From Learning Analytics to Engagement Analytics, a Literature Review and a New Synthesis Matrix

ANONYMOUS

This paper introduces an Engagement Analytics process closely related to Learning Analytics practices. Based on an extensive literature review, we acknowledge that the notion of learner engagement is a multi-dimensional reality (cognitive, emotional, behavioral) and a high-level indicator in learning. Its analysis is of great interest to stakeholders in online education, where asynchronicity and barriers to direct observation make the perception of engagement a challenge. In Learning Analytics, digital traces lead to the computation of learning indicators from which descriptive, diagnostic, predictive or prescriptive reporting can be derived. We transpose this approach to learner engagement with the goal of considering engagement within a continuous optimization process (observation, evaluation, corrective action). The observation is done using digital traces that describe engagement (descriptive level of analysis), evaluation is done using indicators that qualify engagement (diagnostic level of analysis), and optimization is done by devices that trigger and support engagement (predictive and prescriptive levels of analysis). The outcome of this work is a bi-dimensional Engagement Analytics matrix along the cognitive – emotional – behavioral axis and the predictive – prescriptive – corrective axis.

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1 INTRODUCTION

Online learning presents major challenges, including learner engagement. Indeed, while in face-to-face and synchronous learning, it is easy to monitor learners' behavior and support their engagement, the task becomes less obvious in online training, where autonomous involvement of learners is a major issue. In the context of Learning Analytics, digital traces of learning are a valuable tool for addressing this issue. Among the indicators typically constructed from digital traces, learner engagement appears as a supra-indicator, predictor of success. However, the concept of engagement is complex. First, we need to define it clearly, and then examine how to effectively promote it in online learning.

Works in Learning Analytics have focused on this subject and provided different approaches and representations. In this paper, we review (Section 2) and discuss (Section 3) the literature on these approaches to learner engagement in order to present a sufficiently comprehensive and up-to-date overview (Section 4).

To achieve this, two research questions will guide our investigation:

- What are the approaches to learner engagement in the Learning Analytics literature?
- Can we conduct an objective analysis of learner engagement?

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2 LEARNER ENGAGEMENT: A LITERATURE REVIEW FROM A LEARNING ANALYTICS PERSPECTIVE

Learner engagement is addressed in various disciplines, such as Educational Sciences and Psychology. In this paper, we are interested in how it is handled in Learning Analytics. We present the results of our study under four headings: the importance of engagement, its definitions, its dimensions, and its indicators.

2.1 The Importance of Learner Engagement

Dehaene [11], cited by Treuillier et al. [47], indicates that student engagement is essential to a quality learning process. Tang [45], cited by Willans et al. [51], also explains that engagement in learning is generally considered a desirable trait in students. They also point out that there is a wide range of definitions and interpretations of what exactly engagement refers to and how to achieve it.

Based on the literature, the importance of engagement is generally measured by its role as a learning indicator and its function as a predictor of success (learning outcomes).

2.1.1 Learner Engagement as a Learning Indicator. Iksal [19] defines an indicator as an observable element that is significant in educational terms, calculated or established through observations, and testifying to the quality of the interaction or learning activity. It is defined according to an observation objective and motivated by a pedagogical goal. With that said, many learning indicators are conceivable and widely considered in the literature. Some of these indicators relate to educational tools (audience), others to educational content (learning curve), and still others to users such as learners or teachers (behavior or engagement).

Engagement is, therefore, a learning indicator that concerns users (learners in our case). It can be considered a higher-level indicator because its measurement is carried out using several other indicators, called engagement indicators. These include presence, participation, perseverance, and performance.

The measurement of these engagement indicators makes it possible to establish engagement profiles [42]: active engagement (participative presence), passive engagement (non-participative presence), non-engagement (absence), high engagement (above-average number of activities), moderate engagement (average number of activities), low engagement (below-average number of activities), and disengagement (abandonment of activities). Chi and Wylie [6] describe four modes of engagement: interactive, constructive, active, and passive, each of which is associated with different learning behaviors. These modes allow for more or less in-depth learning processes, with varying consequences on learning outcomes.

Thus, engagement is a major indicator of learning; it encompasses other indicators that allow for its assessment and helps identify engagement profiles or modes.

2.1.2 Engagement as a Predictor of Success. Learner engagement is crucial for academic and educational success [39]. Many authors [48] argue that learner engagement is often correlated with success, although the notion of success or achievement must be defined within each educational context. They suggest that a high level of engagement most often corresponds to better learning outcomes. For these authors, learner engagement is difficult to measure but vital to learning success; it encompasses more than just participation, motivation, and self-regulation.

2.2 Definitions of Learner Engagement

Various definitions of engagement exist in the literature. As both an indicator of learning and a predictor of success, engagement is an observable variable that fluctuates according to different parameters. Three key parameters from the literature help frame the different approaches to the concept: activity (events), time, and process.

2.2.1 Engagement According to the Quantity of Actions. Fredricks et al. [16] describe engagement as the extent to which a learner performs actions, participates, and is involved in learning activities. In this sense, engagement is measured by the quantity of activities, actions, or events. This view of learner engagement aligns with Kiesler's perspective [23], cited by Pirot et al. [34], which posits that only actions truly engage us. For these authors, engagement is directly proportional to the quantity of actions: the more actions, the more engagement.

2.2.2 Engagement as a Variable Based on the Amount of Time. Student engagement typically refers to the time and effort students devote to their academic experiences (Jennings and Angeloc [20], or Kuh [24], cited by Ma et al. [26]).

Since effort is difficult to measure, time is often used as the primary criterion for assessing engagement.

2.2.3 Engagement as a Variable Based on the Quality of Learning Behavior. Kuh et al. (2007) [25], cited by Trowler [**?**], define engagement as a combination of access, compliance, and investment. Fredricks, Blumenfeld, and Paris [16] also emphasize the notion of compliance, defining behavioral engagement as "*doing the work and following the rules.*"

Other authors focus on engagement as a quality of learner behavior. For instance, D'Mello et al. [14] argue that behavioral engagement broadly refers to learners' participation in learning, including effort, persistence, and concentration.

Newmann, Wehlage, and Lambourn [28], cited by Gérard et al. [17], define engagement as psychological investment and effort directed toward learning, understanding, mastering knowledge, and developing the expected skills or abilities. From this perspective, engagement is seen as a quality of goal-directed behavior.

2.3 Dimensions of Learner Engagement

Prégent, Bernard, and Kozantis [37], cited by Gérard et al. [17], consider engagement according to two dimensions: behavioral engagement and cognitive engagement. Behavioral engagement relates to the student's conduct, while cognitive engagement refers to the student's intellectual investment, including concentration, attention, and learning strategies.

Fredricks et al. [16] identify three dimensions of engagement: behavioral, cognitive, and emotional engagement. The emotional dimension, also called motivational, refers to the learner's affective and emotional responses towards the institution and the teacher [17].

Reschly and Christenson [36] define learner engagement in terms of four dimensions: behavioral, cognitive, academic, and psychological or emotional. The academic dimension is linked to the learner's extrinsic motivation to meet institutional requirements.

2.4 Engagement Measurement

In this section, we highlight the main indicators used to measure engagement as found in the literature.

Social presence: Ngoyi et al. [30] define social presence as the interaction among students and between students and instructors, which enhances learning. Social presence has three dimensions: social context, online communication, and interactivity [35].

Cognitive presence: Kanuka and Garrison [22] emphasize that cognitive presence requires sustained communication and interaction among students and with content. It reflects the learner's qualitative participation in learning activities.

Participation: Often measured in collaborative learning contexts, participation can be active (reading and posting messages), passive (reading messages but not posting), or non-existent (neither reading nor writing messages) [53]. Participation is a key engagement indicator.

Contribution: Similar to participation, contribution refers to the learner's input in collaborative tasks, such as the number of revisions or words modified in a writing task [29]. For example, the number of revisions or the number of words modified by a learner in a task of collaborative writing can be considered as their contribution.

Distraction: A negative indicator of engagement, distraction refers to engaging in activities unrelated to learning during sessions, such as consulting irrelevant materials [38].

Performance: The outcome of learning assessments, such as tests and exams, serves as a performance indicator [40].

Failure: Refers to not achieving the learning objective and scoring below the required threshold, often seen as under-performance [1, 13].

Perseverance: According to Soussia [42], perseverance reflects cognitive engagement, such as repeated attempts to succeed in exercises or exams.

Learning activity order: This refers to how learners sequence their activities. The linearity of task completion in MOOCs can affect learning outcomes and engagement [8].

Conformity: Willans et al. [51] define conformity as following the established learning schedule and standards.

Regularity: A critical indicator in online learning, regularity reflects consistent study habits. Many learners face challenges in time management and often struggle with procrastination [5]. You [54] highlights that calendar-related indicators, such as the regularity of online learning activities, warrant detailed analysis. Regularity is examined across two dimensions: temporal regularity (maintaining consistent study times) and action regularity (consistent patterns of activity during learning sessions) [42].

Frequency: Similar to regularity, frequency refers to the rhythm of learning activities, including access and participation rates [8]. Various measures are employed to track frequency, such as login counts, video view rates, forum participation, and the use of downloadable resources.

Access: Access describes a student's presence in a learning environment without necessarily indicating active engagement [51].

Time allocated: Time spent on learning activities is an important predictor of success and engagement in online learning [4].

Responsiveness: Refers to the time delay between the availability of an activity and a learner's first access to it. It is a predictor of achievement [7, 8].

Procrastination: A counter-indicator of engagement, procrastination refers to postponing tasks until the last minute or beyond the deadline [52, 55].

Motivation: Motivation is a predictor of engagement and participation. Barba et al. [15] study three aspects of motivation: interest, achievement goals and value beliefs.

Perception: A learner's perception of pedagogy (content, style, tools) influences engagement and is often collected through self-reported measures [29].

Interest: According to Harackiewicz et al. [18], interest is a powerful motivational force that drives engagement, influences academic trajectories, and is essential for success. It is both a psychological state of attention and emotional involvement towards a particular object or subject, as well as a lasting predisposition to re-engage with it over time.

Satisfaction: Learner satisfaction, often related to the learning environment and relationships with peers and teachers, is an important indicator of engagement [44, 53].

Completion: Completion rates are important indicators of success and engagement in online learning [2, 10, 49].

Dropout: Failure to complete a course is a counter-indicator of engagement [1, 13].

Investment: Willans et al. [51] define investment as going beyond the minimum requirements, such as engaging deeply in forum discussions or retaking quizzes for higher scores.

Study skills: Study techniques, including computer proficiency and academic literacy (intellectual aptitude), play a significant role in engagement and success in online learning [31].

3 DISCUSSION AND SUMMARY

3.1 The Dimensions of Learner Engagement

Learner engagement is a multidimensional construct, encompassing cognitive, affective, motivational, psychological, behavioral, and academic dimensions. These dimensions, while essential to engagement, are not necessarily cumulative. In other words, productive engagement can be triggered by the presence of one dimension alone. However, the presence of multiple dimensions tends to result in more effective engagement. The relevant dimensions must be tailored to each educational project.

For each learning context, engagement should be personalized to focus on the dimensions most critical to success. In this paper, we define learner engagement as the cognitive (intellectual), behavioral (physical), and emotional (affective) investment of the learner in learning activities (see Fig 1).

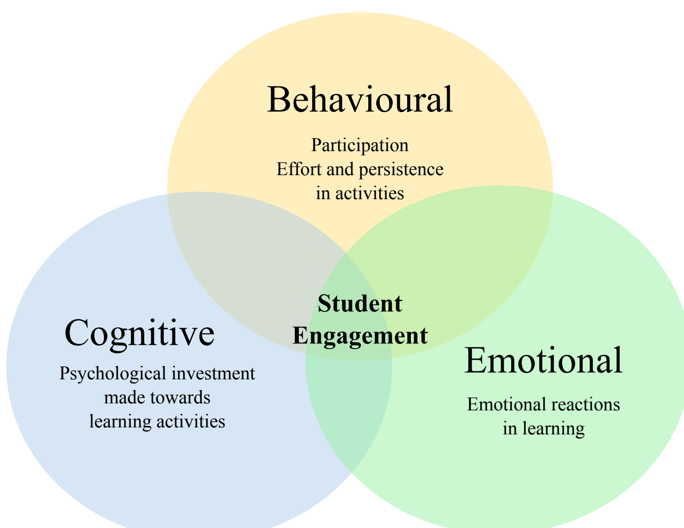

Fig. 1. Dimensions of student engagement [32]

- Cognitive engagement refers to the learner's mental involvement in learning, encompassing effort, persistence, and intellectual investment.
- Emotional engagement refers to the learner's affective involvement, including the desire and motivation to learn.
- Behavioral engagement refers to the learner's physical interaction with their learning environment, involving active participation and interaction with learning materials.

Our analysis of learner engagement in online learning will focus on these three dimensions, which are complementary and vital for building optimal engagement in both formal and extracurricular learning contexts.

3.2 Definitions of Learner Engagement

The various definitions and indicators of learner engagement discussed in Section 2.2, are more complementary than contradictory from a Learning Analytics perspective. Together, they offer a comprehensive view of engagement, encompassing two primary dimensions: quantitative and qualitative.

- Quantitative View: Engagement is often seen as an observable and measurable phenomenon. Indicators such as the quantity of activities, time spent, number of pages viewed, messages read, or mouse and keyboard activity represent the learner's active presence.
  However, learners often engage with external sources not captured in the digital learning environment, such as exercises performed offline, downloaded materials, or books. Engagement with these resources may go unrecorded. Additionally, engagement cannot be fully reduced to mere interaction quantity or time spent online. The time learners need for reflection and knowledge assimilation, as well as how they integrate this knowledge, is crucial but often overlooked in quantitative measures.
- Qualitative View: While quantitative measures provide an objective approach, they must be complemented by a qualitative analysis that evaluates learning behavior [14, 16, 17, 25]. Aspects like perseverance, regularity, concentration, and compliance offer insight into how learners engage cognitively and emotionally.
  A limitation of this approach is the tendency to generalize engagement profiles as normative for all learners. In reality, each learner develops unique strategies and tactics to achieve their learning goals, making it difficult to impose a standardized engagement model.

The engagement indicators observed in the literature often overlap, referring to similar parameters. For example, participation and contribution both relate to a learner's involvement in peer or teacher interactions. Similarly, access and time spent measure engagement through similar metrics. Indicators like reactivity and procrastination reflect the same underlying reality of time management. Thus, many engagement indicators share common meanings across different approaches.

3.3 Our Definition of Learner Engagement

We have explored various definitions of learner engagement in Learning Analytics, highlighting parameters such as the quantity of interactions, time invested, and quality of learning behavior. These definitions, while diverse, are complementary and together provide a holistic understanding of the concept.

In our approach, we consider engagement as a learning indicator that concerns the user-learner. Engagement is defined as a variable dependent on both quantitative data (time, events) and qualitative data (processes). We consider it as a high-level indicator composed of lower-level indicators derived from digital traces and other collected data, providing a comprehensive picture of the learner's progress and engagement throughout the learning process.

4 ENGAGEMENT ANALYTICS

The strong correlation between learner engagement and academic success is well established in research. A growing focus now is on how to effectively monitor and support engagement throughout the learning process. In this section, we propose an approach to Engagement Analytics, inspired by research findings, which aims to observe, evaluate, and optimize learner engagement.

4.1 A Three-Step Approach: Observe, Evaluate, and Optimize

Analysis involves breaking down complex systems into their constituent elements to better understand their state and interrelationships. In the context of Engagement Analytics, this means identifying the components of learner engagement to gain insights into how they can be optimized for better learning outcomes.

Building on the methods used in Learning Analytics, we extend similar practices to Engagement Analytics. This involves utilizing digital traces of learner activity to construct engagement indicators, which can then be organized and presented based on four levels of analysis: descriptive, diagnostic, predictive, and prescriptive. In doing so, we effectively translate the analytical practices of learning analysis into engagement analysis.

Thus, Engagement Analytics is the systematic process of observing and evaluating engagement data with the goal of optimizing learner involvement. This process can be broken down into three key steps:

Observation: This stage involves the collection, storage, and description of digital traces that represent various forms of learner engagement (e.g., time spent on tasks, frequency of participation, interaction levels).

Evaluation: In this step, the collected data is measured, diagnosed, and analyzed to identify patterns, trends, and potential areas of concern. Evaluation includes both quantitative measures (such as time spent) and qualitative insights (such as motivation and engagement quality).

Optimization: The final step focuses on utilizing the insights gained from observation and evaluation to enhance engagement. This could involve adjusting teaching strategies, providing targeted feedback, or using motivational techniques to foster greater learner involvement. The goal is to optimize engagement in a way that supports individual learner success and promotes overall learning effectiveness.

This three-step framework ensures a continuous cycle of improvement, where engagement is regularly assessed and refined based on real-time data, leading to a more effective learning experience.

4.2 Engagement Analytics Lifecycle

(1) **Observe the Data** Our data analysis system is driven by the evidence collected from learners' interactions within digital learning environments. This data is traced by collectors such as xAPI[1] or Caliper[2], which provide observable evidence of activities using their respective syntax. For instance, xAPI uses the Actor/Verb/Object structure, while Caliper adopts the Actor/Action/Activity schema. The syntax helps answering essential questions about learner behavior, such as who did what, when, and where.

(2) **Evaluate the Indicators** The second phase focuses on constructing relevant engagement indicators from the collected traces. This involves analyzing the data to generate insights on engagement patterns, modes, and learner profiles. Depending on the outcome of this evaluation, various engagement profiles or modes can be identified and addressed.

[1]https://xapi.com/
[2]https://www.1edtech.org/standards/caliper

(3) **Optimize or Proactively Trigger Engagement** The final phase of the system aims to optimize engagement through proactive interventions. These interventions are designed to either enhance or maintain engagement by leveraging educational tools and strategies that trigger or support learners' motivation and participation.

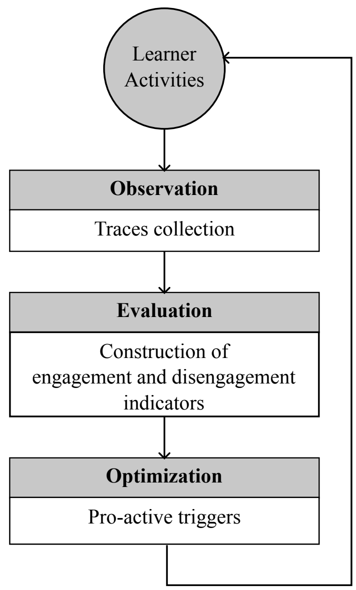

Fig. 2. General outline of learner engagement analysis

This three-phase engagement analysis cycle is iterative (see Fig 2), and can be applied across all dimensions of engagement—cognitive, emotional, and behavioral.

4.3 Engagement Analysis Matrix

To achieve a detailed analysis of learner engagement, we adopt a two-pronged approach:

- First, by analyzing according to the dimensions of engagement (cognitive, emotional, behavioral).
- Second, by applying a structured process across the stages of analysis (observation, evaluation, and optimization).

Engagement	Cognitive	Emotional	Behavioral
Observe	Cognitive engagement traces	Emotional engagement traces	Behavioral engagement traces
Evaluate	Cognitive engagement indicators	Emotional engagement indicators	Behavioral engagement indicators
Optimize	Cognitive engagement devices	Emotional engagement devices	Behavioral engagement devices

4.4 Analysis of Cognitive Engagement

4.4.1 Traces for Cognitive Engagement Observation. Observation of cognitive engagement is done by means of traces linked to activities that demonstrate the mental involvement of the learner:

the time allocated to an activity; the frequency of connection to the online platform; the number of repetitions of an activity; the number of attempts at an exercise; the number of answers to a test; the assessment result (grades, score); the progress; the number of levels completed; the number of badges obtained; the number of challenges completed; the number of assignments returned on time or late.

These traces make it possible to observe cognitive engagement and build the indicators described in next section.

4.4.2 Indicators for Cognitive Engagement Evaluation. To assess, and thus measure cognitive engagement, positive or negative indicators can be calculated with the traces previously collected.

Positive indicators of cognitive engagement: performance; perseverance; cognitive presence; contribution; completion; study skills.

Negative indicators of cognitive engagement: failure; dropping out.

4.4.3 Devices for Cognitive Engagement Optimization. To support and improve cognitive engagement, certain educational devices are useful.

Interaction

- **Learner-Teacher Interaction** is a proactive cognitive engagement device that maintains the pedagogical role of the teacher, emphasizing its importance to the learner in online learning. Even though the teacher and the learner are no longer face-to-face as in traditional teaching, communication between these two stakeholders remains beneficial during the learning process.
  For Oladipupo et al. [33], the concept of student-teacher interaction encompasses both formal and informal relationships, as well as the many responsibilities that faculty members have in educational institutions, serving as role models, advisors, instructors, sources of advice, mentors, and tutors.
  In a digital learning ecosystem, learner-teacher interaction must be considered a significant vector of learner engagement, as it fosters a sense of belonging to a shared institution. The forms of interaction between learners and teachers often include motivational feedback or question-and-answer systems.
- **Interaction between learners** corresponds to collaborative learning systems where learners can interact with their peers. These environments improve the engagement since they create a feeling belonging to a group, a team or a community. The forms of interactions between learners are often forums or group work.

Interest transfer is a proactive device for learner engagement in online learning. Knowing a learner's interests through their learning experience, it is possible to recommend content to them through advice to adjust their interests or preferences to the educational objective.

Formative assessment (assignments, exams, MCQ, surveys, inquiries) is a proactive learner engagement device. It is often used in online training for its motivational impact.

Registration (or enrollment) in learning: for Tatel et al. [46], course registration data constitute measures of significant interest in the learning process. In the same way that learning management system tracking data acts as a behavioral indicator of cognitive engagement with course content, course enrollment behavior acts as an indicator of cognitive engagement in planning for program completion.

4.5 Analysis of Emotional Engagement

4.5.1 Traces for Emotional Engagement Observation. The traces that allow us to observe emotional engagement are generally of the self-declared type. These are survey data, and questionnaire data. In addition to these subjective data, emotional engagement can also be observed through language data that are more objective if they are sincere (*e.g.* not involving sarcasm or irony). To do this, it is important to collect texts produced by the learner, and to observe their emotional engagement through means of Natural Language Processing, for instance.

4.5.2 Indicators for Emotional Engagement Evaluation. We can identify four indicators of emotional engagement: satisfaction; interest; perception; intrinsic motivation.

4.5.3 Devices for Emotional Engagement Optimization.

- Survey tools
- Discussion forums

4.6 Analysis of Behavioral Engagement

4.6.1 Traces for Behavioral Engagement Observation. The traces that allow behavioral engagement to be observed are generally those of interaction with the learning environment. These traces related to the learner's behavior are the most abundant: the start time and date of a specific activity; the end time and date of a specific activity; the duration in milliseconds of this activity; the amount of use of the mouse wheel during the activity; the number of clicks made with the mouse wheel; the number of left and right clicks and left clicks in an activity; the distance traveled by mouse movements; the number of keystrokes; the number of pages viewed, at what time, in what order; the number of student accesses per course; the number of student interactions per course; the average number of minutes spent by students per course; the number of student accesses per specific content; the number of student interactions per specific element; the frequency of navigation in courses; the frequency of consultation on the forum; the frequency of contribution on the forum; the frequency of viewing courses; the number of sessions; the total duration; the active days; the interactions with course videos: loading, playing, pausing, searching backward, searching forward and stopping; the total number of actions (or activities) performed on the course page; the number of words entered; the number of completed assessments.

4.6.2 Indicators for Behavioral Engagement Evaluation.

- **Positive indicators of behavioral engagement:** participation; frequency; regularity; responsiveness; access; compliance; investment; order of activities; synchronous time invested; social presence.
- **Negative indicators of behavioral engagement:** drop out; procrastination; distraction.

4.6.3 Devices for Behavioral Engagement Optimization.

Gamification is one of the most effective methods used to increase student engagement, which can create appealing learning experiences. Daghestani et al. argue that gamification is a way to increase student engagement by using game elements in a non-gaming context called Serious Gaming. It also promotes student engagement by integrating competition, leader boards, upgrade opportunities, achievement rewards, and other game mechanics into classroom activities [9].

Learning tactics and strategies: knowledge of learning tactics and strategies used by learners can lead to establishing learning and learner profiles for personalized instruction with better engagement. By knowing the tactics and strategies learners deploy for their trained, it is possible to build a learner-centered pedagogical approach.

Granularity in training design where granularity refers to the size of the constituent entities of the system. The level of the granularity of a system is measured by the size of its smallest elements. This is significant in online learning, because each entity calls for an action; and each action generates a trace, likely to be of interest. Granularity can both be considered in its temporal aspect as it can with respect to didactic units.

- **Temporal granularity:** for Jovanovic et al. in a course spanning several months, students' learning behaviors may not change significantly in a few weeks; on the other hand, in an intense learning activity, significant changes can occur in learning behaviors within a few hours [21].
- **Didactic granularity:** concerns the level of detail of implemented training scenarios. It contributes to the opportunities of measuring certain indicators. Behind each click, there is a message related to learning. The higher the content granularity, the more abundant the collection of evidence of learning but requires to be taken into account from the very design phase of the learning scenarios [53].

Collaborative learning occurs when different learners interact and modify each other's work. Collaborative learning system creates learner participation and contribution [29], [46].

Pace of learning can be declined in two main situations: instructor-paced learning or self-paced learning. An instructor-paced MOOC uses a linear and sequential course structure guided by the instructor. The self-paced course has a more adaptive learning path, where the learner can decide in what order to view content, because the orientation of the learning is student-centered. Instructor-paced learning can promote cognitive presence which is linked to learner engagement. However, Campbell et al. suggest that an independent learner is less dependent on an instructor and would therefore likely prefer the self-paced structure for a MOOC [3]. This means that self-paced learning may be more motivational for independent learner profiles.

The cohort is a special case of instructor-regulated learning where the course has a start and end period. Learners enrolled for the same period form a cohort [27] which appears as a class. It creates a sense of belonging to a group and reduces the dropout rate among students [41]..

Synchronous online sessions were investigated in [4] within the context of a graduate program. One of its findings was that, in this context, the time spent in synchronous online sessions was correlated with learner engagement and success.

The peer helper is a potential answer to the learners' needs to get support during their learning process. It provides a means to scale up from instructor managed discussion forums where the learner can seek help. When the number of learners is high, and the discussion forum becomes overloaded, it is difficult to find the adequate help that one may need. The peer helper is a possible (partial) replacement for the teacher to meet the needs of a learner, at the appropriate level of capability. A peer helper recommendation system in an online learning environment can be beneficial for engagement and success [12].

Learning Analytics (LA)

- **The LA dashboard system** results from the work of Wang et al., who show the importance of Learning Analytics in online learning for teachers and learners [50]. An LA dashboard provides students with personalized learning suggestions and a better understanding of their individual progress. It also presents students' learning outcomes and will thus help instructors to using the data to update their teaching styles and methods to adapt to the needs of students.

  As a consequence, Learning Analytics make a significant contribution to improving teaching and learning. The teacher dashboard provides information about the learner and the learning in general in order to improve pedagogy. The learner dashboard provides information about their activities and results, which can be a source of motivation and engagement. Learning Analytics can help the learner in self-regulating their learning [43].

- **The early warning system:** Learning Analytics can also be used to set up an early warning system in for motivational dynamics towards learners in order to improve their engagement [43].

5 CONCLUSION

This paper presents a study aimed at leveraging Learning Analytics techniques to observe, evaluate, and optimize engagement in online learning.

From the literature review on how learner engagement is handled in Learning Analytics, it has become clear that the concept of engagement is rich, multifaceted, and complex to model. The state of the art on approaches and representations highlights various aspects of the concept: it is a major indicator of learning and a convincing predictor of success; it is defined as a variable with both quantitative (time, actions) and qualitative (manner) parameters; it is multidimensional (cognitive, emotional, behavioral); and it includes several indicators such as perseverance, motivation, and frequency.

Secondly, we developed an engagement analysis methodology based on the learning analysis process. Our approach includes three stages: observation, which concerns traces of engagement; evaluation, which concerns engagement indicators; and optimization, which concerns engagement-triggering and support devices. Engagement analysis is intended as a transposition of learning analysis, specifically focused on the object of engagement.

We apply the analysis to the respective dimensions of engagement: cognitive, emotional, and behavioral, all of which are applicable within both learning (curricular) and extra-curricular contexts.

This work offers a global, synthesized, and organized overview of fragmented data from the literature on engagement in digital learning. It provides a structured means to conceptualize engagement analysis along two axes: the dimensions of engagement and the stages of the analysis process.

Our work will continue into an experimental phase, during which we will set up digital devices to analyze engagement. This is part of an ongoing project, with data expected to become available in the next 12 to 18 months.

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