quality instruction (as discussed above).

Relevant articles were found through online searches on Databases (including Ebscohost, ERIC, Psychinfo, IEEE Xplore, www.irrodl.org, ejournals.bc.edu, doaj.org, Google Scholar, Jstor and Researchgate), and using keywords on their own and in combination. The keywords related to learning analytics (LA), learning analytics and knowledge (LAK), educational data mining (EDM), interactions, forecasting, e-learning, online behaviour, navigational pattern, risk prediction, good teaching practice, quality instruction.

Systematic literature studies served as examples of appropriate research methodology, and sources of relevant literature in the LAK and EDM fields and relationships between online behaviour and study success. These systematic studies include:

- Sergis and Sampson (in Peña-Ayala, 2017), who tabulated and cited 54 studies published between 2005 and 2016 in the emerging research field of teaching and learning analytics (TLA), and looked at aims and statistical methods used.
- Avella et al. (2016), who describe the concept of LA, its data sources, its aims, its techniques and uses.
- Papamitsiou and Economides (2014), who compared studies on the use of LA and EDM from 2008 to 2014. They found that these studies aimed at student–student behaviour modelling, prediction of performance, increasing self-reflection and self-awareness, prediction of dropout and retention, improving feedback and assessment services, and recommendation of resources.

Classic works on pedagogics between 1978 and 2020 were included. Learning analytics, EDM and e-learning research reported in the years between 2010 and 2020 were used. Zotero was used to collect and cite suitable articles and to compile the reference list.

The studies' main ideas were paraphrased, they were sorted into tables, and categorised under headings as they emerged. For example, the found articles reported a number of significant positive/negative or no relationships (used as the largest category for classification). Small categories such as 'total study time', 'timing of access' and 'time on task' emerged under positive/negative relationships, and were then combined to form larger categories such as time factors. No judgements were made. Research findings are reported as they were found, and are listed in the following section.

FINDINGS FROM RESEARCH COMMUNITIES

A wide variety of studies on this topic were found. They range from systematic overviews to investigations of the effects of single behavioural aspects. Some researchers, such as Conijn et al. (2017), found there is not much value in using LMS data for the purpose of early intervention. Strang (2016, p. 280) found "very little correlation between student online practices" and the academic outcomes, which he explains as being due to the small sample of students used in his study and the nature of the course. Other researchers found positive and also negative correlations between online interaction and behavioural factors and student success. These factors are listed and briefly described below.

Online environment/interaction/behavioural factors linked to success or failure

Student activity

High and specific activity. Kotsiantis et al. (2013) found that high student activity (total number of actions) and viewing specific sections (access to the forum, user view, assignment view, and glossary view) were associated with excellent grades. Lack of interest in viewing assignments was associated with fail grades. Bainbridge et al. (2018) found that the "relative number of forum posts and amount of content read" (p. 256) are factors linked to success. Macfadyen and Dawson (2012) found a significant correlation between student learning outcomes (final grade) and the use of engagement tools (discussions, mail, use of LMS-based course content materials, and visits to the My Grades tool).

Total number of logins/total hits/clicking. Bainbridge et al. (2018) found that students that "show high relative levels of reading forums and opening online sessions multiple times" (p. 256) have a greater likelihood of performing poorly. The number of total login/total hits, therefore did not predict success (Firat, 2016). Rienties et al. (2016) found a weak positive relationship between clicking and academic performance, explaining around 10% of the variation.

Time investment and management

Time on task. Successful students invest sufficient amounts of time on tasks and actively participate in the learning process (Jo et al., 2016). Also, Keskin et al. 2016) and Firat (2016) found that more time spent on the LMS is linked to success. Kovanovic et al. (2015) linked time on task (seen as an estimate of the amount of effort a student puts in) as a predictor of success.

Timing of access. Baker et al. (2015) found that early and continuous accessing of resources throughout the early weeks of the course are linked to success. As expected, not engaging indicates risk. Cluster analysis of all available data showed high academic performance was positively associated with early submission of intra-semester assessment tasks. Agnihotri et al. (2020), Levy and Ramim (2012), and Colthorpe et al. (2015) all report a strong correlation between procrastination and poorer chances of success. However, Hunt-Isaak et al. (2020) found recent participation to be a more relevant predictor of ultimate success than past participation.

Regularity of study. The regularity of learning has a significant effect on learners' performance (Jo et al., 2016). Logging "into the LMS more steadily from the beginning of a class to the end" correlates with better performance (Jo et al., 2015). They explain that this "involves neither temporal access at a certain point nor merely one long time visit, but rather conscious learning with awareness over a relatively long term" p. 222).

Navigational patterns

Keskin et al. (2016) used interaction themes such as homepage, content and discussion. They found no difference in the navigational patterns followed by successful and unsuccessful students, but they found that successful students spent more time on each login.

Interacting with staff and other students

Live interactive environments versus lecture recordings. Colthorpe et al. (2015) found a negative correlation between performance and using lecture recording review as a learning strategy. Li et al. (2020) conclude that live interactive environments with teachers teaching the materials and prompting and questioning students are associated with a far lower drop-out rate than environments using solely recordings.

Student–student interaction in forums and discussions. Kotsiantis et al. (2013) and Bainbridge et al. (2018) found participation in forums was linked to success. Macfadyen and Dawson, (2012) describe a correlation between participation in discussions (student–student interaction) and achievement of learning outcomes.

Student–teacher email interaction. Macfadyen and Dawson (2012) observe a positive correlation between email (student–teacher interaction) and students achieving the learning outcomes.

Assessment results and feedback

Success in formative or previous assessments. According to Baker et al. (2015), good performance in formative activities is linked to success in the course. Rienties et al. (2016) report a positive link between final results and performance during continuous assessments. Romero et al., Romero-Zaldivar et al. and Shih et al. (cited in Papamitsiou & Economides, 2014) identify the number of quizzes passed as an important predictor of success.

Responsive feedback on assessments. Automated relevant, suitable, and personalised recommended remedial sections in textbooks in response to knowledge deficiencies as exposed by online assessment outcomes are linked to positive outcomes (Thaker et al., 2020).

Studies about online behaviours resulting from 'other factors'

'Other factors' describe studies where data, obtained through LMSs, are combined with data obtained by instruments that are not part of the e-learning platforms (surveys, previous assessment results, questionnaires and psychological instruments, or administrative data).

Access and attitude related to learning technologies. Ellis et al. (2013) and Monteiro and Leite (2016) found significant relationships between academic achievement, positive attitudes to learning technologies and valuing ongoing formative assessment. They explain that to benefit from e-learning, students should view the online resources as essential and valuable. A low access frequency and the perception of the LMS system as difficult to use are related to low performance (Kotsiantis et al., 2013), so fail grades can be predicted by the lack of a computer at home and low self-efficacy. Zha and Adams (2015) conclude that a student's perceived proficiency in using the LMS significantly affected their interaction with the content.

Student background and psychological factors. In the German context, research by Berens et al. (2019) found that administrative data (biographical data) strongly predict student success or failure. The use of student background data in predicting at-risk students in the American context is evident in the work of Pelaez et al. (2019). These findings imply (although not stated), that the student's background may determine their online behaviour leading to success or failure. This is a strong possibility in the light of the findings of the role of psychological factors. Jo et al. (2016) attribute online behavioural patterns to underlying psychological factors. Self-regulatory ability and time-management strategies drive regular login activity, which results in high performance. They used SEM modelling to analyse their data, and confidently conclude that a student's self-regulation abilities could be deduced from their online log variables alone without using any other instruments.

Rienties et al. (2016) found that learners' activities during continuous assessments (behaviour) and "learning motivations and emotions" (attitudes) (p. 2) explain up to 50% of the variance in performance. Bainbridge et al. (2018) identified that the biggest predictors of risk include a low "previous cumulative GPA and partial grades in the course" (p. 257).

RESULTS

The findings from the LAK (LA) and EDM research communities as given above will be discussed here in the light of the characteristics of quality instruction, as described by the chosen three pedagogical theories. The characteristics of the three theories are combined to focus on interactions and co-operation, active learning, feedback and adequate time, as explained at the end of the background section.

Interaction and co-operation among students, between students and teachers/designers, and students and content are key features of all quality instruction whether face to face or online (Anderson, 2003; Chickering & Gamson, 1999; Ewell & Jones, 1996). E-learning platforms offer a variety of interaction and co-operation tools. These involve the use of online forums, blogs, wikis, synchronous or asynchronous online discussions, student-led discussions and small-group activities, which could be followed up by large-group activities.

Both students and staff (teachers) are active on e-learning platforms: teacher–student interactions occur mostly through announcements, online discussions, emails and online conferences. There are ways in which researchers can analyse social interactions in online discussion forums and on social media, using qualitative methods and interaction analysis combined with learning analytics (Gunawardena et al., 2016). Hernández-García et al. (2016), using Gelphi as a social-network learning-analytics tool, analysed data generated by the messages sent and received in an e-learning platform. They report that this type of analysis can help instructors to identify lurkers, who are following the course without actively participating in it, and students who are active readers but are not performing well. It can further provide insight on which users are contributing the most valuable and interesting content.

Interaction between the teachers/designers and the users of e-learning platform resources through the use of interviews, surveys and feedback is described by Ain et al. (2016) and Berridge et al. (2012). This allows the designers to find out what the user wants in the website, update the interface, and perform iterations and validations. In this way, the user's mental model and designer perception are optimally aligned.

But student–teacher and student–student interactions can also happen outside these platforms on social media, chat rooms and in communities. Platforms designed for social interactions like Facebook, Adobe Connect, Sococo, Skype, Google Hangouts, Zoom, Microsoft Teams, Google team drives, etc., could be used for communicating with students. Data about these interactions would therefore not be captured by the e-learning platforms.

The term 'active learning' describes the type of learning where there is a search for new information, that information is organised in meaningful ways and explained to others *(*Allen & Tanner, cited in Khan et al., 2017). Walsh et al. (2011, p. 3) define the aim of active learning as allowing students an opportunity to "reflect on their own learning and become self-regulated and self-directed." Active learning can therefore be related to students being successful in a course by managing to learn from the formative or previous assessments, as reported by Romero-Zaldivar et al. (cited in Papamitsiou & Economides, 2014), Baker et al. (2015) and Rienties et al. (2016).

Colthorpe et al. (2015) found a negative correlation between performance, the use of reviewing of lecture recordings as a learning strategy, and accessing the online lecture recordings. This confirms that listening to a lecture (Anderson, 2003), whether it is online or face to face, is still passive learning. In a face-to-face lecture the teacher will ask questions, leading to medium levels of student–teacher and student–content interaction with low levels of student–student interaction. In a recorded lecture the student–teacher interactions also become low unless other engagement tools, such as worksheets, quizzes, or discussions, are used. This may also explain the finding of Bainbridge et al. (2018), Firat (2016) and Strang (2016), that the number of total logins/total hits/ opening sessions was either inversely related to success or not at all related. Passively listening to a lecture or clicking casually through a module could demonstrate what Ellis et al. (2017) describe as "fragmented conception of learning" leading to a surface learning, as opposed to "cohesive and integrated conceptions of learning" (p. 159) leading to deep approaches to learning.

The findings above contradict the results of Jo et al. (2016), who found the frequency of logins to be a predictor of success. One may assume that logins/total hits, although easily measurable, are complex and multidimensional, as they have different aims, such as logging in to study actively, to skim read, or to passively stare at resources. If logins/total hits mean students are logging in in quick succession to different areas/courses, or for short periods at a time, this would reflect that students are just opening links without meaningful interaction; seeing a lot and staying busy, but without absorbing much or linking it to their prior knowledge to construct schema. Even though the student seems to be active, this behavioural pattern does not represent active learning – an essential feature in quality courses (Chickering & Gamson, 1999; Ewell & Jones, 1996) – nor does it represent a high level of student–content interaction (Anderson, 2003). Since there is practically no engagement, the cognitive load is irrelevant, or may be perceived to be too high or too low (Paas et al., 2003).

Another possible deduction of the negative correlation between the number of logins/total hits/opening sessions and results (Bainbridge et al., 2018; Firat, 2016, p. 85) is that poor instructional design may unintentionally increase the extraneous cognitive load (ECL) (Yen et al., 2015; Pociask et al., 2013). The design of some course pages may encourage clicking by perhaps including distracting elements such as "irrelevant images, illogical learning paths or outbound links that lead the user away from the course" (Hetsevich, 2009, p. 3). These features may shorten the time on task and may inhibit students' prospects of high levels of interaction, success and deep learning. Some students may be more prone to distraction than others. Niemi (2018, p. 82) states that detailed data about "students clicking through irrelevant content or inappropriate activities" may be worthless in explaining the optimum ways of online interaction. Ideal interactions to track would be those with "research-tested, learning- and motivation-focused content and activities."

Meaningful, constructive, individualised and actionable feedback and input help students to learn in a timely way from their mistakes in procedures, thinking and understanding (Poll & Weller, 2014). The link between success in formative or previous assessments (Baker et al., 2015; Bainbridge et al., 2018; Shih et al., cited in Papamitsiou & Economides, 2014) may be related to the feedback that they receive immediately and frequently from the system. The positive effect of appropriate, relevant feedback is emphasised by the work of Thaker et al. (2020) on responsive online feedback using the TextRec + DynRemRec student model to refer students to textbook sections to correct the specific deficiencies exposed in the assessment.

But feedback can go much further and achieve much more than simply giving information on how assessments have gone. Feedback on their learning processes can make students more aware of how they can improve their interactions and their learning techniques. Enhancing student feedback by using results from LAK and EDM is a strategy already being used by some institutions. At the Open University in the UK, data obtained from e-learning platforms form part of an integrated plan for student support; for example, Analytics4Action (Rienties et al., 2016). Bainbridge et al. (2018) discuss a model (with an 80% success rate in predicting at-risk students) for tracking and feeding back to students to alter their behaviour, and mention other models, such as the Marist College OAAI project and the Purdue University Course Signals (explained by Baker et al., 2015), that have a predictive value between 44% and 80% depending on the variables.

Adequate time is a requirement in quality instruction, and correlates with the research findings that successful students spend more time online (Bainbridge et al., 2018; Kovanovic et al., 2015; Firat 2016; Jo et al., 2016; Keskin et al., 2016; Kotsiantis et al., 2013). Three factors are involved: total login time, login frequency and login regularity. Learners are more successful if they show high ability to prioritise tasks, are aware of their tasks, check their tasks regularly, and spend their time evenly rather than procrastinate and cram (Jo et al., 2016).

All activities do not give an equal return on the time spent on them. Park (2017) reports that for the same time spent on the task, design/development-based learning activities may involve deeper learning than discussion-based learning activities. This highlights the importance of setting up e-learning course pages for supporting success without increasing the cognitive load through unnecessary and time-consuming features.

The timing of access seems to be a factor in predicting success: early access and getting a head start in the early weeks of a course is linked to success (Baker et al., 2015; Levy & Ramim, 2012), as is the early submission of assignments (Colthorpe et al., 2015). This supports the advice of Poll et al. (2014) that students must be given time to prepare for the course by posting the syllabus and making the course available – as well as communicating the dates and times of synchronous activities in advance – at least a week before it is due to begin to enable students to plan time for adequate interaction.

Content with a high cognitive load will take a longer time to process. Therefore, very long browsing times may be warning signs that the material's cognitive load exceeds the students' cognitive resources (such as the working memory with its limited capacity), that students may have less prior knowledge than anticipated, that students lack the cognitive skills to construct schemas of storage in their long- term memories for retention, or that the instructional design unnecessarily introduces extraneous cognitive load that hinders instead of promotes learning processes (Yen et al., 2015; Pociask et al., 2013).

POTENTIAL CURRENT AND FUTURE USES OF THE RESULTS OF LAK AND EDM FOR ACADEMICS

Exciting research themes using the results from LAK and EDM include:

- Prediction models tracking and feeding back to students to optimise their interactions and behaviour (Bainbridge et al., 2018; Rienties et al., 2016).
- Creating students' awareness of the learning methods that they use and in doing so contribute to metacognition and self-directed learning (Marzouk et al., 2016).
- Adaptive and responsive models intervening in a timely way to adjust the cognitive level and channel students towards work that has a higher or lower cognitive level, or enabling tools (Yen et al., 2015).

- Appropriate and relevant feedback given in response to answers in assessments (Thaker et al., 2020). (Some researchers, such as Friesen [2013], however, see this automation of learning as a threat to self-monitoring and self-regulation by the learner.)
- Enhanced and personalised learning interventions that can be constructed based on students' behaviours if more accurate prediction models are available. According to Jo et al. (2016), individual learners' psychological factors such as self-efficacy can be explored based solely on their login patterns (including login frequency, login time, and regularity of login interval) without the use of any other external instruments.
- Experience sampling method (ESM) to supplement web log analysis (WLA) can be used to collect data on learners' emotion and cognitive involvement in different learning tasks (Park, in Hokanson et al., 2015).
- Combining educational data mining (EDM) with multimodal learning analytics, which gather and analyse multiple sources of data (video, logs, text, artefacts, audio, gestures, biosensors) to examine learning (Blikstein & Worsley, 2016).
- Combining EDM with social-network learning-analytics tools to model interactions on forums, discussions and social media (Gunawardena et al., 2016).
- Graphical user interfaces (GUI) (such as SLAM-KIT) simplify researchers' journeys through complex learning environments by revealing basic features and visualising their statistical characteristics (Noroozi et al., 2019).

Potential future research

For teachers/designers, the application of CLT specifically in the design and development of online activities offers an exciting field of research. Open-ended questionnaires, interviews and focus groups could be used to gain an understanding of how certain resource design features can enhance or inhibit student experience. Measurable attributes that hinder or promote learning speed and depth can be analysed with the available learning analytics. The model in Figure 2 can serve as a framework to analyse and evaluate online resources as well as serve as a checklist when designing resources.

CONCLUSION

There are some contradictory findings in the researched literature regarding online behaviour and interactions that can serve as indicators of success or risk of failing. While some researchers report no behavioural patterns linked to success in courses, others found evidence that students' success or failure depends on whether students interact long enough with the content, perform well in formative activities and interact in a manner that fosters deep learning. Others found a combination of factors (such as time spent interacting with the course materials and regularity of login intervals combined with the number of logins) gave a better prediction of success.

It can be concluded that information compiled using LAK and EDM has the potential for teachers to track their students' progress, and for course designers to improve their designs. It seems useful to identify and act on alarming patterns of behaviour (such as inactivity, irregularity of logins, continuously logging in, late logins, and poor results in formative assessments). These research fields offer possibilities to enable teachers and designers to customise materials for specific student needs, build scaffolds where certain behaviours are observed, and, combined with additional instruments, determine the attitudes and biases of students to address issues that may inhibit progress. These tools can be utilised to give feedback to students about their learning processes and time management, and to teachers/designers to optimise the interface.

An important aspect touched on in this study is how certain page features could distract or focus students' attention, and lead to superficial or deep learning: this is something that the designer can control. Studying login and click behaviour (frequency, intervals between, duration, time on task and clicking sequences) could help designers to better understand the strengths and weaknesses of different page layouts and compositions.

Pedagogical theory could provide useful backgrounds for analyses of data from LAK and EDM. It can contribute to understanding how to apply the insights gained from these analyses and make them useful in optimising courses and interfaces. Anderson's Equivalency Theorem urges the course designer to aim for an optimal mix of interactions in the online environment with at least high levels of student–content interaction. The generally accepted pedagogical principles of quality instruction can all be achieved in an online environment. Cognitive load theory warns that students spending long periods on tasks without success and/or tackling further tasks, can serve as warning signs of a mismatch between the readiness of students for the demands of the task, insufficient support or distracting features of the online environment. Application of other principles, such as collaboration and the use of cognitive tools, can help to draw students into deeper engagement with the course. Ultimately, the test for the contribution of LAK and EDM research is in the prospective long-term impact that they may have on student pedagogical practice (Gašević et al., 2015).

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