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When, how and for whom changes in engagement happen: A transition analysis of instructional variables

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A R T I C L E I N F O

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A B S T R A C T

The pace of our knowledge on online engagement has not been at par with our need to understand the temporal dynamics of online engagement, the transitions between engagement states, and the factors that influence a student being persistently engaged, transitioning to disengagement, or catching up and transitioning to an engaged state. Our study addresses such a gap and investigates how engagement evolves or changes over time, using a person-centered approach to identify for whom the changes happen and when. We take advantage of a novel and innovative multistate Markov model to identify what variables influence such transitions and with what magnitude, i.e., to answer the *why*. We use a large data set of 1428 enrollments in six courses (238 students). The findings show that online engagement changes differently —across students— and at different magnitudes —according to different instructional variables and previous engagement states. Cognitively engaging instructions helped cognitively engaged students stay engaged while negatively affecting disengaged students. Lectures —a resource that requires less mental energy— helped improve disengaged students. Such differential effects point to the different ways interventions can be applied to different groups, and how different groups may be supported. A balanced, carefully tailored approach is needed to design, intervene, or support students' engagement that takes into account the diversity of engagement states as well as the varied response magnitudes that intervention may incur across diverse students' profiles.

1. Introduction and background

Over the past decades, online learning has grown in scale of adoption, extent of application, and pace of development (Valtonen et al., 2022). As online learning has rapidly evolved, so has the importance of students' engagement. The emergence of COVID-19 has further emphasized the centrality of engaging online learners and the challenges of creating an engaging online environment (Martin & Borup, 2022). On the one hand, online learning environments offer self-paced learning, multimedia-rich instructions, and flexible delivery that transcends the constraints of time and location (Valtonen et al., 2022). On the other hand, online learning environments are inherently challenging, requiring students to have additional technological skills in how to learn, stay motivated and ask for help (Bond, Buntins, Bedenlier, Zawacki-Richter, & Kerres, 2020). Put another way, online learning environments have their own unique

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affordances and constraints (Bergdahl, 2022; Li & Lerner, 2011).

The majority of the existing literature on student engagement has addressed in-person learning environments and often has not considered the unique and significant affordances and constraints that exist in the online environment (Li et al., 2022; Martin & Borup, 2022). Furthermore, there is a dearth of studies about longitudinal engagement in online learning (Salmela-Aro, Tang, Symonds, & Upadyaya, 2021). The existing face-to-face literature has addressed a limited number of time points using self-reported surveys and rarely used person-centered methods (Salmela-Aro et al., 2021; Smith & Tinto, 2022). A gap, therefore, exists in our knowledge about how online engagement evolves and how it is influenced by the affordances and constraints of online learning environments (Smith & Tinto, 2022). Our study builds upon the gaps identified in recent literature syntheses (Salmela-Aro et al., 2021) as well as the recent calls for longitudinal research in online learning (e.g., Crook, 2019; Martin & Borup, 2022). We use a large longitudinal dataset and take advantage of the latest advances in person-centered methods to identify *who* is likely to be engaged, stay engaged, or transition to another engagement state (Yang et al., 2023). More importantly, we focus on *why* students transition between engagement states, *what* variables influence their transition, and to *what* extent each variable influences such transitions. Identifying such variables and their influence would allow a nuanced understanding of the variables that boost or derail engagement, which consequently, allow us to intervene or support students *when* needed. Our research questions (RQs) are as follows.

- RQ1: Which engagement states can be identified and how do the states differ?
- RQ2: How and to what extent do students transition between engagement states, and how are the transitions influenced by instructional variables?
- RQ3: To what extent are transitions between engagement states associated with performance?

The next section of the paper reviews engagement as a concept, the dimensions of engagement, and the variables that influence engagement, as well as a review of related literature.

1.1. Engagement

The understanding of engagement has evolved over time, as well as the conceptualization of the construct, theoretical framing, and measurement methods (Martin & Borup, 2022; Reschly & Christenson, 2022). Today, there is an agreement on the value of engagement, the multidimensional nature of the construct, and the importance of engagement in learning and teaching. However, disagreement prevails when it comes to definitions, theoretical underpinnings, and frameworks (Martins, Cunha, Lopes, Moreira, & Rosário, 2021; Smith & Tinto, 2022).

The concept of engagement is commonly used to describe the extent of student involvement, commitment, and investment in their learning. In our study, we rely on the recent definition by Martin and Borup (2022) that addresses online engagement, which states: "Online learner engagement is the productive cognitive, affective, and behavioral energy that a learner exerts interacting with others and learning materials and/or through learning activities and experiences in online learning environments'' (Martin & Borup, 2022, p. 170). As mentioned earlier, it is widely agreed that engagement is an overarching multifaceted construct that includes behavioral, cognitive, and emotional dimensions (J. A. Fredricks, Blumenfeld, & Paris, 2004; Martin & Borup, 2022). A conceptual overlap exists across engagement dimensions that oftentimes blurs the distinction between such constructs (Bergdahl, 2022; Sinatra, Heddy, & Lombardi, 2015). Furthermore, engagement dimensions exhibit a considerable interplay and mutual influence. For instance, emotional engagement drives cognitive and behavioral engagement (Sinatra et al., 2015). Whereas several other dimensions have been proposed —as well as different labels for existing constructs— they received little agreement among scholars. For instance, Henrie, Halverson, and Graham (2015) cited a social, agentic, and psychological dimension. Thereupon, we focus in our study on the three widely accepted dimensions: behavioral, cognitive, and emotional dimensions.

Behavioral engagement refers to the observable behavior that reflects a student's effort to learn, comply with school duties, perform learning tasks and participate in the learning process (Li et al., 2022). In online learning, behavioral engagement is commonly operationalized through, for example, counts of logins, frequency of access to learning resources, number of postings, time spent online, and interaction with the online resources (Henrie et al., 2015). The link between behavioral engagement and other dimensions of engagement is well established. As Martin and Borup (2022, p. 165) state, "in many ways, behavioral engagement is the physical representation of cognitive and affective engagement".

Cognitive engagement is commonly defined as investing significant efforts in learning, going beyond what is required, and persistence (Halverson & Graham, 2019; Martins et al., 2021). Cognitive engagement requires students to comprehend complex concepts, tackle challenging learning tasks, and invest cognitive effort in learning and problem solving (Martin & Borup, 2022; Sinatra et al., 2015). Nevertheless, an overlap exists between cognitive and behavioral engagement, which makes it —sometimes— difficult to separate either construct. For instance, time on task, persistence, and effort are commonly used by researchers as manifestations of either construct (Sinatra et al., 2015).

Emotional engagement refers to students' affective reactions to learning subjects or the emotions students associate with learning activities. Such emotions can be positive and activating (e.g., enjoyment, happiness, and interest) or negative and deactivating (e.g., boredom, frustration, confusion, and anxiety) (Reschly & Christenson, 2012; Sinatra et al., 2015). Emotional engagement often includes motivational constructs such as task value, relevance, and importance for students' future careers (Martin & Dowson, 2009). Some researchers include community building, relatedness, a sense of community, and belonging as manifestations of emotional engagement (Halverson & Graham, 2019). Both positive and negative emotions have been used to drive students' engagement. Nonetheless, most research so far has focused on the positive effects of emotional engagement with achievement (Sinatra et al., 2015).

Research has shown that all aspects of engagement are associated with academic achievement, lower dropout rates, better well-being, and fewer behavioral problems (Li et al., 2022; Martins et al., 2021). Engaged students are more likely to have better career prospects, a stable social life, and to become productive members of society (Skinner & Pitzer, 2012; Yang et al., 2023). More importantly, engagement is malleable, that is, responsive to intervention that targets individual variables, teachers, or instructional environment (Kassab, El-Sayed, & Hamdy, 2022; Zielińska, Lebuda, & Karwowski, 2022). Such malleability of engagement stands in contrast to the immutable biological and sociodemographic variables (J. A. Fredricks, Reschly, & Christenson, 2019). According to Pino-James, Shernoff, Bressler, Larson, and Sinha (2019, p. 104), improving the learning environment may have a strong proximal impact on students' engagement that may "overcome bioecological influences such as academic domain, student gender, age, socioeconomic status, and cultural background".

It is important to differentiate between indicators (reviewed above) and facilitators or drivers (the forthcoming section) of engagement. Indicators are outward signs and manifestations of engagement (e.g., behavioral, cognitive, or emotional activities). Facilitators are variables that help enhance engagement, such as environmental variables and affordances. Identifying which instructional variables that influence engagement could help us tailor our interventions by acting on such variables, which is a question our study aims to answer.

1.1.1. Theoretical frameworks for driving engagement

Since the earliest work on student engagement and persistence in education, the temporal process has been recognized. Tinto's (1975) conceptualization of persistence and engagement in college as a longitudinal process of interaction between the students' experiences and the academic and social environment where positive experiences lead to further engaging and positive outcome. Tinto's recent work further clarifies the longitudinal mechanisms that describe how "increased motivation furthers subsequent engagements that enhances learning over time" (Tinto, 2022, p. 374). Such a longitudinal process leads to persistence and completion (Tinto, 2022). A feedback loop ensues, where positive learning outcome kindles more motivation that again kindles engagement and positive outcome. Similar conceptualizations of engagement as a driver of positive outcome over time are present in other theoretical frameworks (e.g., Finn, 1989). Finn describes a longitudinal process where participatory engagement leads to success, identification, and further completion. The notion of engagement as a driver of a long-term process that connects contextual and instructional variables to relatedness, and persistence or success is also present in other theoretical models as well (Skinner, Furrer, Marchand, & Kindermann, 2008). Skinner describes Self-System Processes where personal resources are developed over time as the students interact with their contexts. The model postulates that *self needs* for autonomy, competence, and relatedness lead to action (engagement) which in turn leads to outcome (achievement). A question arises, as whether engagement is a mediator or an outcome. As Reschly and Christenson (2012) clarify, in the short-term, engagement can be an outcome (e.g., participation in classes) whereas, in the long term, engagement can be a mediator (Reschly & Christenson, 2012). Nevertheless, a complete understanding of the temporal scales of engagement overtime remains far from complete (Archambault, Janosz, Olivier, & Dupéré, 2022).

The relationship between motivation and engagement is rather complex with significant interactions and overlap. We concur with the view that motivation, as aforementioned in Tinto's (2022) model —and emphasized by Skinner and Raine (2022)— is inextricably intertwined with engagement and offers a complementary perspective for the understanding of engagement as a process. Such complementary perspectives —as summarized by Skinner and Raine (2022)— support that motivation helps provide conditions for learning, mediates positive perceptions and choice of learning contexts, drives students effort regulation, and boosts positive communications.

1.2. Drivers of engagement

The recent work of Martin and Borup (2022) builds on the aforementioned frameworks and offer an overarching conceptualization of engagement facilitators which are the variables we seek to address in our study. As such, we rely on the said framework as a base for categorizing the drivers of engagement. The framework proposes five categories of engagement drivers, namely, communication, collaboration, interaction, presence, and community, which we concisely review here.

Research has shown that all types of **communication** (synchronous, asynchronous, or mixed) can increase engagement. For instance, engaging instructional materials were found to boost students' engagement in asynchronous online courses (Draus, Curran, & Trempus, 2014; Ong & Quek, 2023). Teachers' communication through video, teaching style, and course design were important variables that helped engage students in synchronous learning (Martin, Parker, & Deale, 2012). Saqr & López-Pernas, 2022 found that using a synchronous online platform for group discussions has helped students to be more engaged, responsive, and productive. In the same way, **collaboration** can increase students' engagement when designed, structured, or supported with pedagogy in mind. As Jeong, Hmelo-Silver, and Jo (2019) noted, collaborative group work enhances students' engagement with learning resources and stimulates critical thinking and deep understanding. Collaborative learning may also increase online engagement through shared knowledge construction and productive collaborative interactions, although it may also constitute an important source of frustration and challenge among learners (Järvelä & Hadwin, 2013).

By the same token, the engaging role of **interactivity** has long been recognized (Moore, 1989) and empirically supported (Bempechat & Shernoff, 2012; Bernard et al., 2009). Engagement is viewed as a product of temporal interactions with learning activities, learning tasks, peers, teachers and the elements of the learning environment (Bempechat, Shernoff, Wolff, & Puttre, 2022). According to Bernard et al.'s (2009) meta-analysis, all three types of interactions (students' interactions with content, with the teacher, and with peers) boost student cognitive engagement and achievement.

Teachers are important drivers of students' positive engagement (Ong & Quek, 2023; Rafique, 2022). The presence of a teacher may enhance students' positive perceptions of the classroom and thus serve as a motivational stimulus that promotes active participation and engagement. Teachers can also actively enhance or facilitate students' engagement in case it is needed (Pianta, Hamre, & Allen, 2012). Findings have consistently emphasized that students benefit from teacher support and responsiveness, which may drive students to invest time and effort in doing school work (Martins et al., 2021). For instance, teachers' facilitation and positive feedback were reported to enhance students' cognitive engagement with the study modules (Guo, Chen, Lei, & Wen, 2014). Similar results were reported by previous works about interactive learning environments (Baker, 2010; Kucuk & Richardson, 2019). Teachers' positive influence was demonstrated to have a positive impact on students' engagement after controlling for demographic variables (Zhang, Lin, Zhan, & Ren, 2016).

The last facilitator in Martin and Borup's (2022) framework is the **community**. Students' sense of school as a supportive community provides students with basic needs of sense of belonging and relatedness and enhances students' commitment to school, attendance, and positive emotions about school, e.g., enjoyment, interest, and happiness (Chiu, 2022; Li & Lerner, 2011; Martin & Dowson, 2009a). By the same token, students' relationships and interactions with peers have also received considerable empirical support as positive drivers for engagement (Bond et al., 2020).

While we have summarized the variables that enhance students' engagement according to Martin and Borup's (2022) model, a comprehensive review is beyond the scope of our paper. A more in-depth discussion of the theoretical frameworks and the status of the field is well summarized in the recent work of (Reschly & Christenson, 2022) where the authors list and discuss each of the theories and framework of engagement. A very detailed and elaborate discussion of how motivation is related to engagement with a full overview of theoretical frameworks, a discussion of points of overlap is presented in the recent work of Skinner and Raine (2022).

1.3. For whom?

Evidence is mounting that human behavior, emotions and cognition are heterogeneous and varies considerably among different subgroups of a population (Bolger, Zee, Rossignac-Milon, & Hassin, 2019; Yang et al., 2023). Learning and, in particular, engagement, are no exceptions (Salmela-Aro et al., 2021; Yang et al., 2023). That is, different subgroups of students have different engagement profiles and engagement trends. In their review of longitudinal engagement research, Salmela-Aro et al. (2021, p. 267) found that almost all studies relied on variable-centered methods, which the authors have described as "problematic" given the existence of "several recent person-oriented analyses of student engagement showing diverse profiles of engagement occurring within different samples and timescales". Therefore, modeling heterogeneity using person-centered methods is needed to capture the hidden (or latent) patterns of engagement. Person-centered methods allow researchers to find homogenous groups that share similar characteristics and represent distinct "states", for instance, engagement states in our case (Hickendorff, Edelsbrunner, McMullen, Schneider, & Trezise, 2018; Yang et al., 2023). This is particularly important in longitudinal studies to avoid trends canceling each other out. That is, a rising trend within a subgroup cancels a decreasing trend within another subgroup, giving rise to a wrong conclusion of a flat trend (Asikainen & Gijbels, 2017). In our study, we use person-centered methods to explore the different patterns of engagement and transitions thereof. We, thus, follow the recent paradigm shift in learning analytics that advocates focusing on the individual rather than the group, referred to as idiographic learning analytics (Saqr & López-Pernas, 2021).

1.4. How does engagement evolve?

Research on engagement has commonly addressed a single time point, course, or task. Less often, research has looked at the longitudinal evolution of engagement across time (Salmela-Aro et al., 2021; Smith & Tinto, 2022). The majority of the extant research has focused on classroom engagement and used self-reported surveys and online trace data (Poquet, Jovanovic, & Pardo, 2023; Lopez-Pernas & Saqr, 2021; Zhu et al., 2016). Nevertheless, today, there is evidence that engagement has a cross-course pattern, where students engaged in a course are likely to continue to be engaged in the following course (Li & Lerner, 2011; You & Sharkey, 2009). While earlier studies have reported contradictory evolution patterns, evidence suggests that engagement has a heterogenous evolution pattern, i.e., varies by engagement intensity or pattern. That is, highly engaged students may evolve differently from disengaged students. Such a pattern —with variations— has been demonstrated in face-to-face settings (Archambault & Dupéré, 2017; Zhen et al., 2020) and online settings (Saqr & López-Pernas, 2021). For instance, previous research has clustered students according to their engagement intensity and found that a subgroup of students are likely to stay engaged across the program and another group who are predominantly troubled or disengaged across the program (2017; Janosz, Archambault, Morizot, & Pagani, 2008; Zhen et al., 2020). Similar results were reported by Saqr and López-Pernas (2021) in an online program.

In the same token, momentary research, which seeks to study the longitudinal evolution of engagement across small time scales, for instance, hours or minutes, has reported similar subgroups of different evolution patterns. Schmidt, Rosenberg, and Beymer (2018) identified six distinct momentary engagement profiles. The authors reported a similar, relatively stable high-achievement group as well as a troubled, yet stable disengaged group. Symonds, Schreiber, and Torsney (2021) found seven momentary task engagement profiles. Two main profiles consisted of students that were consistently highly engaged (28%) or consistently disengaged (13%) in all indicators. Other profiles included students with contradictory scores on the indicators (e.g., higher on one and lower on the other). The focus of our study is the transition between engagement states. Below, we review the concept concisely and look at the papers that have used similar methods.

Transition and change analysis is rather scarce in education despite the need for understanding the dynamics of learners' behaviors. The few existing examples have been mostly descriptive: i.e., they described the transition probabilities without estimating the variables influencing the transitions. Among such examples, Li et al. (2016) analyzed skill mastery evolution and transitions and found that students frequently improved rather than decreased their mastery levels of the skills they already excelled at. Other studies (Saqr, López-Pernas, Jovanović, & Gašević, 2023; Fryer & Vermunt, 2018) investigated the transitions in university students' learning strategies and found that superficial strategies were the most stable, i.e., students did not naturally improve in their use of strategies (Lau, Sinclair, Taub, Azevedo, & Jang, 2017). Similarly, Gillet, Morin, and Reeve (2017) found that both students with the highest and lowest motivation profiles were rather stable, while students with moderated motivation were more fluctuating. Probably the closest study on engagement was conducted by Saqr, López-Pernas, Helske, & Hrastinski, 2023, where the authors studied longitudinal engagement and estimated the transition probabilities between such engagement states. Their findings have pointed to infrequent transitions between high-achievement states, whereas the medium and lower-achievement states were less stable. Yet, the study by Saqr and López-Pernas (2021) focused on engagement state evolution and described the transitions without studying the "why", i.e., which factors led students to maintain their engagement state or transition to another one.

The emergence of learning analytics has enabled opportunities for capturing data in an unobtrusive way (i.e., passive data capture) where the students and the teachers are undisturbed (Poquet et al., 2023; Zhu et al., 2016; Lopez-Pernas & Saqr, 2021). Researchers contend that using trace log data is accurate compared to self-reports which may suffer from recall inaccuracies (Zhou & Winne, 2012). Another concern about self-reports data is that they reflect the intention to study not the actual studying (Gasevic et al., 2017). Another advantage of learning analytics is that trace logs are time stamped which provides an excellent opportunity for fine-grained temporal analysis. As such, the study of engagement has become an important theme in learning analytics research (Poquet et al., 2023; Zhu et al., 2016). Learning analytics researchers have studied online engagement measurement (Caspari-Sadeghi, 2022; Zhu et al., 2016), shown how engagement evolves over time, and addressed the consistency of engagement (Poquet et al., 2023; Zhu et al., 2016). Recently, longitudinal research has attracted the attention of learning analytics researchers (Saqr & López-Pernas, 2021; Barthakur et al., 2021).

2. Methods

2.1. Context

The study was conducted in a healthcare program at Qassim University. The courses in the program were arranged sequentially; that is, students participated in one course at a time. Although each course covered a different healthcare-related topic, all courses had a similar structure based on the problem-based learning (PBL) paradigm. An exception was some practical courses (e.g., clinical skills) which took place throughout the whole year and had a different pedagogical approach. Such courses were excluded for the purpose of this study. The courses followed the well-known PBL seven-jump approach (Wood, 2003). At the beginning of each week, the students are presented with a problem related to the course topic. They start by having a face-to-face meeting where they discuss the problem and set the learning objectives. Throughout the week, the rest of the PBL takes place online on the Moodle Learning Management System (LMS) platform. The students carry out discussions about the problem in the forum and consult the lectures available online. As a result, even though part of the learning happened offline, engagement in the program's online component was essential for student success. The students also have face-to-face lectures related to the problem topic, practical sessions, as well as seminars. The study involved six courses that were taught sequentially over the first and second years.

Student performance was measured through their GPA (Grade Point Average), which was the sum of all course grades in the program. The course grades were divided into three parts: (1) the level of engagement in the online forums, (2) the continuous evaluation of student performance in the learning tasks and class participation, and (3) the final exam. The final exam made up 80% of the final grade, while the remaining 20% was divided among the last components: 10% for continuous assessment (e.g., seminar preparations, practical assignments, participation in lectures, and course duties), 5% for online forum participation (not the frequency), and 5% for in-person PBL group meetings and participation in lectures and seminars. To avoid inclusion of grades allocated to engagement or participation, we only used the final exam grades, whereas the continuous assessment grades were not used in the analysis.

2.2. Measures and operationalization

Data collection was informed by the literature about measuring online engagement with learning analytics methods (Henrie et al., 2015; Sinatra et al., 2015; Zhu et al., 2016), as well as the recent conceptual model of Martin and Borup (2022). In learning analytics research, online engagement is commonly operationalized through observable online traces recorded by computers as trace logs (Gasevic et al., 2017; Poquet et al., 2023; Zhu et al., 2016; Lopez-Pernas & Saqr, 2021). The trace logs are used to compute indicators of students' access and investment in online learning such as the frequency of postings, frequency of learning resource views, and the time spent online (Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Zhu et al., 2016). Such online traces can reflect both behavioral and cognitive engagement while barely accounting for emotional engagement. Researchers contend that there is a close interrelation between engagement dimensions, in that behavioral engagement is an "outward manifestation" of cognitive and emotional engagement (Halverson & Graham, 2019). As Martin and Borup (2022, p. 165) state, "in many ways behavioral engagement is the physical representation of cognitive and affective engagement". Thus, "researchers may infer internal processes from external behaviors, and while those behaviors are not trivial, they still can be recognized as the outward displays of the mental and emotional energies that fuel learning" (Halverson & Graham, 2019, p. 153). As such, we collected online trace data and computed a set of indicators that represent the two types of engagement that are possible to capture from LMS data: behavioral and cognitive engagement (Gasevic et al., 2017).

In our study, behavioral engagement was captured by the frequency of usage and time spent on the online resources. Cognitive engagement was captured by engagement in cognitively challenging learning activities (i.e., problem solving) which requires students to read ill-structured problems and engage in a critical analysis of the problem. It also requires that students construct arguments, counter-arguments, debate the solutions of others and provide alternative explanations or solutions. The said activities of problem-solving are cognitively challenging by design to allow students to make deep connections between past knowledge and the existing problem scenario, and link information across several domains of knowledge (Henrie et al., 2015; Rotgans & Schmidt, 2011). Such PBL activities capture the definition of cognitive engagement according to Borup, Graham, West, Archambault, and Spring (2020, p. 813): "the mental energy exerted towards productive involvement with course learning activities". It is worth noting that there is an overlap between behavioral and cognitive engagement; going "beyond the required" (cognitive engagement) necessitates that a student first performs the required (behavioral engagement) (Sinatra et al., 2015). To that end, our operationalization of engagement followed such views as well as informed our data collection and indicators.

2.3. Indicators

Following the latest literature reviews (Ahmad et al., 2022; Wang & Mousavi, 2023) and guides on measuring online engagement unobtrusively (Caspari-Sadeghi, 2022) and based on the aforementioned frameworks (e.g., Martin & Borup, 2022), two types of indicators of engagement were calculated from students' LMS logs: resource-specific indicators and general indicators. The resource-specific indicators were calculated for the following events: browsing the course main page, viewing lectures, and reading or composing a post in the PBL forums: *Course browsing* reflects students' engagement with the course content, announcements, news, and updates of learning resources and events. *Lecture viewing* reflects students' access to the learning resources, such as presentations of lectures, summaries of lectures, videos, or links to online resources (Ahmad et al., 2022; Qiu et al., 2022). *Composing PBL posts* reflects students' involvement in problem solving through writing posts which requires investing cognitive mental energy to synthesize, connect and contribute to the PBL interactions. *Reading PBL posts* reflects students' involvement in problem solving, reading others' perspectives, and learning from others. Also, students need to read the whole discussion thread and keep up with updates to compose a reply (Jeong et al., 2019; Kristianto & Gandajaya, 2023).

To capture the full breadth of students' engagement with each resource, we calculated the *frequency*, *active days*, and *regularity* of each of the events mentioned in the previous paragraph (resource-specific indicators). The *frequency* of an event is the number of instances (total cumulative count) of the event throughout the course (Ahmad et al., 2022; Wang & Mousavi, 2023). The *active days* is the count of days where a student had at least one event of that type (Wang & Mousavi, 2023). The *regularity* of students' online behavior was measured by the *entropy* (degree of consistency) (Wang & Mousavi, 2023). To calculate the entropy for each type of event, we counted the number of events of that type that each student had per day (if any), and we divided each daily count by the total number of events of that type throughout the course. The resulting ratios were used as probabilities in Shannon's entropy formula (Jovanović, Saqr, Joksimović, & Gašević, 2021). For example, in a course that is three days long, where a student published in the forum once on the first day, five times on the second day, and did not publish at all on the last day, 1/6, and 5/6 would be the probabilities used as an input in Shannon's formula to calculate the forum composing entropy (the third day is not counted as it did not have any events of that type). Altogether, we computed the following resource-specific indicators: *Frequency Course Browse*, *Frequency Lecture Viewed*, *Frequency Forum Consume*, *Frequency Forum Contribute*, *Active Course Browse Days*, *Active Lecture View Days*, *Active Forum Consume Days*, *Active Forum Contribute Days*, *Course Browse Entropy*, *Lecture View Entropy*, *Forum Consume Entropy*, and *Forum Contribute Entropy* (Ahmad et al., 2022; Wang & Mousavi, 2023).

Two general indicators were computed to represent how engaged students were: (1) the number of events in the course (*Total Events*), including all course browsing and navigation activities, and (2) the *Session Count*, which is the total cumulative number of sessions. The session count was computed as the number of uninterrupted series of events in which there were no more than 15 min between any two consecutive activities (Jovanović et al., 2017). The cut-off value of 15 min used to determine when to start a new session corresponds to the 95th percentile of the time between any two consecutive events in the dataset. All the above-mentioned indicators (14 in total: 12 resource-specific and 2 general ones) were calculated for each student across 6 sequential courses, i.e., each student had 6 sets of (14) indicators (one for each course).

2.3.1. Covariates

To investigate the variables that affect transition, covariates that could affect students' online engagement were computed. In an online learning environment, we need to capture how engaging the learning environment and the learning resources were (contextual variables), as well as the teacher's involvement in the course (teacher variables). These contextual covariates are proxy indicators of the value and importance of the content and the overall interactivity of the course as well as course design (Artino, 2009; Wigfield & Eccles, 2000). Such an assumption is supported by a large body of research on subjective task value, beliefs, and motivation (Chiu, 2022; Wigfield & Eccles, 2020). As Artino (2009, p. 123) concluded, "subjective perceptions of the learning environment may ultimately shape students' motivational and behavioral engagement in that environment." We refer to such variables as contextual variables. For each student, contextual variables were computed as the total number of events of all "*other*" students' in the given course. The second type of covariates were the teacher variables: the number of lectures created by the teachers, the number of forums created, the number of course board editions, and the number of active days (Quin, 2017). Since covariates will be entered in a regression model, we have to avoid redundancy and use a parsimonious model. As such, we used a single variable for each covariate (e.g., teacher number of created lectures) to avoid collinearity with other possible variables (e.g., teacher number of clicks on lectures). All covariates were calculated for each student across the six sequential courses in the program. The teacher-related covariates were the same for all the students in the same course. The contextual covariates related to other students were calculated individually for each student and course as the mean value of each covariate for all the students in the course except for himself/herself. Fig. 1 shows the operationalization of the variables and covariates: the variables were used in an Latent Markov Factor Analysis (LMFA) model, where factors and states were identified. The covariates were then used to identify their effect on the transition probabilities.

2.4. Data analysis

Studying the transitions between engagement states requires specialized methods that allow the identification of engagement states and the estimation of the transition tendencies —often referred to as probabilities— between such engagement states; that is, when and to what extent students change their engagement state. For such a purpose, multi-state models are the gold standard (Hickendorff et al., 2018; Jackson, 2011). Modern implementations of multi-state models allow the inclusion of time-varying covariates, which allow the dynamic estimation of the effect of the variables (e.g., teachers or instructional materials) on the transitions at each time point. One such implementation is Latent Markov Factor Analysis (LMFA). LMFA is a novel method that allows the discovery of latent states, the evaluation of the qualitative difference between such states, as well as the modeling of transitions and the variables influencing such transitions (Vogelsmeier, Vermunt, van Roekel, & De Roover, 2019; Vogelsmeier, Vermunt, & De Roover, 2022). In our study, we take advantage of LMFA to study engagement states, transitions, and the variables that influence transition (covariates).

The data analysis was performed using LMFA, a method that combines multistate modeling with mixture factor modeling. Mixture factor models allow us to capture the multifaceted nature of students' engagement (through factor models) as well as the modeling of transitions between different engagement states throughout the six courses of the program. Furthermore, LMFA is a person-centered method that captures qualitative differences in response patterns over time (Lubke & Muthén, 2005; McLachlan & Peel, 2000), while having the strength of latent Markov modeling to track changes in response patterns over time (Bartolucci, Farcomeni, & Pennoni, 2012; Collins & Lanza, 2009). More specifically, LMFA classifies individual and time-point-specific observations based on response patterns (i.e., students' engagement at a certain measurement occasion) into latent classes. These latent classes are referred to as "states'' because individuals can transition between them from one time point to the next. For example, a particular student may transition from a disengaged state in one course to an actively engaged state in the next course. The probability of transitioning between states may depend on external circumstances (covariates), such as instructional variables. For example, engaging interactive forums created by the teacher may increase the probability of transitioning to an active engagement state in that course. Note, however, that not all individuals need to transition. Some students may stay in the same state across their entire participation, perhaps because they are actively engaged regardless of the presence or absence of instructional variables.

Two types of parameters describe the transitions between the (engagement) states. The initial state probabilities indicate the probability of starting in a given state, whereas the transition probabilities determine the probability of being in a state at the current measurement occasion (i.e., a certain course in our study), given the state membership at the previous measurement occasion. To understand what increases or decreases the probabilities of either starting or transitioning towards or away from the states, one can relate time point-specific covariates to the transition probabilities. In our study, these are covariates that represent the instructional variables and the teacher variables (see Covariates section).

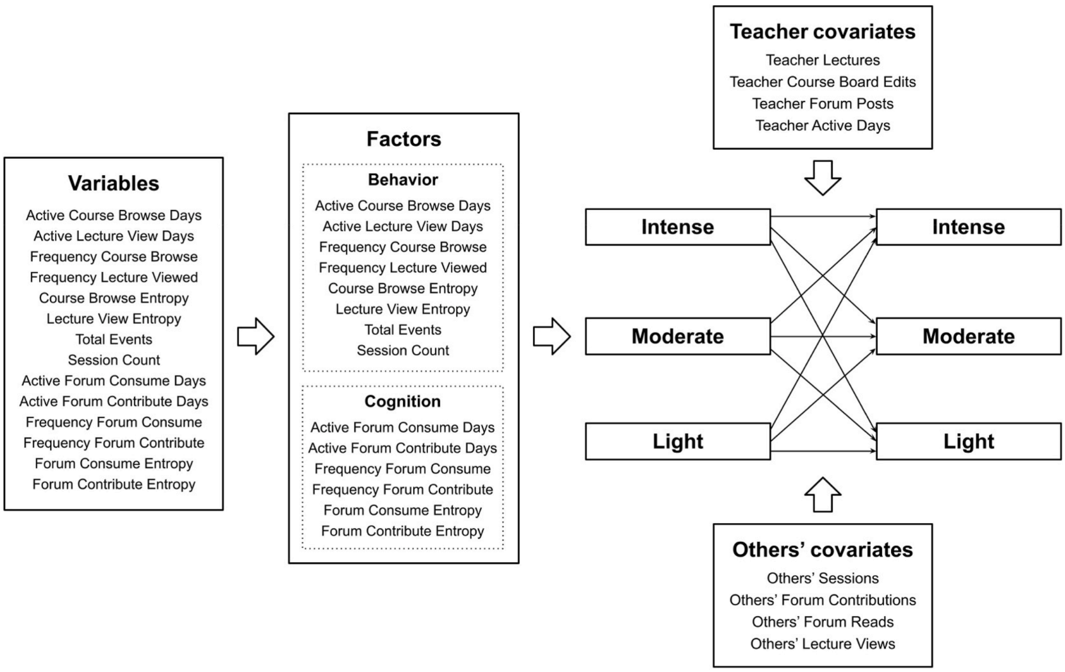

Fig. 1. An illustration of the variables, factors and covariates used to study students' states and transitions.

The responses within the latent states are modeled using factor analysis, a multivariate analysis method aiming to explain the covariances between variables by a smaller number of unobserved or latent variables, which are called factors (Lawley & Maxwell, 1962). Using factor analysis within the states has two advantages for our student data. First, factor analysis facilitates modeling engagement states in the presence of many variables, thus allowing the capturing of the multifaceted aspects of students' online behavior (e.g., frequency, time, and regularity of posting). Second, the response patterns in the engagement states can differ not only regarding the average item scores but also with regard to how items are related to the underlying latent factors. This is more realistic than assuming identical item-factor relations and is also substantially relevant since research has shown that not all online activities are similar (e.g., composing a PBL response is effortful cognitive energy compared to clicking a link to download a lecture file).

To answer RQ1 and RQ2, we apply LMFA to our data (for details, see Vogelsmeier, Vermunt, Bülow, & De Roover, 2021, 2019). In order to fit LMFA to our data, we use the open-source R package '*lmfa*'. This package splits the estimation into three steps: (1)

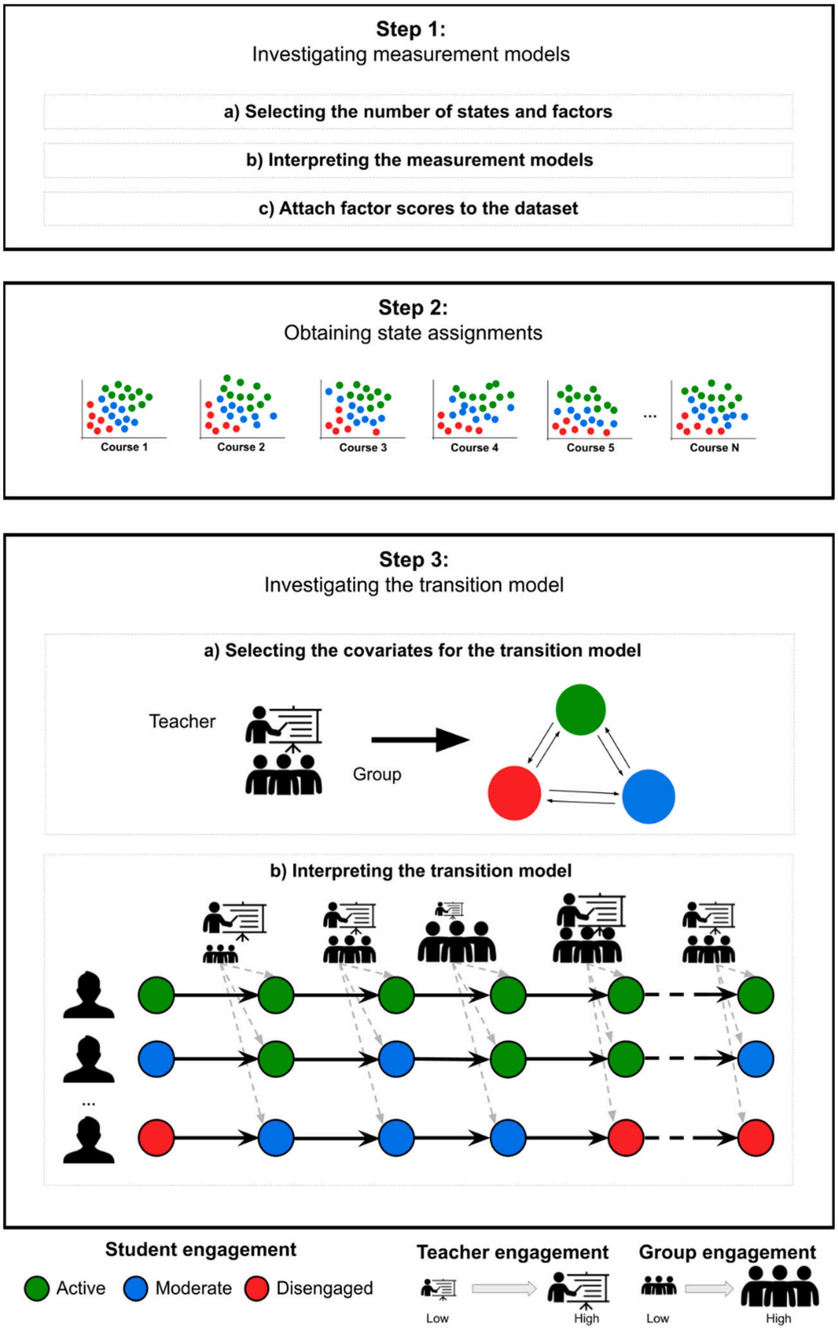

Fig. 2. Summary of the three steps of LMFA data analysis (Vogelsmeier, Vermunt, & De Roover, 2022).

investigating the factor models, (2) obtaining state assignments (and classification errors), and (3) investigating the covariate-specific transition model. Below, we describe the three steps and how they answer our RQs (for details, see Vogelsmeier, Vermunt, & De Roover, 2022). The three steps are summarized in Fig. 2.

First, in step 1, all observations are treated as independent in order to estimate the state-specific engagement response patterns. It is not known a priori how many engagement states are present and how response patterns differ; that is, both the number of latent states and latent factors per state are unknown and need to be determined by estimating several plausible models and selecting the best one according to a model selection criterion that balances fit and parsimony. The *lmfa* package automatically ranks the converged models by their BIC (Bayesian Information Criterion) values. After choosing the best model according to this criterion, we can answer RQ1; that is, which engagement states can be identified and what their characteristics are. To understand the differences in the states, we inspect the item means and item-factor relationships. A total of 122 models were estimated with all possible combinations of the number of states (1:5) and the number of factors (1:5). Note that only converged models are considered in the model selection.

Next, in step 2, the individual and measurement-occasion-specific observations are assigned to the engagement states. As LMFA is a probabilistic model, the observations belong to all states with a certain probability, and in step 2, they are assigned to the state they most likely belong to. Note that observations are typically assigned to one state with probabilities approaching one. Nevertheless, some classification errors are always present. However, this is automatically accounted for in step 3 of the analysis, described next.

In step 3, the engagement states are treated as fixed, and individuals' transitions between the engagement states are estimated. In this step, it is possible to add measurement-occasion-specific covariates to the model; that is, the instructional variables. In this study, we add the student's performance to the initial state probabilities. This is because the grades affect students' initial engagement state (Lei, Cui, & Zhou, 2018). The instructional variables that we included as covariates for the transition probabilities were the number of lectures created by the teacher (*Teacher Lectures*), the number of course board editions by the teacher (*Teacher Course Board Edits*), the number of forum posts created by the teacher (*Teacher Forum Posts*), and *Teacher Active Days*, as well as *Others'* number of sessions (*Others' Sessions*), forum composing frequency (*Others' Forum Contributions*), lecture viewing frequency (*Others' Lecture Views*) and forum readings (*Others' Forum Reads*). Which covariates have significant effects are evaluated using Wald test statistics. By investigating the evolution of state membership across the six courses and comparing the transition probabilities for different scores on the instructional variables, we answer RQ2; that is, to what extent students transition between engagement states and how likely the transitions are influenced by instructional variables (Jackson, 2011; Vogelsmeier et al., 2019).

To answer RQ3, a linear regression was performed where the final performance was the dependent variable, and the integration index was the independent variable. The integration index measures the capability of a student to assume a favorable state (an intensely engaged state) or return to the engaged state after descending to a lower state (disengaged state) (Gabadinho, Ritschard, Müller, & Studer, 2011). The integration index is calculated as "the sum of the position numbers occupied by the selected state in the sequence over the sum of all position numbers" (Gabadinho et al., 2023, p. 113). Formally, for a sequence *s* of length *L*, and numbering the positions *i* from 1 to *L*, the integration index can be calculated using the following formula:

$$integr = \sum_{i \mid s_i = state} i^{pow} \Big/ \sum_{i} i^{pow}$$

where *state* is the favorable state (an intense engaged state in our case). The exponent *pow* gives more weight to the latest position in the sequence. In other words, it is a measure of the likelihood of transitioning to and remaining in an engaged state and ending in it. Students who transition to, remain and end in an engaged state have the highest values, and vice versa. Please note that since a moderate state can be —arguably— a favorable state too, we also fitted the model with this possibility. The regression model assumptions were met regarding the error distribution, the linearity of the variables, and the absence of outliers. The amount of explained variance was evaluated using R^2, which measures the fraction of variance explained by the model (Nakagawa & Schielzeth, 2013).

3. Results

The descriptive statistics of each engagement indicator can be seen in Table S1, including the mean and standard deviation of each indicator per student and course. Each student was active on the LMS an average of 23.7 days per course (*Active Course Browse Days,* SD = 9.6), out of which they viewed the online lectures a mean of 12.9 days (*Active Lecture View Days*, SD = 7.6). On average, students visited the course main page 63.9 times per course (*Frequency Course Browse*, SD = 43.9), and the lectures 49.9 times (*Frequency Lecture Viewed*, SD = 40.3). The mean regularity of a student visiting each course's main page according to the entropy formula was 4.1 (*Course Browse Entropy*, SD = 0.4), and the mean regularity of viewing the course lectures was 2.9 (*Lecture View Entropy*, SD = 1.0). Students had an average of 354.8 clicks of any type per course (*Total Events*, SD = 208.8), and of 55.5 sessions (*Session Count*, SD = 31.8). Regarding forum activity, students were active readers of others' comments an average of 14.4 days per course (*Active Forum Consume Days*, SD = 7.8), and contributed to the discourse an average of 7.5 days (*Active Forum Contribute Days*, SD = 4.2). On average, a student read the forum 164.2 times per course (*Frequency Forum Consume*, SD = 117.3), and posted 64.8 times (*Frequency Forum Contribute*, SD = 50.1). The mean regularity of a student reading the forum was 3.1 (*Forum Contribute Entropy*, SD = 0.9), and the mean regularity of writing a post was 2.5 (*Forum Consume Entropy*, SD = 0.9). The descriptive statistics of the covariates are listed in the appendix Tables S2 and S3.

RQ1. Which engagement states can be identified using Latent Markov actor analysis and what are the state's

characteristics?

The best LMFA model according to BIC value was a three-state model with two factors. The average probabilities with which the observations were assigned to the three states were 0.92, 0.93, and 0.92, respectively. The total classification error was 0.07, and R^2 entropy was .83. These fit values show that the states were clearly separated with very low classification errors. A comparison of means using Kruskal–Wallis one-way analysis of variance showed that the comparisons of indicators across states were statistically significant with a large effect size in almost all variables (Table S4).

The three engagement states were labeled according to activity indicators as *Intense*, *Moderate* and *Light*. Table 1 shows the mean value of each indicator per state and Table 2 shows the factor loadings. In all states, the first factor encompasses activities that are mainly related to ***behavioral engagement***, where the factor loadings are high for the variables of lecture access, course browsing, total events, and the number of sessions. The second factor encompasses activities related to problem-solving and interactions in the PBL forums (e.g., frequency of composing forum PBL posts, reading others' contributions, regularity and active days of composing or reading the PBL forums). Therefore, the second factor is mainly related to ***cognitive engagement,*** where students have to invest cognitive energy to read, contribute and follow the PBL discussions, and advance the arguments. Below we describe the characteristics of each state:

The ***Intense*** state (358, 25%) shows, compared to the other states, higher activity on all indicators. As such, students in ***Intense*** state were actively and regularly engaged with activities that require mental energy, i.e., problem-solving, reading others' contributions (*Frequency Forum Consume* = 0.80), and contributing to problem solving and discussions (*Frequency Forum Contribute* = 0.55). Similarly, the students in the ***Intense*** state showed a higher number of lecture reads (*Frequency Lecture Viewed* = 0.70), course browsing (*Frequency Course Browse* = 0.92), active days (*Active Course Browse Days* = 0.68), session counts (*Session Count* = 0.88), as well as higher values of regularity, compared to the other clusters (*Course Browse Entropy* = 0.42). The factor loadings were consistently high across all indicators of both factors (Table 2). Therefore, we could say that the ***Intense*** cluster was behaviorally and cognitively highly engaged.

The ***Moderate*** state (737, 51.6%) shows intermediate levels of activity across all indicators that revolved around the average. Thus, the ***Moderate*** state has slightly below-average lecture view counts (*Frequency Lecture Viewed* = −0.16), session counts (*Session Count* = −0.05), and course browsing (*Frequency Course Browse* = −0.14). They also had slightly above average active days (*Active Course Browse Days* = 0.08), regularity values (*Course Browse Entropy* = 0.22), forum composing (*Frequency Forum Contribute* = 0.09) and reading indicators (*Frequency Forum Consume* = 0.03). Therefore, the students in the ***Moderate*** state were moderately and actively engaged on both the behavioral and the cognitive dimensions. The factor loadings were rather consistent across the behavioral factor and inconsistent on the cognitive factor, where the loading was highest on the frequency of forum composing and reading.

The ***Light*** state (333, 23.3%) shows low levels of activities across all indicators which is lowest in forum reading (*Frequency Forum Contribute* = −0.71), active forum reading days (*Active Forum Consume Days* = −0.88), total events (*Total Events* = −0.86), and active course browsing days (*Active Course Browse Days* = −0.81). Their lecture view activities (*Frequency Lecture Viewed* = −0.40), and the number of days they engaged with the lectures (*Active Lecture View Days* = −0.57) are relatively more frequent than all of the other activities, which indicates that the students in this state were slightly behaviorally engaged and cognitively disengaged. The factor loadings were distributed across the two factors and were the lowest in frequency indicators.

RQ2. How and to what extent do students transition between engagement states, and how likely are they influenced by instructional variables?

The rate at which students transition from an engagement state to another engagement state (this could be a different state, or the same different state) is the transition rate we are interested in here. The observed transition rates between each state at each time point are depicted in Fig. 3. Generally, students were more likely to assume an engagement state and persist in such a state. More specifically, students in the *Intense* state were more likely to remain *Intense* (overall transition rate = 56%), students in the *Moderate* state were more likely to remain Moderate (62%), and students in the *Light* state were more likely to remain *Light (50%)*. Transitioning between *Intense* and *Light* was rare (6%) and slightly higher from *Light* to *Intense* (8%). Transitioning away from the *Moderate* state was relatively higher

Table 1
Mean count of each of the engagement indicators per student and course in each state.

Variable	Intense	Moderate	Light
Active Course Browse Days	0.68	0.08	−0.81
Active Lecture View Days	0.61	−0.01	−0.57
Frequency Course Browse	0.92	−0.14	−0.65
Frequency Lecture Viewed	0.70	−0.16	−0.40
Course Browse Entropy	0.42	0.22	−0.79
Lecture View Entropy	0.47	0.09	−0.62
Total Events	0.94	−0.04	−0.86
Session Count	0.88	−0.05	−0.78
Active Forum Consume Days	0.63	0.14	−0.88
Active Forum Contribute Days	0.32	0.14	−0.56
Frequency Forum Consume	0.80	0.03	−0.85
Frequency Forum Contribute	0.55	0.09	−0.71
Forum Consume Entropy	0.40	0.24	−0.80
Forum Contribute Entropy	0.22	0.17	−0.50

Table 2
Factor loadings for each of the three engagement states.

	Intense		Moderate		Light	
Variable	Behavior	Cognition	Behavior	Cognition	Behavior	Cognition
Active Course Browse Days	0.86	0.02	0.79	−0.03	0.59	0.24
Active Lecture View Days	1.02	−0.09	0.66	0.03	0.83	−0.08
Frequency Course Browse	0.98	0.03	0.45	0.15	0.30	0.09
Frequency Lecture Viewed	0.85	−0.26	0.28	0.13	0.59	−0.09
Course Browse Entropy	0.73	0.04	0.67	−0.10	0.77	0.37
Lecture View Entropy	0.78	0.01	0.62	0.03	1.06	−0.10
Total Events	0.55	0.33	0.16	0.64	0.22	0.22
Session Count	0.94	0.16	0.49	0.20	0.33	0.16
Active Forum Consume Days	0.42	0.27	0.37	0.13	0.05	0.63
Active Forum Contribute Days	−0.03	1.12	0.12	0.48	−0.01	0.92
Frequency Forum Consume	0.25	0.47	0.03	0.69	0.03	0.30
Frequency Forum Contribute	−0.07	0.66	−0.10	0.81	0.02	0.36
Forum Consume Entropy	0.29	0.50	0.32	0.02	0.05	1.06
Forum Contribute Entropy	0.01	1.02	0.13	0.34	−0.04	1.16

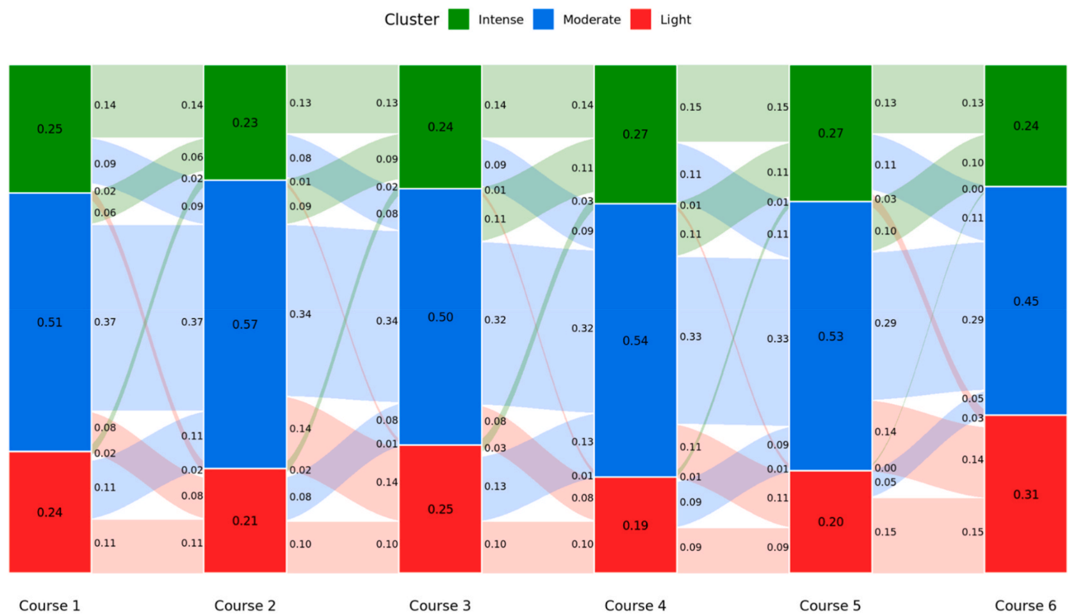

Fig. 3. Evolution of state membership across the six courses. The labels in each bar represent the percentage of students in each cluster at each time point. The labels in the transitions represent the percentage of students transitioning between two engagement states from one course to the next.

Table 3
Wald's test for covariates significance.

	Wald	df	p-value
Final grade standardized (initial)	0.05	2	.97
Teacher Lectures	92.42	6	<.001
Teacher Course Board Edits	−25.89	6	1.00
Teacher Forum Posts	115.36	6	<.001
Teacher Active Days	−461.40	6	<.001
Others' Sessions	9417.94	6	<.001
Others' Forum Contributions	581.09	6	<.001
Others' Forum Reads	2073.91	6	<.001
Others' Lecture Views	85.56	6	<.001

—than from *Intense or Light*— transition to *Intense* was 17% and from *Moderate* to *Light* was 21%.

In addition to examining the observed transition rates, we are interested in the influence of covariates on the overall transition probabilities, and the statistical significance of such covariates (e.g., Li et al., 2016; Vogelsmeier et al., 2021). Table 3 shows the significance level of all covariates according to Wald's test. The covariates of *Teacher Active Days* and *Teacher Course Board Edits* were

Table 4
Effect on transition probabilities for each state when covariates are increased by one standard deviation. The value left of the arrow indicates the original transition probability; the value right of the arrow indicates the transition probability after increasing the covariate, and the value in parentheses indicates the increment/decrement between the two values. The color of the cell is green when the transition probability increases when increasing the covariate value by one standard deviation, and red when it is decreased when increasing the covariate value. The strength of the color indicates the magnitude of the effect.

	Covariate	From	Intense	Moderate	Light
1.	Teacher Lectures	Intense	.31 → .25 (-.06)	.46 → .57 (+.11)	.23 → .17 (-.06)
		Moderate	.17 → .15 (-.02)	.54 → .71 (+.17)	.28 → .14 (-.14)
		Light	.19 → .27 (+.08)	.53 → .54 (+.01)	.28 → .19 (-.09)
2.	Teacher Course Board Edits	Intense	.31 → .33 (+.02)	.46 → .44 (-.02)	.23 → .24 (+.01)
		Moderate	.17 → .14 (-.03)	.54 → .55 (+.01)	.28 → .31 (+.03)
		Light	.19 → .14 (-.05)	.53 → .55 (+.02)	.28 → .31 (+.03)
3.	Teacher Forum Posts	Intense	.31 → .39 (+.08)	.46 → .39 (-.07)	.23 → .21 (-.02)
		Moderate	.17 → .15 (-.02)	.54 → .54 (.00)	.28 → .31 (+.03)
		Light	.19 → .14 (-.05)	.53 → .55 (+.02)	.28 → .31 (+.03)
4.	Teacher Active Days	Intense	.31 → .16 (-.15)	.46 → .53 (+.07)	.23 → .31 (+.08)
		Moderate	.17 → .14 (-.03)	.54 → .59 (+.05)	.28 → .27 (-.01)
		Light	.19 → .16 (-.03)	.53 → .53 (.00)	.28 → .31 (+.03)
5.	Others' Sessions	Intense	.31 → .21 (-.10)	.46 → .51 (+.05)	.23 → .29 (+.06)
		Moderate	.17 → .14 (-.03)	.54 → .67 (+.13)	.28 → .19 (-.09)
		Light	.19 → .21 (+.02)	.53 → .51 (-.02)	.28 → .29 (+.01)
6.	Others' Forum Contributions	Intense	.31 → .31 (.00)	.46 → .43 (-.03)	.23 → .26 (+.03)
		Moderate	.17 → .06 (-.11)	.54 → .59 (+.05)	.28 → .35 (+.07)
		Light	.19 → .06 (-.13)	.53 → .59 (+.06)	.28 → .35 (+.07)
7.	Others' Forum Reads	Intense	.31 → .70 (+.39)	.46 → .25 (-.21)	.23 → .05 (-.18)
		Moderate	.17 → .62 (+.45)	.54 → .28 (-.26)	.28 → .10 (-.18)
		Light	.19 → .35 (+.16)	.53 → .28 (-.25)	.28 → .37 (+.09)
8.	Others' Lecture Views	Intense	.31 → .42 (+.11)	.46 → .40 (-.06)	.23 → .18 (-.05)
		Moderate	.17 → .40 (+.23)	.54 → .42 (-.12)	.28 → .18 (-.10)
		Light	.19 → .41 (+.22)	.53 → .41 (-.12)	.28 → .18 (-.10)
9.	All Teacher covariates	Intense	.31 → .34 (+.03)	.46 → .44 (-.02)	.23 → .22 (-.01)
		Moderate	.17 → .33 (+.16)	.54 → .45 (-.09)	.28 → .22 (-.06)
		Light	.19 → .34 (+.15)	.53 → .44 (-.09)	.28 → .22 (-.06)
10.	All Others Students' covariates	Intense	.31 → .53 (+.22)	.46 → .34 (-.12)	.23 → .13 (-.10)
		Moderate	.17 → .50 (+.33)	.54 → .37 (-.17)	.28 → .14 (-.14)
		Light	.19 → .51 (+.32)	.53 → .36 (-.17)	.28 → .14 (-.14)
11.	All covariates	Intense	.31 → .60 (+.29)	.46 → .28 (-.18)	.23 → .11 (-.12)
		Moderate	.17 → .60 (+.43)	.54 → .29 (-.25)	.28 → .11 (-.17)
		Light	.19 → .60 (+.41)	.53 → .28 (-.25)	.28 → .11 (-.17)

statistically insignificant, and other covariates (teachers' and others') were statistically significant. All covariates related to others' were statistically significant.

Table 4 shows the effect on transition probabilities after increasing each covariate by one standard deviation (the first eight row groups) while holding all other variables constant at average levels (mean). Row group 9 shows the influence of increasing ***All Teacher covariates*** combined and row group 10 shows increasing ***All Others Students' covariates*** while keeping all teacher covariates constant at an average level (mean) in all cases. Whereas increasing a single variable or a group of variables while holding all other covariates constant may be unrealistic since student activities are essentially correlated, it is worth examining to reveal the possible influence of individual variables on transition probabilities (Tinto, 2022). Row group 11 shows the influence of increasing ***All covariates,*** which is closer to reality than any other previous scenarios.

Increasing the number of lectures created by the teacher (row group 1, ***Teacher Lectures***) lowers the probabilities of transitioning to the *Light* state (the most disengaged one) for all roles (−0.06 *Intense*, −0.14 *Moderate*, −0.09 *Light*), increases the probabilities of transitioning to a *Moderate* engagement state (+0.11 from *Intense*, +0.17 from *Moderate*, +0.01 from *Light*), and increases the probabilities that students with *Light* engagement become actively engaged (*Intense* +0.08). Yet we see a small decrease of transition from *Intense* to *Intense* (−0.06) and *Moderate* to *Intense* (−0.02). An explanation for this transition pattern may be through examining the next covariate related to the frequency of ***Teacher Forum Posts*** in the forums (row group 3) —a resource that needs more cognitive engagement— which increases the probability of *Intense* transitioning to *Intense* (+0.08), and decreases the probability of *Intense* transitioning to lower engagement states (−0.07 to *Moderate*, −0.02 to *Light*). Also, an increase in ***Teacher Forum Posts*** increases the probability of less engaged states transitioning to the *Intense* state (−0.02 *Moderate* to *Intense*, −0.05 *Light* to *Intense*), possibly due to the fact that forums require high levels of cognitive engagement that the *Intense* students are more willing to engage with.

The number of ***Others' Sessions*** (row group 5) had a mixed influence on *Intense* students with no noticeable pattern. It is probably because students may do several, and diverse actions within the same session, which makes it hard to discern any consistent pattern. An increase in ***Others' Forum Contributions*** (row group 6) was likely to increase the chance of less active engagement states to remain in a moderately engaged state (+0.05 for *Moderate*) or improve engagement (+0.06 for *Light*). In other words, the influence of ***Others' Forum Contributions*** was more positive on the lower engagement states (*Light* and *Moderate*) with a small magnitude. The most consistent covariates with the highest influence were others' forum reads which had the highest positive influence on *Intense* students transitioning to *Intense* (+0.39), *Moderate* students transitioning to *Intense* (+0.45), and *Light* transitioning to *Intense* (+0.16). ***Others' Forum Reads*** also lowered the probabilities of engaged roles transitioning to lower engagement states. Interestingly, the likelihood of staying in a *Light* increased (+0.09). Similarly, with less magnitude and more consistency, ***Others' Lecture Views*** had a positive likelihood that an *Intense* student transitions to an *Intense* state (+0.11), as well as decreased the likelihood of all roles declining to a less engaged state (−0.06 from *Intense* to *Moderate*, −0.05 from *Intense* to *Light,* −0.12 from *Moderate* or *Light* to *Moderate*, −0.1 from *Moderate* or *Light* to *Light*). In other words, engaging forums or lectures had the highest positive and most consistent influence on student transition to an actively engaged state.

Increasing ***All Teacher covariates*** by one standard deviation —while holding students' variables constant at average— consistently increases the transition probabilities from all states to the *Intense* state (the most engaged state), decreasing the probability of transitioning to a *Moderate* state or *Light* state. The influence was lowest in magnitude in the transition from the *Intense* to *Intense* state (+0.03, versus +0.16 and +0 .15 for *Moderate* and *Light* respectively transitioning to *Intense*), as well as on *Intense* transitioning to *Light* (−0.01, versus −0.06 for the other two engagement states decreasing to *Light*). In summary, teachers' activity is more likely to improve all engagement states where the *Intense* students are the least to be influenced.

All Others' covariates combined resulted in a far higher increase —compared to ***All Teacher covariates***— in the likelihood of *Intense* states transitioning to an *Intense* state (+0.22 for *Intense*, +0.33 for *Moderate*, +0.32 for *Light*), as well as a lower (at least 10%) likelihood of transitioning to a *Moderate* or *Light* state. Expectedly, increasing ***All covariates*** combined resulted in a consistently increased likelihood of transitioning to an *Intense* state (+0.29 for *Intense*, +0.43 for *Moderate*, +0.41 for *Light*), with a higher magnitude than any combination of covariates. In the same way, increasing ***All covariates*** together decreased the likelihood of transitioning to a *Light* state more than any other combination of covariates (−0.12, −0.17).

To summarize, teachers' covariates combined, and others' sessions and forum reads had a relatively positive influence on decreasing disengagement in general. Others' forum and lecture reads —an indication of how engaging the content is— have consistently increased the likelihood of transitioning to an *Intense* state as well as decreased the likelihood of transitioning to a *Light* state. Increasing all teachers' covariates, all others' covariates, or all covariates combined had a consistently positive influence on transitioning to an *Intense* engagement state.

RQ3. To what extent does the transition between engagement states explain performance?

To test the possibility that transition to a favorable state (an *Intense*ly engaged state) may explain performance, we fitted a linear regression model (estimated using ordinary least squares, OLS) to predict GPA with the integration index (i.e., the ability to stay or ascend an Intense state). The results are shown in Table 5. The model explained a statistically significant and moderate proportion of

Table 5
Integration index association with performance.

		Est.	S.E.	t	p
Integration to intense	(Intercept)	46.68	1.36	34.28	<.001
	Integration index	12.88	2	6.43	<.001

variance. ($R^2 = 0.16$, F (1, 214) = 41.39, $p < .001$, adj. $R^2 = 0.16$). The effect of Integration index was statistically significant and positive (beta = 12.88, 95% CI [8.93, 16.82], t (214) = 6.43). Therefore, a higher integration index is associated with a higher GPA. In the alternative case, if the favorable state was considered to be either the *Intense* or *Moderate* state, the model explained slightly less of variance ($R^2 = 0.14$, F (1, 236) = 37.75, $p < .001$, adj. $R^2 = 0.13$). The coefficient of integration index was higher (beta = 22.50, 95% CI [15.29,29.71], t (236) = 6.14, $p < .001$).

4. Discussion

This study was implemented to fill a literature gap in longitudinal online engagement (Crook, 2019; Salmela-Aro et al., 2021). In particular, our study addresses *how* engagement evolves or changes over time; using a person-centered approach to identify for *whom* (Yang et al., 2023). We take advantage of a novel and innovative multistate Markov model to identify *what* variables influence such transitions and with *what* magnitude, i.e., to answer the *why*.

Our first step was to identify engagement states using multi-state modeling based on students' activity (McLachlan & Peel, 2000; Vogelsmeier et al., 2021). Our results have indicated three states of engagement (*Intense, Moderate*, and *Light*) corresponding to three levels of highly active, intermediate, and low engagement. These findings are consistent with a large body of the literature that found similar clusters (Barthakur et al., 2021; Jovanović et al., 2017; Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015), although labels may vary among papers. For instance, the most active (*Intense*) state has been referred to as intensive, highly intensive, or active (Barthakur et al., 2021; Jovanović et al., 2017). The *Moderate* cluster was referred to as selective or average (Jovanović et al., 2017; Kovanović et al., 2015), and the *Light* cluster was commonly referred to as inactive or disengaged (Saqr & López-Pernas, 2021; Barthakur et al., 2021). The granularity of levels among studies varies, e.g., the *Moderate* level has been further divided into selective and highly selective (Jovanović et al., 2017), and the *Light* level divided into disengaged and highly disengaged (Barthakur et al., 2021). Longitudinal studies in face-to-face settings have also identified three levels —with variable granularities— in which a highly engaged cluster, a disengaged cluster, and an intermediate cluster or more were reported by most studies (Archambault & Dupéré, 2017; Zhen et al., 2020), and so did the longitudinal online studies (Saqr & López-Pernas, 2021). Nevertheless, the identification of these clusters was the necessary step to model the transitions between such states and the instructional variables that influence them.

Transitions and changes —in general— are rarely studied in education with few examples (Fryer & Vermunt, 2018; Gillet et al., 2017). Such examples have typically reported the rates of transition between states, but not the variables that may influence or explain such transitions. For instance, students identified as having deep learning strategies were found to consistently transition to using deep learning strategies in subsequent courses ()(Saqr, López-Pernas, Jovanović, & Gašević, 2023). Whereas knowledge about observed transitions rates is important in its own right, the question of why and to what extent transitions happen and how can we harness such information to proactively influence a transition to a favorable state or prevent a transition to an unfavorable state remains the article of faith of research aiming to improve education. We know that improving instructional classroom practices can influence engagement in positive ways (e.g., Martins et al., 2021; Pino-James et al., 2019). Nevertheless, little empirical evidence exists about what instructional variables enhance engagement in online learning. (Martin & Borup, 2022). Our study offers such insights; the overarching conclusion is that engaging course materials, interactive resources, and teachers' interactivity can influence online engagement positively and significantly, i.e., help students transition to an engaged state and guard against transitioning to a disengaged state. Yet, such transitions differ by student groups, variables, and intensities, thereupon, a detailed discussion of such variations is presented.

Examining individual variables while holding all other variables at an average level —albeit not a very realistic scenario— can hint about the influence of *what* individual variables and for *whom* the influence happens. For the *Intense* students, increasing the number of teacher interactive, cognitively engaging resources (PBL forums) — while holding all other variables at average— would increase the probability of remaining in an *Intense* state (+.08) and decrease the probability of transitioning to a *Light* (low engagement) state (−0.02). A similar influence was observed on the *other* students' variable levels. That is, when the forums were engaging —as indicated by students' number of views— the probability of remaining in an *Intense* state increased remarkably (+0.39), whereas the probability of transiting to a *Light* state decreased (−0.18). For *Light* students, increasing the teachers' number of lectures or students' lectures views —while keeping all other variables at an average level— resulted in an increased probability of transitioning to an *Intense* state (+0.08 for *Teacher Lectures*, +0.22 for *Others' Lecture Views*) and a decreased probability of remaining in a disengaged state (−0.09, −0.10). Please note that an alternative interpretation of *other's lecture views* could be that the lectures are difficult. Students consume more content aiming at grasping the presented subject. In that case, cognitively challenging content benefits the *Intense*ly engaged students while putting the *Light* students at disadvantage, if not provided with enough support. Increasing the number of forums posts created by the teachers, or by the students seems to increase the probability of remaining in a *Light* state (+0.03 for *Teacher Forum Posts*, +0.07 for *Others' Forum Contributions*). Put another way, cognitively engaging learning resources are likely to kindle the transition of engaged students to an engaged state while negatively affecting disengaged students by slightly increasing their likelihood to transition to disengagement. On the other hand, lectures —a less cognitively demanding resource— seem to increase the transition of disengaged students to an engaged state, while not consistently so for engaged students.

In the case of increasing all teacher-related variables —a more realistic scenario— all students were more likely to transition to a more actively engaged state, and less likely to transition to a disengaged state. Nevertheless, teacher variables were far more likely to influence disengaged students than engaged students. Similarly, albeit more profoundly and consistently across engagement states, the influence of *others'* has —with a higher magnitude compared to teacher variables— increased transitions to engaged states and decreased the transition to disengaged states. Increasing all variables (teachers and *others*) had the highest positive effect across all engagement states. In all of these scenarios, the effect on disengaged states was higher than on the engaged states, probably due to the higher "potential for improvement". Another reason may be that highly engaged students are more self-directed, motivated, and possess the *right* learning strategies, especially meta-cognitive learning skills (Schraw, Crippen, & Hartley, 2006; Yang et al., 2023). That is, they monitor their learning and adjust their approach in various contextual environments to accomplish their learning goals (Lau et al., 2017), so they emerge as actively engaged learners in most courses regardless of the degree of teacher's engagement, course design, or others' degree of engagement. Research has revealed that metacognitive skills are not bound to context, i.e., transferrable to different contexts, and can be thought of as the driver of adaptation and continuity that enable such students to perform regardless of the variations in context (Schuster et al., 2020; Veenman, Van Hout-Wolters, & Afflerbach, 2006).

Our results have also shown that the ability to transition explains a significant and moderate proportion of variance in the final performance. These findings are indicative of the importance of the ability to persist or get engaged after faltering to a lower engagement state as an indicator that is worth monitoring and supporting. Furthermore, it shows the need for more studies to further understand the variables that leads to a favorable transition.

Studies that addressed the variables that affect the transition between engagement states —and most behavioral constructs in general— are lacking. Therefore, a comparison with previous research is not feasible. Longitudinal research on online engagement and learners' behavior in general, e.g., learning strategies is rather scarce (Li et al., 2022; Salmela-Aro et al., 2021). Existing longitudinal research has mostly addressed trends across time, e.g., stability, and decreasing or increasing levels of engagement in the classroom (Smith & Tinto, 2022). As such our study brings novel insights that were largely unexplored. A prime advantage of the transition model is that we can identify which factors could work and for who and to what extent. Such insights are of paramount importance for educators wishing to improve educational outcomes. Additionally, we can test different hypothetical scenarios to understand the differential influence of the targeted intervention.

A central question in a study that addresses engagement revolves around "who, when, and where" (Graham, Henrie, & Gibbons, 2013, p. 14). To answer such a question, previous research has used variable-centered methods —a common approach to empiricism— in which researchers study a whole population of students and assume that the aggregated results represent the typical behavior (Bryan, Tipton, & Yeager, 2021). The average is viewed as "truth", and deviations from the average are regarded as noise or irregularity of measurement rather than natural variability (Yang et al., 2023). The findings in this study emphasize the importance of heterogeneity, variability, and differences among students. Our findings support the view that online engagement not only exists in different states but also changes differently —across profiles of students— and at different magnitudes —according to the type of instructional variables and the previous engagement state.

In the recent work of Archambault et al.'s (2022), where the authors review the theories on student engagement and the state of evidence, three important gaps emerged between the current status of empirical evidence and the existing theories. Two of such gaps are concerned with the longitudinal engagement pathways, and the short- and long-term processes that lead to disengagement (Archambault et al., 2022). Our study has revealed very important insights regarding the variability of transitions to disengagement, which depend on the students' characteristics, the instructional factors, and the initial level of engagement. We also found that students' ability to ascend or remain in an engaged state explains —at least moderately— their final grades. Such novel insights confirm that a person-centered view can capture the variability and has a clear advantage over variable-centered methods which averages trends that are clearly not averageable.

Our findings have implications for instructional designers, teachers and educators who aim to support students' engagement. Course designers need to take the diverse and heterogenous nature of students into account. In that, some instructional activities may influence some students' engagement positively —e.g., cognitively demanding tasks– while negatively affecting others. Therefore, diversifying instructional activities, offering support for low engagement students when introducing cognitively demanding course activities. In the same way, intervention to enhance engagement may need to be tailored to different students' needs and students' subgroups. Clearly, disengaged students require —at least initially—behaviorally engaging tasks whereas introducing cognitively demanding tasks require intense support from teachers. In summary, a one-size course design, support, or intervention to target intervention is less likely to succeed. A carefully tailored crafted approach may be the way forward.

Another contribution of our study is methodological in nature as we demonstrate how to cluster students according to their activity into latent states and understand their transitions between states over time using the novel method LMFA. Mixture factor models identify the factors within the data, which, in our case, helped identify variables belonging —mainly— to the behavioral factor and variables belonging to the cognitive factor. On top of this, the multistate model LMFA allows modeling transitions between the engagement states as well as the inclusion of instructional variables to explain transitions between the states. The latter is highly important for improving students' engagement in education and the variables that could be used as a basis for intervention or inducing a change.

4.1. Limitations

As is the case with all empirical studies, the generalizability of our study needs to be tested in other contexts or replicated before drawing firm conclusions. The results of our study have shown different weights for variables affecting transitions and thereupon, we believe that different contexts would have different magnitudes of influence on transitions according to course design. Yet, we argue that the general conclusions are likely to hold —with some differences— which of course remains to be verified. We have studied students who have spent six courses in the program i.e., with equal enrollment duration to enable comparison across classes, and contextual variables (same courses), as well as to keep the probabilities uniform relative to the count of students. Of course, a model with variable course durations is a worthwhile future research objective. Clustering is far from perfect: classifying students in the wrong cluster may lead to error I (classifying a student as disengaged while the student is engaged) or error II (classifying a student as disengaged while the student is actually disengaged). However, the high values of entropy and classification probabilities indicate that such risk has been highly unlikely. Furthermore, our results are concerned with the relative change in probabilities rather than labeling or diagnosing students' engagement states.

5. Conclusions and implications

Transitions and changes in students' engagement and the factors that lead to such changes have not been sufficiently studied. Our study fills such a gap and offers empirical evidence on *what* variables*,* for *whom,* and how such changes in engagement occurs as well as how researchers can study transitions using an innovative multistate model.

Our study shows that online engagement evolves dynamically across time, such dynamic changes vary across students' subgroups at different rates and the changes differ in each subgroup according to previous engagement states, instructional and teacher variables. Furthermore, the ability to transition to an engaged state explains a moderate and significant proportion of final performance. Cognitively engaging instructions are expected to increase cognitively engaged students' transition to an engaged state while negatively affecting disengaged students. Increasing lectures —a resource that requires less mental energy— helps improve the engagement state of disengaged students. Such differential effects point to the different ways intervention may be applied to different groups, and how different groups may be supported. That is, less engaged students may require more support with cognitively demanding tasks, while cognitively engaged students get increasingly engaged with cognitively engaged instructions. Increasing all teacher variables or engaging instructions (manifest as students' interest in course resources) improves the engagement state of all students with a more profound influence on disengaged students. Similar effects, however, with higher magnitude results from increasing all variables (teachers and instruction engagement). In all such cases, disengaged students were more likely to improve and engaging instructions showed the highest influence on all engagement states. Such insights are relevant to educators who design courses, design interventions, or seek to improve students' support.

The overarching conclusion of our paper is that engagement exists in various states, evolves at different rates among students' subgroups and such changes responds differently to changes in instructional variables. Such findings have implications for instructional designers, teachers and educators who aim to support students.

Credit author statement

MS and LV have contributed to the idea conceptualization, research design, and planning. MS has performed data collection. MS, LV and SLP have contributed to the methods, data analysis and reporting of results and visualization. Visualizations have been conceptualized by SLP. MS, SLP and LV have contributed to manuscript writing and revision. The authors read, revised, and approved the final manuscript.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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