Not Just Pass or Fail: Examining Online Learning Behavior and Rethinking Success in Formal and Non-Formal Online Courses

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Maria Klose

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Dekan:	Universitätsprofessor Dr. Claus H. Carstensen
Betreuerin:	Universitätsprofessorin Dr. Cordula Artelt
Weitere Gutachterin:	Universitätsprofessorin Dr. Ilka Wolter

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What can happen in just five years is unimaginable: a global pandemic, the birth of my two nieces, ~~three~~ four not self-inflicted car damages (still counting, please stop!), becoming a Boulder Bundesliga athlete and climbfluencer, the end of a long-term relationship, countless housewarming parties, and—of course—writing this dissertation. Am I the same person that started this academic journey? Thankfully, not. Instead, I have grown in ways I never anticipated.

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Contents

Abstract

As online courses become an increasingly important part of the educational landscape and technological advancements continue to reshape how learning is delivered and experienced, research on how learners engage with and succeed in these environments is essential. This dissertation examines online learning behavior and success across formal and non-formal online courses covering three studies, each addressing different dimensions of learner engagement. Study 1 employs a meta-analytical approach to explore how course design characteristics influence the relationship between general online activity and learning outcomes in formal online courses. The findings highlight the complexity of digital learning environments and underscore the need for more fine-grained analyses of how specific digital tools are implemented and used. Study 2 investigates motivational trajectories in non-formal online courses, revealing a remarkable stability in intrinsic motivation and discussing the adequacy of traditional success metrics like course completion. Study 3 draws on this perspective, demonstrating that learners' enrollment intentions and commitment to the course, rather than course design features, are key predictors of learners' engagement with self-tests. Together, these studies challenge conventional definitions of learning success and emphasize the importance of aligning course designs with learners' intentions. The findings suggest that effective online course design should go beyond merely providing digital tools and instead focus on fostering meaningful engagement through guidance, personalized interventions, and incentive structures. This dissertation advances a more nuanced, learner-centered understanding of online learning behavior and success in formal and non-formal online courses.

1. Introduction

The continuous advancements of digital technologies is leading to significant changes in education across all disciplines, enabling greater flexibility, personalized learning, and independence from time and place (Mukul & Büyüközkan, 2023). This digital transformation has fundamentally reshaped how knowledge is accessed, delivered, and experienced. Over the past decades, universities and other educational providers have increasingly integrated technology into their educational offerings (Cox, 2013), contributing to the growing shift toward online learning (Araka et al., 2020). The COVID-19 pandemic further accelerated this trend, forcing a global shift from traditional face-to-face settings to fully online courses as a necessity during lockdowns (Ali, 2020). While initially an emergency response, this circumstance established online courses as an integral part of modern educational systems, particularly in post-secondary education.

In higher education, courses are described along a continuum based on the proportion of content delivered online, ranging from traditional courses with no digital components to fully online courses (Allen & Seaman, 2014). More specifically, face-to-face instruction typically involves 0% to 29% online content, including traditional and web-facilitated courses that use digital tools for the provision of supplementary materials. Blended or hybrid courses cover the remaining range of 30% to 79% of content that is delivered online, combining online and face-to-face delivery. Finally, the term online course is used for courses where at least 80% of the content is delivered online (Allen & Seaman, 2013). Along this spectrum, variations in guidance and learner autonomy emerge—while some online courses provide structured support and direct interactions with instructors, others require learners to navigate content independently. Accordingly, when referring to *online courses*, it is important to recognize their considerable heterogeneity.

In addition to formal education, the widespread accessibility of online learning tools and resources enables individuals to engage in non-formal and informal learning beyond institutional contexts (Cox, 2013). Consequently, people increasingly participate in online courses as part of lifelong learning and leisure activities (Autorengruppe Bildungsberichterstattung, 2020; Werquin, 2010). Given the growing popularity of online courses, it is important to examine both their advantages and challenges from multiple perspectives. The following sections explore how researchers, learners, and educators navigate the ever-changing landscape of online courses, each facing unique benefits and obstacles.

1.1 A Researcher's Perspective: Examining Online Courses

From a researcher's perspective, online courses offer new insights into learning behavior, as learners' interactions within digital learning environments can be automatically tracked through log data (Gašević et al., 2016). Log data analyses offer a valuable complement to traditional research methods, such as self-report measures or test data, by unobtrusively capturing directly observable learning behavior (Steger et al., 2021). This is particularly relevant given that self-reported measures of the quantity or duration of digital media use often show weak correlations with actual logged activity (Parry et al., 2021). The availability of log data has given rise to the field of *Learning Analytics*, which involves the systematic collection, analysis, and reporting of large-scale online data to better understand and improve learning processes and environments (Siemens & Gašević, 2012, as defined by the Society for Learning Analytics Research). By using artificial intelligence (AI) algorithms to analyze log data, learning analytics offer new ways to support adaptive and personalized learning (Markauskaite et al., 2022). Besides, technological advancements help mitigate sampling biases—such as reliance on small, homogeneous groups that voluntarily participate in lab-based studies—by enabling large-scale investigations of diverse populations worldwide

(Dufau et al., 2011). This facilitates the exploration of differences and commonalities across different subpopulations, uncovering patterns that may have previously been overlooked or treated as outliers in smaller-scale studies (Fan et al., 2014).

However, working with big data—encompassing vast quantities of observations with high fidelity over extended periods—requires substantial technical and computational expertise (Harari et al., 2016). Proper data handling is essential, including secure storage, thorough documentation, appropriate statistical techniques, and meaningful reporting (Sin & Muthu, 2015). For example, establishing clear data standards, such as defining the completeness of log data, is crucial. Implementing standardized documentation on log data storage enables responsible data cleaning and editing, ensuring reproducible, generalizable, and valid results (Kroehne & Goldhammer, 2018). This is particularly important for cross-study comparisons, as variations in how online platforms track user behavior can lead to inconsistencies in data collection, potentially resulting in erroneous interpretations (Avella et al., 2016). Moreover, the high dimensionality and large sample sizes of big data require researchers to employ advanced statistical methods that can handle data complexity and dependencies effectively. Without robust analytical approaches, issues such as noise accumulation, spurious correlations, and incidental homogeneity may lead to misleading scientific discoveries or erroneous statistical inferences (Fan et al., 2014). Furthermore, the interpretation of big data and learning analytics poses significant challenges (Sin & Muthu, 2015; Viberg et al., 2020). To derive meaningful insights, researchers must ground their data-driven findings in strong theoretical frameworks and pedagogical principles (Banihashem et al., 2024). While learning analytics is sometimes criticized for lacking theoretical foundation (Avella et al., 2016), it is in fact informed by a diverse range of perspectives from, for example, computer science, educational research, or sociology, and therefore draws upon various learning theories from multiple disciplines (Khalil et al., 2023). Lastly, researchers must address ethical and privacy concerns related to data storage and protection (Viberg et al., 2020). Adhering to established standards for privacy, ethics and data security is essential (Hernández-de-Menéndez et al., 2022). Studies utilizing big data require ethical approval (Harari et al., 2016) to ensure key privacy principles, including consent, data accuracy, anonymity and the right to opt out of data collection (Avella et al., 2016 based on the code of practice for learning analytics).

1.2 A Learner's Perspective: Learning with Online Courses

From a learner's perspective, online courses enhance accessibility, enabling learning anytime and anywhere (Cha & So, 2020; Sin & Muthu, 2015). The ever-growing availability of online courses allows learners to select those that best align their interests, preferences, and abilities (Hernández-de-Menéndez et al., 2022), fostering their experienced autonomy while learning. Additionally, innovative course designs, such as gamification elements (e.g., points, badges, leaderboards), can boost motivation and performance by increasing learner engagement (Hamari, 2017; Sailer, 2017). Adaptive learning systems further personalize the learning experience, helping learners to develop knowledge and competencies in a more tailored manner (Hernández-de-Menéndez et al., 2022). For instance, adaptive feedback based on learners' digital traces as they interact with the learning environment can provide learners with immediate feedback on their current performance and specific recommendations on what they should do next or change in their learning to achieve their learning goals (Viberg et al., 2020). Therefore, trace data from online courses can foster self-regulated learning (SRL)—proactive skills such as strategy use, progress monitoring, time management, and goal setting (Zimmerman, 2002). By supporting these skills with adaptive feedback, learners are given the opportunity to exercise SRL (Winne, 2017). As a result, learners might even improve their SRL skills in the long term (Viberg et al., 2020).

However, the shift towards online courses also poses challenges for learners. Since courses with an increasing proportion of online content often provide less guidance and support than traditional face-to-face settings, they place greater demands on learners' SRL skills (Kizilcec et al., 2017). This underscores the need for innovative course designs that actively foster SRL to help learners navigate online courses more effectively. Targeted interventions, such as personalized feedback, have been shown to foster effective learning strategies within specific courses. Yet, an important question remains: to what extent do learners transfer generalizable SRL strategies across different online courses (Viberg et al., 2020)? In addition to difficulties with SRL, learners' motivation to engage in online courses may decline due to technical issues or the absence of social interaction, which can lead to feelings of isolation (Hernández-de-Menéndez et al., 2022). Despite the advantages of increased autonomy in online courses, learners must take full responsibility for initiating and regulating their own learning, as they are solely accountable for their learning decisions (Carpenter, 2023). Especially in non-curricular online courses with no negative consequences for dropping out, learners need to stay committed to complete the course. For this purpose, learners must sustain their motivation, allocate sufficient time, and possess the necessary background knowledge and skills (Dalipi et al., 2018).

1.3 An Educator's Perspective: Designing Online Courses

From an educator's perspective, online courses offer numerous opportunities to enhance both teaching and learning support, for example by applying learning analytics. However, it has yet to be consistently integrated into educational practice because it is not widely used (Viberg et al., 2020). Learning analytics provides valuable insights into course effectiveness, enabling educators to monitor learner progress and offer targeted feedback to improve learning outcomes (Hernández-de-Menéndez et al., 2022). For instance, it can help refine curricula by identifying areas where learners struggle with comprehension (Armayor & Leonard, 2010). Additionally, learning analytics allows educators to align courses more closely with learners' needs and preferences, offering personalized course recommendations based on individual interests and skill levels (Sin & Muthu, 2015). Beyond course selection, learning analytics can also support performance prediction and attrition risk detection, helping educators identify and intervene with underperforming or at-risk learners (Hernández-de-Menéndez et al., 2022; Sin & Muthu, 2015). Across all learners, learning analytics can facilitate SRL through visualizations, feedback mechanisms, and personalized recommendations (e.g., Haag et al., 2023; Viberg et al., 2020). Educators can detect ineffective learning behaviors and address them directly with learners to optimize their online learning experience (Kew & Tasir, 2022). Moreover, learner-centered dashboards and intelligent tutoring systems that provide real-time, personalized feedback can enhance self-awareness and encourage learners to reflect on their learning habits (Viberg et al., 2020). Overall, online courses expand the toolbox for educators to improve and refine their teaching strategies.

A key challenge for educators is translating learning analytics research into effective teaching practices (Hernández-de-Menéndez et al., 2022). To enhance learning conditions, insights from learning analytics must be meaningfully integrated into pedagogy (Viberg et al., 2020). This requires not only technical implementation but also consideration of user experience factors such as usability, aesthetics, and data literacy (Dollinger & Lodge, 2018). Additionally, trained staff with high levels of digital competency are essential, as learning analytics development has traditionally been the responsibility of IT departments (Hernández-de-Menéndez et al., 2022). Besides digital skills and knowledge, educators need to recognize the potential of digital technologies and have a positive attitude towards using technology in teaching (Spiteri & Chang Rundgren, 2020). Moreover, it is essential to look beyond tracked behavior and consider external and internal factors that influence learning, such as instructional design, social context, achievement goal orientation, and epistemic beliefs (Gašević et al., 2015). Another challenge is the limited generalizability of predictive models derived from learning analytics. These models are typically course-specific, as they perform best when tailored to a particular course (Gašević et al., 2016). Consequently, educators must implement customized learning analytics approaches that align with course design, examination modalities, and course difficulty (Viberg et al., 2020).

Online courses offer unprecedented opportunities for researchers, learners, and educators alike. But they also introduce new complexities and challenges that must be addressed. Moreover, the role of online courses for learning depends not only on the perspectives of different stakeholders, but also on the specific characteristics of different learning contexts. Recognizing these contextual differences is essential for making the most of technology's potential in education. The following chapter explores how formal, non-formal, and informal education are uniquely shaped by online courses, highlighting their distinct opportunities and challenges.

2. Theoretical Background

The growing prevalence of online courses has fundamentally changed how a) researchers investigate learning behaviors and outcomes, b) learners access and engage with learning content, and c) educators design and provide learning experiences. The previous chapter outlined general opportunities and challenges arising from the shift from face-to-face to online courses across educational contexts. However, different educational contexts—whether structured and credentialed, voluntary and flexible, or self-directed and unorganized—may be affected by online courses in distinct ways. Traditionally, learning environments are categorized into three overarching contexts: formal, non-formal, and informal education (Eshach, 2007). This distinction provides a useful framework for describing varying degrees of structure, intention, and recognition of learning. The present dissertation builds on this established classification to discuss how online courses have impacted existing categories (see Table 1). The following sections address the broader landscape of formal, non-formal, and informal education by defining their key characteristics and by examining how online courses have reshaped their differentiation.

2.1 Definitions and Examples of Formal, Non-Formal, and Informal Education

The following definitions of formal, non-formal, and informal education are based on the framework provided by the UNESCO Institute for Statistics (2012). Each educational context varies in terms of its level of institutionalization, intentionality, structure, recognition of qualifications, and degree of self-determination.

Formal education. Formal education is institutionalized, intentional, and systematically structured, delivered through recognized public and private organizations within the formal education system. It typically takes place in institutions such as schools, universities, and vocational programs, follows established curricula, and culminates in recognized qualifications. This type of education is characterized by mandatory credentialing, instructor-led delivery, and is usually offered as full-time education for students prior to their initial entry into the labor market such as secondary education, a university degree, or vocational education.

Non-formal education. Non-formal education is institutionalized and intentional, delivered by an education provider, and plays a vital role in lifelong learning. Unlike formal education, it is often short in duration, less structured, and may not follow a continuous pathway. It is typically offered in the form of short courses, workshops, or seminars for learners of all ages. While non-formal education often focuses on voluntary, goal-oriented learning, it may lead to qualifications that are not formally recognized or, in some cases, no qualifications at all. This type of education is highly flexible and learner-driven, addressing diverse needs such as self-development, work skills, or preparation for formal education, and encompasses a wide range of programs covering for example literacy, life skills, and social or cultural development.

Informal education. Informal education is intentional or deliberate but not institutionalized. In contrast to formal and non-formal education, informal education can be described as unstructured and unorganized. It is typically experienced as self-directed learning that takes place in everyday life, family, workplace, or local community, without any curriculum, assessments, or qualifications. This type of education represents context-dependent learning activities such as watching educational videos, reading articles, or engaging in discussions. It can be distinguished from incidental or random learning that are defined as spontaneous and unintentional forms of learning that occur as a by-product of other activities such as listening to a radio program, participating in a meeting, or watching television.

However, there are no clear boundaries to this categorization, making it difficult—sometimes impossible—to classify certain learning experiences in disjunct categories (Colley et al., 2003). For example, some training programs and workshops often resemble formal education in their structured curricula and learning objectives but lack official accreditation, positioning them within non-formal education. Similarly, *Massive Open Online Courses* (MOOCs) can range from informal, self-paced exploration to highly structured courses with assessments and certification that can ultimately lead to validated and recognized learning outcomes (Witthaus et al., 2016). Even within formal education there are variations as there is no formal recognition of the learning outcomes for students who have engaged in structured, institutionalized learning but fail or drop out. These examples highlight the challenge of rigid classification and reinforce the argument that learning can be considered more as a continuum with non-formal education bridging the two extremes of formal and informal education (Souto-Otero, 2021).

2.2 Revisiting the Classification of Educational Contexts Through the Lense of Online Courses

The use of online courses has further blurred the boundaries between formal, non-formal, and informal education, making distinctions even more complex (Nygren et al., 2019). Traditionally, these contexts were often differentiated by the physical location of learning, such as “in school” versus “out of school” (Sefton-Green, 2013). However, with the rise of online courses, access to educational resources has expanded, enabling learners to engage with content anytime and anywhere across all educational contexts (Cha & So, 2020). Building on classification frameworks from previous research (e.g., Eshach, 2007; Johnson & Majewska, 2022) and the definitions from UNESCO Institute for Statistics (2012), Table 1 provides an updated comparison of the similarities and differences among formal, non-formal and informal education, reflecting the impact of online courses.

Table 1

Updated Comparison of Formal, Non-Formal, and Informal Education Considering Online Courses.

	Formal	Non-Formal	Informal
Institutionalization	institutionalized (recognized public and private organizations)	institutionalized (education provider)	not institutionalized (consequence of everyday life)
Intentionality	intentional	intentional	intentional
Structure	systematically structured (mostly linear learning paths)	structured (not necessarily continuous learning paths)	unstructured/ unorganized
Qualification	formally recognized qualifications (e.g., certificates or diplomas)	may lead to qualifications but not formally recognized ones (e.g., proof of attendance)	no qualifications
Self-determination	qualification-bound (mandatory dimension; mainly extrinsic motivation)	usual voluntary (extrinsic vs. intrinsic motivation depending on the enrollment intention of the learner)	voluntary (mainly intrinsic motivation)
Personalization	curriculum-bound (specific requirements for credentials)	mostly self-selected topics or foci	completely self-directed
Guidance	instructor-led	existence of course instructions that can be applied by the learner	learner-led
Time schedule	time-dependent (linked to specific school year or semester)	time-independent (mostly self-paced formats and no deadlines)	time-independent (sometimes even spontaneous)
Accessibility	*online courses: everywhere* (traditionally in formal institutions)	*online courses: everywhere* (traditionally outside of formal institutions)	everywhere (traditionally always accessible from everywhere)
Assessment	mostly summative assessments (e.g., for exam scores or grades)	mostly formative assessments or no assessments	no assessments
Success	tied to summative assessments (e.g., grades, exams, or certifications)	varied metrics (e.g., completion rates, engagement levels, self-reported knowledge gains)	often anecdotal or observed through real-world application
Digital challenge	*adapting traditional curricula to online formats including validity of online assessments*	*high dropout rates (lack of external accountability)*	*unstructured nature makes it difficult to evaluate or track learning behavior*

Note. Changes and extensions of the traditional classification framework are in *italics*.

In terms of similarities, all educational contexts can be characterized as intentional and can therefore be distinguished from incidental or random learning which cover various types of learning that occur spontaneously, without structured organization, or through interactions not intentionally designed for learning (UNESCO Institute for Statistics, 2012). Furthermore, in the context of online courses, they share the advantage of being accessible anytime and from anywhere, offering increased flexibility while simultaneously placing greater demands on learners to regulate their own learning (Cha & So, 2020). Regarding the other dimensions of comparison, non-formal education serves mainly as a bridge between formal and informal education. First, it shares commonalities with formal education, such as being institutionalized and structured, while also overlapping with informal education through its self-directed and time-independent nature. Second, non-formal education represents a kind of intermediate category on the continuum between formal and informal education (Johnson & Majewska, 2024; Werquin, 2010). While formal education grants officially recognized qualifications, such as certificates or diplomas, and informal education does not give any credentials, non-formal education may provide some form of certificate, such as proof of attendance, though these are often not formally recognized (Nygren et al., 2019). In terms of self-determination, formal education is qualification-bound and typically mandatory, often driven by extrinsic motivation. In contrast, informal education is entirely voluntary and primarily sustained by intrinsic motivation. Non-formal education falls in between, as it is usually voluntary, but the type of motivation experienced depends on the learners' enrollment intentions, which can be influenced by both intrinsic and extrinsic factors (Eshach, 2007). The degree of personalization in learning content varies across educational contexts, analogous to self-determination. Personalization is least pronounced in formal education, as topics are dictated by a fixed curriculum with predefined credentialing requirements. In non-formal education, personalization is more flexible—learners can select topics independently (e.g., courses for self-development) while also being guided toward certain subjects (e.g., recommended work skill trainings). In contrast, informal education offers the most pronounced personalization, as learners have full autonomy over their choice of topics (UNESCO Institute for Statistics, 2012). Regarding guidance, formal education is predominantly instructor-led, whereas informal education is entirely learner-led (Eshach, 2007). In non-formal education, guidance varies greatly and is not explicitly specified. While some courses provide detailed instructions or even support from an instructor, the primary responsibility for learning typically remains with the learner. For the remaining dimensions—*assessment*, *success*, and *digital challenge*—there is little overlap between educational contexts, as each has its own distinct characteristics. Since these dimensions are central to the research questions of the present dissertation, the following chapter will explore how they manifest within formal, non-formal, and informal education, highlighting their unique implications for each context.

2.3 Theoretical Rationale and Study Motivations: New Dimensions of Measuring Success

A key distinction among educational contexts lies in how learning is assessed, success is defined, and which digital challenges must be addressed (see Table 1). These factors shape the effectiveness of online courses and influence their impact on learners. The following chapter examines the role of assessment, operationalization of learning success, and digital challenges across formal, non-formal, and informal education, offering valuable perspectives that have motivated the research presented in this dissertation.

First, in formal education, the operationalization of learning success is closely tied to the type of assessment. Summative assessments are used to evaluate students' learning progress based on the course curriculum, typically for the purpose of grading or certification at mid-term or at the end of the course (Bloom et al., 1971). Therefore, clear metrics for learning success are established, as summative assessments generate grades or exam scores that allow for straightforward comparisons of student performance—better grades or higher scores indicate superior learning outcomes. As formal education is the most clearly defined among the three educational contexts, it has been the primary focus of empirical research so far (Johnson & Majewska, 2022). The extensive body of research on formal education allows for meta-analytic approaches to synthesize findings on learning success and explore new insights gained through the transition from face-to-face to online courses, such as log data analysis. Building on this foundation, Study 1 of the present dissertation examines how general online learning activities, captured through log data, relate to learning success in formal settings. Traditionally, face-to-face teaching and on-site exams were considered the gold standard in formal education, ensuring the validity of assessed learning outcomes (Rovai, 2000). However, with ongoing digital transformation—and especially since the COVID-19 pandemic—the demand for online courses increased drastically. This shift has compelled formal institutions to reconsider long-established standards and adapt learning to digital environments (Ali, 2020). A key challenge in this transition is ensuring that traditional curricula are effectively adapted to online formats while maintaining, for example, the validity of assessments (Timmis et al., 2016). At the same time, online courses offer valuable insights into students' learning by enabling the recording and analysis of log data, which capture directly observable learning behavior (Dawson et al., 2014).

In contrast, non-formal education lacks standardized characteristics for assessment and learning success. It is often vaguely described as "usually not evaluated" (Eshach, 2007, p. 174), or "may be recognised or measured through qualifications" (Johnson & Majewska, 2022, p. 4). The presence and type of assessments depend on the specific course context—ranging from summative assessments, such as a final examination at the end of a course (Witthaus et al., 2016), to formative assessments that accompany the learning process by providing immediate feedback throughout a course in the form of self-assessments (Werquin, 2010; for the definition of formative assessment see Wiliam & Black, 1996), or, in some cases, no assessments at all (Eshach, 2007). Consequently, non-formal education is inherently complex and difficult to define, making it challenging to systematically capture and analyze (Johnson & Majewska, 2024). Accordingly, there is no straightforward answer to the question "What is learning success in non-formal education?". Without assessments, there are no objective measures of learning success. But even when assessments are available, traditional definitions of learning success from formal education cannot be directly applied to non-formal education (Henderikx et al., 2017). One of the most frequently discussed challenges—or even criticisms—of non-formal online courses is their high dropout rate (see Huang et al., 2023 for a systematic review). On average, less than 13% of learners who enroll in non-formal online courses complete them (Jordan, 2015). Much of the existing literature has treated course completion as the primary indicator of success for non-formal online courses (e.g., Handoko et al., 2019; Moore & Wang, 2021; Wang & Baker, 2018). However, it remains debatable whether completion truly equals success—or, put differently, dropout truly equals failure. While in formal education, the primary goal is to obtain a recognized qualification (UNESCO Institute for Statistics, 2012), learners in non-formal online courses have diverse enrollment intentions (Moore & Wang, 2021), making a singular definition of success more complex. Enrollment intentions among non-formal online learners range from extrinsically motivated intentions—such as "relevant to job", "for career change", or "to earn a certificate" —to intrinsically motivated intentions like "general interest in topic", "for personal growth and enrichment", or "for fun and challenge" (Kizilcec & Schneider, 2015, p. 5). While extrinsically motivated behaviors are driven by the pursuit of external rewards, intrinsically motivated behaviors are performed for their own sake (Deci et al., 1991). Given that intrinsically motivated intentions, particularly interest, appear to be a key factor in learner retention within non-formal online courses (Tsai et al., 2018), Study 2 of the present dissertation examines how intrinsic motivation evolves throughout a non-formal online course, offering an alternative perspective on successful learning behavior. Building on these findings, Study 3 aims to bridge the assessment metrics known from formal education with the flexible nature of non-formal education by examining learners' engagement with self-tests as an objective measure of learning success, while also considering personal characteristics such as enrollment intentions and motivations.

Lastly, informal education lacks external assessments (Callanan et al., 2011). While it also involves the acquisition of knowledge, understanding, or skills, there are no standardized criteria for measuring success. Instead, learning outcomes are subjectively defined by learners based on their personal experiences, self-recognition of achievements or perceived significance (Livingstone, 2001), making success largely anecdotal. As a result, interindividual comparisons are difficult due to the absence of quantifiable metrics. Digital learning environments allow for the automatic tracking of online learning behavior (Gašević et al., 2015); however, in informal education, the challenge remains in capturing and evaluating spontaneous learning, as it follows irregular time and space patterns (Livingstone, 2001). Understanding the shared and distinct features of educational contexts provides a foundation for the research presented in this dissertation. While informal education is an important component of lifelong learning (Werquin, 2010), it is not the focus of this dissertation. The present studies investigated formal and non-formal education because these contexts provide structured online courses where learning behaviors and outcomes can be systematically observed and analyzed. Informal education, by contrast, is harder to quantify or track, given its decentralized and spontaneous nature. While informal education is not directly examined, its inclusion in this theoretical discussion highlights the broader implications of online courses for lifelong learning. By focusing on online courses across formal and non-formal contexts, this dissertation examines how structured learning environments are influenced by digital formats, offering insights that may be also relevant to informal education.

3. Empirical Studies

This chapter summarizes the three empirical studies conducted for this dissertation. Each study addresses a different dimension of success as outlined in the previous section (i.e., online activity metrics, the maintenance of motivation, and engagement with self-tests). The chapter is structured to provide a brief overview of the research aims, methods and key findings of each study, as well as transitions that clarify how the studies are connected and build upon another.

3.1 Study 1 – Decrypting Log Data: A Meta-Analysis on General Online Activity and Learning Outcome Within Digital Learning Environments

One of the key question in higher education research is which factors best predict students' academic performance, including self-reported psychological constructs (Richardson et al., 2012), and observable learning behaviors (Hoge & Luce, 1979). Traditionally, learning behavior was assessed through direct human observation in face-to-face settings. However, the growing integration of online courses enables researchers to examine digital traces of learning behavior, such as students' log data from learning platforms (Gašević et al., 2015). These data provide direct indicators of student engagement—such as general online activities like *total login time* or *login frequency* (Beer et al., 2010)—and have been explored as predictors of academic success (Huang et al., 2020).

Despite the potential of log data analyses, existing research has yielded inconsistent findings regarding the relationship between general online activity and learning outcomes. Some studies reported a positive correlation (e.g., McCuaig & Baldwin, 2012), while others found no association (e.g., Broadbent, 2016), or even a negative correlation (e.g., Ransdell & Gaillard-Kenney, 2009). Given these mixed results, the first study of this dissertation aimed to meta-analytically summarize the existing findings and examine potential moderators that could explain the variation in previous research.

To address these inconsistencies, we investigated four potential moderators: First, differences in course formats were considered by comparing *fully online* courses to *blended* courses. We expected the association between general online activity and learning outcomes to be stronger in fully online courses than in blended courses, as the latter include substantial offline learning behaviors that remain undetected by log data (Mwalumbwe & Mtebe, 2017). Second, we examined whether courses that provide explicit instructions for engaging in online discussions would show a higher correlation between general online activity and learning outcomes, as clear guidance could encourage more meaningful participation (Lee & Martin, 2017). Third, we investigated the impact of incentivizing online participation, assuming that courses in which specific online learning activities contribute to grading would result in higher correlations between general online activity and learning outcomes (Tempelaar et al., 2019). Finally, we compared two operationalizations of general online activity by distinguishing between total login time and login frequency to determine whether these two indicators differ in their association with learning outcomes (based on the *model of school learning*; Carroll, 1963; or *activity theory*; Engeström, 1987).

Using a three-level random-effects meta-analytic model based on 41 primary studies (N = 28,986) covering 69 independent samples and 104 effect sizes (Cheung, 2014; Viechtbauer, 2010), we found a small but statistically significant pooled correlation of $r = .25$, $p = .003$, 95% CI [.09, .41], indicating that students who spend more time online or log in more frequently tend to achieve better learning outcomes. This finding was robust across various sensitivity analyses. However, the meta-analysis revealed high heterogeneity between studies, $Q(103) = 3{,}960.04$, $p < .001$ that could not be explained by our moderator analyses conducted as meta-regressions, as they were based on the limited contextual information provided in the primary studies.

These findings highlight both the potential and the limitations of using log data as indicators of student learning behavior. To further investigate the relationship between log data and academic success, future research should examine contextual variables in greater detail, particularly those enabled by learning analytics. This includes dashboards that visualize learning progress (Verbert et al., 2013), gamification elements designed to enhance motivation (Looyestyn et al., 2017), and adaptive learning systems that provide personalized feedback tailored to individual needs (Shemshack & Spector, 2020). Additionally, future studies should analyze more fine-grained log data while ensuring objectivity. This might be challenging due to various degrees of freedom in data tracking, collection, and cleaning (Avella et al., 2016). Finally, future research should examine whether these findings generalize beyond higher education to other educational contexts.

The findings from Study 1 highlight the potential of log data as indicators of learning success in formal education, where academic performance is typically measured through grades or course scores. However, in non-formal education, defining and assessing learning success is far more complex due to the absence of objective success criteria. Since a meta-analytical approach requires comparable operationalizations to synthesize findings, the varying definitions of learning outcomes across educational contexts make a straightforward comparison difficult, if not impossible. Unlike formal education, where learning outcomes are often objective and quantifiable, non-formal online courses cover a wide range of learner motives, from career advancements to personal enrichment. As a result, traditional success metrics, such as course completion or grades, may not fully capture meaningful learning experiences in these settings. Given this challenge, Study 2 shifts the focus from externally defined academic success to internal learner experiences, specifically examining how intrinsic motivation evolves over time in non-formal online courses. By exploring motivation as a key factor in learners' engagement and retention, Study 2 offers an alternative perspective on what constitutes learning success in digital learning environments beyond formal education.

3.2 Study 2 – Not Easy to Get off Track: Motivational Trajectories of Learners Completing a Non-Formal Online Course

Non-formal online courses have become an integral part of lifelong learning (Werquin, 2010), leading to a steady increase in both course offerings and participant numbers. Learners often start highly motivated (de Barba et al., 2016), but completion rates tend to be low (on average <10%; Jordan, 2014). This raises the question of how learners' motivation evolves throughout the course. While motivation in formal education has been well documented longitudinally (Corpus et al., 2020), most research in non-formal education relies on cross-sectional data, leaving motivational trajectories largely unexplored.

Based on the framework of Self-Determination Theory (Ryan & Deci, 2017), we conceptualized motivation as a dynamic state that can fluctuate due to learning experiences (i.e., *situational motivation*; Guay et al., 2000). Motivation can be described on a continuum of experienced relative autonomy ranging from *amotivation* (the lack of intention to act) to *external regulation*, *introjected regulation*, and *identified regulation* (extrinsic motivations to attain some kind of separable outcome increasing in their experienced autonomy) culminating in *intrinsic motivation*, characterized by interest, enjoyment, and inherent satisfaction and full autonomy (Ryan et al., 2022). Given that non-formal online courses are characterized by a high degree of autonomy and that learners need to be intrinsically motivated to self-regulate their learning (Biwer et al., 2021), Study 2 aimed to examine interindividual differences in the initial levels and changes in intrinsic motivation over the duration of the course in more detail.

To identify potential influencing factors, we examined three personal characteristics that support autonomy in learning and are theoretically linked to intrinsic motivation. First, we assumed a positive association of *situational interest* with situational intrinsic motivation, as course topics that align with learners' interests and preferences facilitate intrinsic motivation (Krapp & Prenzel, 2011). Second, we expected that the effective use of *SRL strategies* facilitates intrinsic motivation by empowering learners to independently manage their learning behavior (Dever et al., 2020). Third, we presume that *mastery goal orientation* enhances the experience of intrinsic motivation while accomplishing learning progress (Spinath & Steinmayr, 2012).

Study 2 included 450 learners aged 16 to 77 years (*M* = 36; *SD* = 14.10) who completed one of 49 non-formal online courses offered by Bavarian universities and participated in up to three online questionnaires throughout the course. Using latent profile analysis based on all five motivational subtypes to descriptively capture the multidimensional nature of motivation, we identified four distinct profiles—all of which demonstrated remarkable stability in motivation among course completers. The profiles mainly differed in their levels of the five motivational subtypes, aligning with learners' enrollment intentions. A bivariate latent change score model of intrinsic motivation and situational interest including self-regulation and mastery goal orientation as additional predictors revealed a statistically significant change in intrinsic motivation from T1 to T2 ($\sigma^2 = .841$, $p < .001$) that could only be predicted by self-regulation ($\beta = .199$, $p = .029$), indicating a growth in intrinsic motivation for learners' with higher levels of self-regulation. However, as expected, initial intrinsic motivation was positively correlated with all three personal characteristics.

The findings emphasize the importance of intrinsic motivation in non-formal online courses, as most of the learners were assigned to the profile characterized by high levels of intrinsic motivation and identified regulation (i.e., autonomous types of motivation) and low levels of the other subtypes. Moreover, intrinsic motivation seems to be quite stable over time but learners with lower levels of initial intrinsic motivation might experience a growth in intrinsic motivation that can be predicted by self-regulation. For a deeper understanding of learners' trajectories of intrinsic motivation in non-formal online courses, future research should not only examine completers but also learners that drop out before course completion as naturally not all learners aim to receive a certificate when enrolling (Henderikx et al., 2017). Consequently, future research could conduct repeated, frequent assessments directly accompanying the online learning process to capture real-time states of situational motivation to examine within-person effects in more detail in order to better distinguish between course completers and dropouts (Wrzus & Neubauer, 2023). Moreover, app-based ambulatory assessments of motivational processes (Hoppmann & Riediger, 2009) might allow to better integrate follow-up surveys that cover learners' reason for dropout. Finally, future research is needed to examine whether our results can be generalized for other populations or online learning platforms as participants and course offers vary greatly in non-formal education.

While Study 2 highlights the role of intrinsic motivation in shaping engagement and retention in non-formal online courses, it primarily focuses on learners who completed the course. However, non-formal education attracts a diverse range of participants with varying enrollment intentions (Moore & Wang, 2021). Consequently, course completion alone does not fully capture learning success, as many learners might engage with course materials without necessarily aiming to obtain a confirmation of participation (Henderikx et al., 2017). To provide a more comprehensive understanding of learning behavior across all enrolled learners, Study 3 moves beyond motivation to examine learners' engagement with self-tests, regardless of course completion—thus addressing the limitation of Study 2, which focused solely on course completers. Building on the future research directions outlined in Study 1, Study 3 introduces an objective measure of learning outcomes in non-formal education, operationalized as the percentage of correct test answers throughout the course. Rather than directly linking this measure to log data indicators of general online activity, Study 3 takes a step back to investigate which motivational aspects from Study 2, along with additional learner and course characteristics, predict learners' engagement with self-tests.

3.3 Study 3 – Embracing the Challenge: Predicting Self-Testing in Non-Formal Online Courses Using Machine Learning

In non-formal online courses, formative assessments—usually implemented in the form of self-tests—are a key tool to provide automated and immediate feedback in order to support the learning process (Werquin, 2010). Engaging with self-tests enhances learners' SRL by helping them identifying knowledge gaps and effectively manage their own learning behavior (Carpenter, 2023). While self-testing is widely recognized as an effective learning technique for improving retention and comprehension (Rivers, 2021), not all learners use self-tests voluntarily, often perceiving it as a tedious task (Dunlosky et al., 2013). Moreover, mastering learning material requires more than merely taking self-tests; learners must also invest sustained effort in self-testing as SRL technique until they achieve correct answers, which is a form of *cognitive engagement* (Lawson & Lawson, 2013). In highly autonomous learning environments like non-formal online courses (Biwer et al., 2021), learners decide for themselves to use learning techniques such as self-testing. As learners tend to underuse effective learning techniques (Carpenter et al., 2022), Study 3 investigates which learners are willing to engage with self-tests and under which conditions they persist until they achieve correct answers by identifying learner and course characteristics that might have an impact on learners' engagement with self-tests.

The final analysis sample consisted of 1,261 learners, aged 16 to 84 years ($M = 37$; $SD = 14.30$), who enrolled in at least one of 45 courses offered by Bavarian universities. To predict learners' engagement with self-tests, we conducted elastic net regressions using 50 predictor variables covering learner and course characteristics derived from self-reports, process, and meta data. While the data originated from the same research project as Study 2, for the present analyses only cross-sectional questionnaire data from the first survey was included. Additionally, courses that solely offered a final exam as self-testing opportunity were excluded from the analyses. Our results revealed substantial differences in learners' engagement with self-tests in non-formal online courses. 17.2% of learners answered all self-tests correctly, hence making use of all available self-testing opportunities. In contrast, 36.3% did not answer a single test item correctly. To better understand the factors driving this variation, we used a machine learning-based prediction model, which identified important predictors and achieved an acceptable explained variance of $R^2 = .11$. Two predictor variables turned out to be particular important across all analyses. First, learners who participated in our survey multiple times within different courses demonstrated greater commitment, progressing more thoroughly through the course and answering more self-tests correctly compared to those who participated in our survey once within a single course. This finding emphasizes the interplay between SRL and commitment within non-formal online courses found in previous literature (Kim et al., 2021). Second, learners who enrolled with the intention to obtain a confirmation of participation were more likely to complete self-tests, underscoring the role of extrinsic incentives in fostering engagement (Kizilcec & Schneider, 2015). While enrollment intentions in general proved to be important for predicting learners' engagement with self-tests, socio-demographic variables such as gender, age, or current occupation had no notable impact. These findings highlight the importance of learners' intentions over demographic characteristics in shaping learners' engagement with self-tests in non-formal education.

Since 89% of the variance in learners' engagement with self-tests could not be explained, future research should investigate additional predictors that might be important. For example, log data that reflects learners' behavioral engagement covering general online activity indicators like those from Study 1, or even more fine-grained log data reflecting SRL processes could lead to a more insightful understanding of online learning achievement (You, 2016). Beyond log data, future studies could explore psychological constructs more directly linked to learners' perceptions of test situations, such as achievement goal orientations (Elliot & Murayama, 2008), or test anxiety (Weissgerber & Reinhard, 2018). Moreover, the decision to include all learners rather than only course completers, as in Study 2, resulted in a highly heterogeneous sample and a dataset with several missing values. To gain deeper insight into learners who disengage from non-formal online courses after their initial enthusiasm, future research should employ more tight-knit sampling methods (e.g., ecological momentary assessment; Shiffman et al., 2008). Lastly, as Study 3 focused on courses from a single learning platform, future research should examine structural differences across various non-formal online courses to better capture how course characteristics might influence learners' engagement with self-tests.

4. Discussion

All three studies of the present dissertation collectively contribute to a more nuanced understanding of online learning behavior and success in formal education (Study 1) as well as in non-formal education (Study 2 & 3) by integrating different methodological approaches and theoretical perspectives. The main finding of Study 1 was that log data can serve as meaningful indicators of learning behavior in formal education, where learning success is traditionally measured through grades or course scores. We demonstrated the potential of learning analytics by linking log data to academic outcomes but also highlighted the challenge of transferring traditional success metrics from formal to non-formal education due to differing learner intentions and definitions of success. Therefore, Study 2 shifted the focus from formal education and traditional performance-based measures to non-formal education and internal motivational processes as an alternative perspective on learning success. The findings indicated that intrinsic motivation plays a crucial role in learners' engagement and retention in highly autonomous learning environments such as non-formal online courses. Overall, motivational trajectories among course completers remained notably stable, with most learners experiencing continuously high levels of intrinsic motivation. However, a latent profile analysis revealed that learners completing the course varied in their motivational compositions. Beyond those with high intrinsic motivation, some learners were categorized in profiles emphasizing extrinsic motivations like introjected or external regulation. By considering these diverse motivational profiles alongside learners' enrollment intentions, Study 2 offered a differentiated perspective on success in non-formal education, highlighting the complexity of motivation beyond simple success metrics. Study 3 builds on the findings of

Study 2 by including all learners, not just completers, to provide a more comprehensive understanding of the complexity and heterogeneity of learning behavior in non-formal online courses. It bridges traditional assessment perspectives from formal education with the autonomous and flexible nature of non-formal online courses. By predicting learners' engagement with self-tests based on various learner and course characteristics, Study 3 highlights that engagement with self-tests varies widely among learners—with a notable share either fully utilizing or entirely neglecting self-testing opportunities. The most important predictors of learners' engagement with self-tests were course commitment, reflected in multiple participations within different courses, and enrollment intentions, especially the intention to obtain a confirmation of participation, emphasizing the role of extrinsic incentives in shaping SRL behaviors like self-testing.

4.1 Key Findings and Contributions Across Studies

A central theme across all three studies is the multifaceted nature of learner engagement in online courses. In general, learner engagement plays a crucial role in shaping learning outcomes (Wong et al., 2024). In addition to a positive association with academic achievement, it is linked to an improved persistence and retention, and has also been proven to be a predictor of learner dropout (Bond et al., 2020). Learner engagement comprises three dimensions: (1) *behavioral engagement*—covering participation and involvement in learning activities, (2) *affective engagement*—involving interest and a positive attitude towards learning, and (3) *cognitive engagement*—including self-regulation and investment in learning (Appleton et al., 2008). This tripartite framework offers a theoretical conceptualization for the joint consideration of the empirical studies of the present dissertation: Study 1 primarily captured behavioral engagement, operationalized through log data indicators of general online activity in a formal educational context. Study 2 examined antecedents of affective engagement by focusing on motivations that drive learners to persist in a non-formal context.

Finally, Study 3 addressed cognitive engagement, assessing the extent to which learners actively invested effort into self-testing as a SRL technique.

By investigating all three dimensions of learner engagement across formal and non-formal online courses, this dissertation integrates multiple perspectives on online learning behavior and success within a joint theoretical framework. It demonstrates how dimensions of learner engagement manifest across learning contexts and how they relate to different indicators of learning success by (1) investigating the association of log data indicators with traditional formal success metrics, (2) examining motivational trajectories among course completers, and (3) predicting learners' engagement with self-tests.

The following sections elaborate on the central contributions of this dissertation with respect to theory, methodology, and practice. Section 4.1.1 synthesizes how integrating different perspectives on engagement advances our understanding of online learning behavior and success. Section 4.1.2 outlines the application of innovative methodological approaches within the present dissertation. Lastly, Section 4.1.3 discusses practical implications for designing effective online learning environments that support different forms of engagement.

4.1.1 A Theoretical Perspective on Online Learning Behavior and Success

By integrating a synthesis on log data analyses (Study 1), motivational processes (Study 2), and self-testing behavior (Study 3), this dissertation provides a holistic view of online learning behavior and success across different educational contexts. The findings emphasize that traditional performance metrics—such as grades and completion rates—fail to fully capture learning success in non-formal online courses. Instead, Study 2 and 3 propose alternative approaches, such as motivational trajectories and engagement with self-tests, to reconsider what constitutes meaningful learning outcomes in online courses.

A key strength of the present dissertation lies in its broad coverage of multiple aspects of investigating online courses. By combining Study 1 that focuses on formal education with

Study 2 and 3 that examine a non-formal learning context, the dissertation examines online courses across a spectrum of different learning settings. In terms of data sources, Study 1 and 3 rely on log data indicators to assess different types of engagement, whereas Study 2 uses self-reported motivation, thus considering both objective and subjective measures of learner engagement. Moreover, the dissertation combines different theoretical perspectives: Study 1 draws on Carroll's (1963) *model of school learning* and Engeström's (1987) *activity theory*, Study 2 is grounded in the *Self Determination Theory* framework (Ryan & Deci, 2017), and Study 3 covers concepts from *Self-Regulated Learning* (SRL; Zimmerman, 2002). These frameworks are not treated in isolation, but jointly inform how different types of learner engagement unfold in online courses, as each study represents a different facet of learners' engagement: Study 1 explores behavioral engagement, Study 2 examines antecedents of affective engagement, and Study 3 focuses on cognitive engagement (Bond et al., 2020). In doing so, the dissertation provides an empirical foundation for understanding online learning behavior and how it relates to indicators of success. While Study 1 relies on traditional success metrics relevant to formal education (UNESCO Institute for Statistics, 2012), Study 2 and 3 advance non-formal education research by challenging conventional definitions of success. Course completers represent only a selective subpopulation—those who commit to finishing the course. However, due to the highly autonomous and self-determined nature of voluntary non-formal online courses (Biwer et al., 2021), a substantial number of learners never intend to complete the course. These learners may either fail to master the course content, or conversely, achieve their learning goals without demonstrating success through formative assessments. This raises an important issue: in non-formal education, course completion should not be the sole criterion for success.

Unlike formal education, where structured progression and formally recognized certification is central, non-formal learners engage with courses for diverse reasons (Moore & Wang, 2021). Some learners achieve their goals by accessing specific course materials and leaving once they have acquired the desired knowledge. Their success is not reflected in completion rates but in their ability to fulfill their individual learning needs (Zheng et al., 2015). Others enroll in courses out of curiosity and drop out early, which is possible due to open and free access and no negative consequences (Bezerra & da Silva, 2017). In some cases, learners may lack a clear understanding of course requirements, leading to unrealistic expectations about the course difficulty or their ability to complete it (Onah et al., 2014). The diverse learner population in non-formal courses also includes individuals with varying levels of commitment, prior knowledge, and SRL skills, which makes a standardized definition of success problematic. All in all, whether in terms of motivation or the use of SRL techniques like the engagement with self-tests as alternative perspectives in contrast to course completion, it is generally essential to consider learners' enrollment intentions. Depending on their goals, some individuals may not seek to complete a course or master an entire topic but rather focus on acquiring specific information (DeBoer et al., 2014). Accordingly, course completion does not necessarily indicate successful learning behavior, as success in online courses is relative to individual intentions and may reflect personally meaningful goals rather than standardized outcomes. By moving beyond traditional performance metrics and considering alternative success measures, this dissertation contributes to a new theoretical perspective on online learning behavior and success. Future research should refine success definitions in non-formal education, integrating learners' intentions, SRL strategies, and motivational trajectories to develop a more learner-centered perspective on online learning success.

4.1.2 A Methodological Perspective on Online Learning Behavior and Success

From a methodological perspective, the dissertation contributes to the examination of online learning behavior and success in formal and non-formal online courses by applying diverse analytical approaches. Research on online courses presents distinct methodological challenges, particularly due to the high dimensionality of data, large sample sizes, and multilevel structures (Fan et al., 2014). Without advanced statistical approaches, analyses may yield misleading conclusions. To derive meaningful and reliable insights, researchers must employ methods that effectively handle data complexity (Harari et al., 2016) while remaining grounded in strong theoretical frameworks and pedagogical principles (Banihashem et al., 2024). This dissertation addresses these challenges by incorporating three different methodological approaches: a meta-analytical approach to synthesize research on log data and learning outcomes in Study 1, longitudinal modeling to examine motivational trajectories in Study 2, and machine learning techniques to predict learners' engagement with self-tests in Study 3.

Study 1 responds to the increasing number of learning analytics studies (Kew & Tasir, 2022), which investigate the relationship between log data indicators and learning outcomes. Despite this growing body of research, course-specific prediction models have yielded inconsistent and sometimes contradictory results, highlighting the complexity of learning processes and the lack of a one-size-fits-all-solution (Gašević et al., 2016). To address this issue, a meta-analytical approach was used to estimate an overall effect size and examine potential sources of variability. By aggregating findings from multiple primary studies in a quantitative way, this analysis enhanced statistical power and precision while also accounting for heterogeneity related to course design, sample characteristics, and methodological differences (Döring & Bortz, 2016). Additionally, as some primary studies reported more than one effect size, a multilevel modeling approach was used to account for those dependencies (Cheung, 2014). Unlike traditional narrative or systematic literature reviews, which are often more qualitative and subjective, meta-analyses provide a quantitative synthesis that allows for an objective assessment of research trends and inconsistencies (Harrer et al., 2019).

Study 2 introduces a longitudinal approach by applying bivariate latent change score models (McArdle, 2009) to examine intrinsic motivation in non-formal online courses. While numerous longitudinal studies have investigated motivation in formal learning contexts (Corpus et al., 2020), little research has explored how motivation evolves over time in more autonomous learning environments such as non-formal education. The longitudinal design enabled the examination of dynamic motivational processes, revealing patterns of change (or rather stability) that cross-sectional studies cannot capture. By accounting for the clustered structure of our data using cluster robust standard errors (McNeish et al., 2017), we controlled for contextual influences on motivational trajectories as learners were nested within different courses. While results indicated that intrinsic motivation remained relatively stable at a high level for most learners, an additional latent profile analysis (Spurk et al., 2020) revealed different motivational profiles when considering multiple motivational subtypes, demonstrating the complexity of motivation in non-formal online courses.

Study 3 extends the methodological scope by employing machine learning techniques to analyze leaners' engagement with self-test in non-formal online courses. Given the large and complex dataset—including over 1,000 learners across 45 courses with 50 predictor variables—traditional multiple regression models would have been insufficient to predict a complex learning behavior such as self-testing. Instead, elastic net regression (Zou & Hastie, 2005), which combines ridge regression (Hoerl & Kennard, 2000) and LASSO regression (Tibshirani, 1996), was used as shrinkage and variable selection method. This approach prevents overfitting while allowing for the inclusion of multiple intercorrelated predictors, resulting in a parsimonious, interpretable, and generalizable prediction model. To account for the nested data structure and to ensure unbiased model evaluation, we used a blocked cross-validation approach (Roberts et al., 2017). Unlike conventional data splitting approaches, which neglect the hierarchical structure of the data and can lead to overly optimistic estimates, our approach provided a more realistic assessment of predictive performance, highlighting the importance of implementing appropriate statistical techniques. Beyond prediction, the study also examined the relative importance of different predictors, offering deeper insights into the key factors influencing learners' engagement with self-tests.

Together, these methodological approaches contribute to the ongoing development of online learning research, offering a foundation for more nuanced and reliable future studies in digital education.

4.1.3 A Practical Perspective on Online Learning Behavior and Success

The findings across all three studies offer valuable insights into the design of effective online courses. While Study 1 highlights the complexity of course design and the need for a more fine-grained examination, Study 2 and 3 emphasize the importance of considering learners' enrollment intentions in non-formal online courses. Together, these studies suggest that simply providing online learning tools is not sufficient—effective course design must also support learners to engage with these tools in meaningful ways.

Study 1 sought to determine whether specific course design characteristics influence the relationship between general online activity and learning outcomes in formal education. However, due to limited reporting of contextual variables in primary studies, the meta-analysis could not identify statistically significant moderating effects for course type (fully online vs. blended), explicit instructions for discussion board usage, or the inclusion of graded online course activities as participation incentives. This finding highlights a broader challenge in learning analytics research: while online courses can provide a wide range of digital tools (Lust et al., 2012), learners do not automatically benefit from them unless they receive explicit guidance on how to use these tools effectively (Kebritchi et al., 2017). Consequently, future research might describe implemented digital tools in more detail by elaborating on the concrete design, instruction and pedagogical alignment to better understand how they influence learners' online behavior. Using the example of assessments, quizzes are commonly implemented in online courses to monitor the learning progress (Knight, 2020) or enhance engagement (Tempelaar et al., 2019), but their impact on learning may vary depending on their frequency, spacing, format (summative vs. formative assessment), and whether they are mandatory or voluntary. More nuanced research is needed to determine not just whether quizzes are present in courses, but also how they are integrated into the learning experience. Additionally, while learning analytics hold great potential for supporting learners (Viberg et al., 2020), their adoption was still in its early stages at the time of data collection for this meta-analysis. Today, the application of AI and generative AI in education fuels innovations for adaptive learning, real-time support and personalized educational experiences (Kasneci et al., 2023). Future research should examine how these technologies combined with learning analytics affect learners' online behavior and overall learning outcomes. Understanding how technological advancements shape learning behavior will be critical for developing more effective online learning environments.

Study 2 examined learners' motivational trajectories in non-formal online courses, providing relevant considerations for course designers. While the study did not recommend specific course design interventions, it highlighted the potential value of repeated, real-time assessments of learners' motivational states (Hoppmann & Riediger, 2009) to inform future course design decisions. In particular, understanding the reasons behind course dropouts is essential—some learners may leave courses due to personal learning goals rather than a lack of motivation or dissatisfaction with the course design (DeBoer et al., 2014). Therefore, motivational interventions should be tailored to individual enrollment intentions to ensure their effectiveness.

Study 3 reinforced this perspective by demonstrating that learners' engagement with self-tests in non-formal online courses was primarily driven by their course commitment and enrollment intentions rather than course-specific characteristics. This finding suggests that instead of focusing solely on course design, educators should consider strategies that foster learners' commitment and motivation to engage with course components (Zepeda et al., 2020). For example, Study 3 highlighted that learners who enrolled with the goal of obtaining a confirmation were more likely to engage with self-tests. Even though the tests were originally intended as formative rather than summative assessments (Wiliam & Black, 1996), the completion of a certain number of self-tests was a requirement to obtain a confirmation of participation. Therefore, one potentially effective approach might be the integration of extrinsic incentives, such as confirmations of participation. Encouragingly, extrinsic motivation in this context did not appear to undermine intrinsic motivation, as learners continued to engage with self-tests even after fulfilling the requirements for receiving a confirmation. These findings align with previous research suggesting that certification opportunities can serve as an effective motivator for increased engagement in non-formal online courses (Kizilcec & Schneider, 2015). Accordingly, course designers could implement more fine-grained incentive structures, such as badge systems (Ortega-Arranz et al., 2019), to further enhance engagement. By implementing gamification elements that provide incremental rewards for consistent participation (Sailer, 2017), educators may encourage the use of specific learning techniques, ultimately leading to a deeper cognitive processing of course material, better retention, and understanding.

Overall, the findings from these studies suggest that online course design goes beyond simply providing learning tools. It should actively foster engagement by providing clear guidance on how to use these tools effectively and by considering learners' individual motivations and enrollment intentions. Future research should continue to explore how learning analytics, incentive structures, and personalized interventions can enhance engagement and learning outcomes in both formal and non-formal online courses.

4.2 Limitations and Outlook

While the previous sections of the discussion chapter have outlined the key findings and contributions of this dissertation, it is equally important to situate these findings within current educational developments and to reflect on their limitations. Although AI has been applied in education for around 30 years (Zawacki-Richter et al., 2019), recent advances in natural language processing (NLP) and large language models (LLMs), such as GPT-4, have revolutionized education and research (Alqahtani et al., 2023). This is a major development that falls outside the scope of the present dissertation. Nowadays, AI-based models are omnipresent in all domains of our lives (Sarker, 2022). The rapid technological evolution of AI also provides new ways to implement learning analytics (e.g., Darvishi et al., 2022; Ouyang & Zhang, 2024). However, it remains important to consider the human-centered perspective for the design of online courses that rely on innovations from AI (Alfredo et al., 2024), which is addressed by the dissertation's focus on the learner perspective. Through the application of AI-enhanced learning analytics, online courses increasingly draw on automated systems described as "intelligent" or "smart" (Sarker, 2022). However, future research should focus not only on advancing these technologies and making systems smarter, but also on ensuring that learners (and educators) can keep up with these rapid technological developments and are empowered to use them effectively (Markauskaite et al., 2022). With the rise of AI-based feedback tools within online courses, learners increasingly interact with systems rather than instructors. As learning processes become more automated, future research needs to address where human interactions remain indispensable—and where human-computer interactions might provide equivalent or even superior support.

At the same time, the growing diversity of online learning contexts raises additional challenges for educational research. As discussed in Chapter 2, non-formal education exists on a continuum between formal and informal education, lacking a clear-cut definition (Souto-Otero, 2021). This ambiguity, or fuzziness, complicates research efforts. Large-scale datasets covering lifelong learning and diverse global populations offer a promising avenue for addressing sampling biases (Dufau et al., 2011), yet they also introduce new difficulties. The heterogeneity of non-formal learners—spanning different ages, educational backgrounds, and motivations—makes it challenging to disentangle meaningful subgroup differences from random variation or contextual influences (Fan et al., 2014). Future research must refine methodologies for investigating non-formal education, developing frameworks that account for its flexible nature while still allowing for meaningful analysis.

Understanding how to navigate the balance between automation and human support as well as how to account for diverse learning contexts is essential for designing inclusive and future-ready learning environments. As online courses continue to evolve, so must the methods used to study them, ensuring that findings remain relevant in an increasingly complex and interconnected learning landscape.

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Appendix A

List of Original Contributions

1. Klose, M., Steger, D., Fick, J., & Artelt, C. (2022). Decrypting log data: A meta-analysis on general online activity and learning outcome within digital learning environments. *Zeitschrift für Psychologie, 230*(1), 3–15. https://doi.org/10.1027/2151-2604/a000484

2. Klose, M., Handschuh, P., Steger, D., & Artelt, C. (2024). Not easy to get off track: Motivational trajectories of learners completing a non-formal online course. *Computers in Human Behavior, 159*, Article 108322. https://doi.org/10.1016/j.chb.2024.108322

3. Klose, M., Handschuh, P., Steger, D., & Artelt, C. (2026). Embracing the challenge: Predicting self-testing in non-formal online courses using machine learning. *Computers & Education, 242,* 105507. https://doi.org/10.1016/j.compedu.2025.105507

Appendix B

Manuscript 1

Decrypting log data: A meta-analysis on general online activity and learning outcome within digital learning environments

Maria Klose

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Diana Steger

University of Kassel, Germany

Julian Fick

Technische Universität Braunschweig, Germany

Cordula Artelt

Leibniz Institute for Educational Trajectories (LIfBi), Germany

University of Bamberg, Germany

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Abstract

Analyzing log data from digital learning environments provides information about online learning. However, it remains unclear how this information can be transferred to psychologically meaningful variables, or how it is linked to learning outcomes. The present study summarizes findings on correlations between general online activity and learning outcomes in university settings. Course format, instructions to engage in online discussions, requirements, operationalization of general online activity, and publication year are considered moderators. A multi-source search provided 41 studies (N = 28,986) reporting 69 independent samples and 104 effect sizes. The three-level random-effects meta-analysis identified a pooled effect of r = .25 p = .003, 95% CI [.09, .41], indicating that students who are more active online have better grades. Despite high heterogeneity $Q(103)$ = 3,960.04, p < .001, moderator analyses showed no statistically significant effect. We discuss further potential influencing factors in online courses and highlight the potential of learning analytics.

Keywords: online learning, log data, learning analytics, academic achievement, meta-analysis

Decrypting Log Data: A Meta-analysis on General Online Activity and Learning Outcome within Digital Learning Environments

Until recently, face-to-face teaching and on-site exams were considered gold standard in formal higher education. Universities face an increased demand, as the amount of students constantly grows (Araka et al., 2020) and not least because of the COVID-19 pandemic, the need for online learning in higher education increased drastically (Ali, 2020). However, only little is known about how students use online classes and how their learning behavior is linked to learning outcomes. Online learning environments, so-called *Learning Management Systems* (LMS), make it easier to obtain information about students' learning behavior by analyzing automatically tracked log data from students' interactions with the LMS (Gašević et al., 2016). Although interest in learning analytics constantly grows (Dawson et al., 2014) and uses of trace data are increasing (Winne, 2020), the potentials of using process generated data for purposes of summative and formative assessments is yet an emerging research field in which common concerns about the potential limitations are addressed. Concerns relate to the weak relation between overt learning behavior operationalized via log data with complex learning behavior. Henrie et al. (2018) describe them as strongly simplified proxies for complex learning behavior, which ultimately questions their usefulness for the evaluation of online classes. Consequently, there is an ongoing debate whether log data are a valid predictor for learning outcomes (e.g. Agudo-Peregrina et al., 2014; Campbell, 2007), or whether they fail to predict learning outcomes—either because it is difficult linking log data to learning behavior, or because courses with substantial online elements are too heterogeneous to draw a general conclusion (e.g. Gašević et al., 2016; Macfadyen & Dawson, 2010). Although added value of using fine-grained and event-related process data for certain unobtrusive assessment purposes has been demonstrated (e.g. measuring intra-individual change; Barthakur et al., 2021), the use of log data for platform-, domain- and demand independent assessment of successful digital learning activities is still a matter of debate. Since systematic reviews about the value of broad log indicators are missing, the present meta-analysis summarizes findings on the relationship between these online activities derived from log data and learning outcome within LMS. We focus on two broad log data indicators of general online activity (i.e., total login time and login frequency), which can be classified as access-related log events (Kroehne & Goldhammer, 2018) and are commonly used as measures linked to students' achievement (see You, 2016 for a detailed discussion of this issue). Accordingly, in the case of learning outcomes, we focus on indicators of learning success (i.e., course grade or course score).

General Online Activity and Learning Outcomes

One major advantage of online learning for educational research is the availability of a vast amount of information that can be derived automatically and unobtrusively. For example, courses offered via LMS allow to collect an enormous amount of log data about interactions with the platform (Campbell, 2007). However, the primary use of explorative approaches for analyzing log data results in lack of theoretical grounding (Winne, 2020). Besides the number of studies comprising data-driven approaches for the decision which log data to examine, several researchers have considered pedagogical theories (see Tempelaar et al., 2015 for a review). For example, general online activities, as for example *total login time* or *login frequency*, are considered indicators for learning engagement (Beer et al., 2010). Furthermore, according to Carroll's (1963) *model of school learning*, time spent on learning is one of the crucial factors for students' performance. Thus, time spent on learning online might also be a crucial factor for web-based achievement (Jo et al., 2015). Besides, login frequency is associated with Engeström's (1987) *activity theory*, which states that mere activity produces meaningful learning, leading to higher learning outcomes (Kupczynski et al., 2011). Finally, total login time and login frequency are considered proxies for time management strategies, as they are indicators for a sufficient time investment and thus, key factors for performance (Jo et al., 2015). However, there is a debate on the type of log data suitable to serve as a measure of learning behavior (Agudo-Peregrina et al., 2014). Critics suggest to focus on quality, not quantity of online learning behavior (You, 2016): As active participation is crucial for success, indicators that do not distinguish between active and passive engagement are problematic (Ransdell & Gaillard-Kenney, 2009). Overall, these contradictory assumptions on the usefulness of broad log data indicators go along with inconsistent findings on the association between those indicators of general online activity and learning outcomes: some studies reported no association (Broadbent, 2016), negative correlations (e.g., Ransdell & Gaillard-Kenney, 2009; Strang, 2016), or positive correlations (e.g., Liu & Feng, 2011; McCuaig & Baldwin, 2012; Saqr et al., 2017). Other studies that examined various online courses simultaneously obtained mixed results across different courses (e.g., Conijn et al., 2017; Gašević et al., 2016), indicating that online courses might be too heterogeneous to draw a general conclusion about the link between general online activity and learning outcomes.

The Present Study

Our aim was to provide a systematic review of findings on the relationship between two log data indicators of general online activity and learning outcomes within LMS. To guarantee a minimum level of comparability between classes, we focused on online university courses, because they are more structured than informal online courses (Song & Bonk, 2016) and because they are usually graded, offering a measure of learning outcomes. With respect to general online activity, we focused on total login time and login frequency to assess the applicability of these broad measures derived from log data as a proxy of online learning behavior, and to examine how they are linked to educational outcomes (i.e., course grade or course score). Moreover, we examined the impact of several moderators to explain the inconsistent findings reported in previous literature, since in the course of recent technological developments (Palvia et al., 2018), teaching tools became more sophisticated and online courses became more diverse.

First, we use the term “online course” to describe all courses that include substantial online elements, that is, courses that are taught exclusively online (*fully online* courses), and courses that combine online and face-to-face delivered content (*blended* courses; Allen & Seaman, 2014). Compared to fully online courses, blended courses offer more structure through regular face-to-face sessions (Means et al., 2013), as well as the opportunity to easily get in touch with peers regularly (Broadbent, 2016). However, the varying parts of face-to-face teaching in blended courses cannot be tracked via log data (Mwalumbwe & Mtebe, 2017). Therefore, we expect a stronger relationship between general online activity and learning outcomes within fully online than within blended learning courses, as for the latter, substantial parts of learning might remain unreflected by log data (*Hypothesis 1*).

Second, online courses vary with respect to the emphasis that is put on the use of online discussion boards. An explicit instruction to use discussion boards that is implemented within the LMS might foster deeper learning while being online, and lead to better achievement (Song et al., 2019). Although interactions in discussion forums are considered as an essential part of learning (Uijl et al., 2017), the mere existence of a discussion board is not enough for promoting active participation within the LMS (Lee & Martin, 2017). Since active content engagement is crucial for students' achievement (Ransdell & Gaillard-Kenney, 2009), we expect higher correlations between general online activity and learning outcomes for courses with an instruction for discussion board usage (*Hypothesis 2*).

Third, online courses differ in their grading systems. For the present study, it is important to what extent online activities are explicitly incentivized. While some courses do not incentivize online participation at all, other courses either offer bonus points for regular online participation or even require online activities within the LMS (e.g. online group discussions, quizzes, or online assignments) as part of the final grade. These incentives encourage active online engagement (Tempelaar et al., 2019) and offer guidance for students to effectively use the tools and materials provided within the LMS. Therefore, we expect a higher correlation between general online activity and learning outcomes for courses that incentivize certain online activities through their grading systems (*Hypothesis 3*).

Fourth, we compare the operationalization of general online activity as total login time, or as login frequency. Ever since the growing popularity of investigating log data, there is the challenge to capture log data that might be translated into psychologically meaningful variables (Seifert et al., 2018). As both operationalizations are theoretically reasoned with either Carroll's (1963) *model of school learning* or Engeström's (1987) *activity theory*, we want to explore if general online activity operationalized as *total login time* versus *login frequency* differ in their relationship with learning outcomes (*Hypothesis 4*).

Lastly, we considered publication year as potential moderator. In face of rapid technological advancements (Palvia et al., 2018), we expect changes in how LMS are used to provide education. Through technological change, LMS tools become more advanced, and multiple types of learning tools can be implemented to foster students' active engagement within the LMS (Kebritchi et al., 2017). Therefore, students ought to be enabled to benefit from a more interactive online learning experience, and online activity within recent studies might result in higher achievements than within older studies (*Hypothesis 5*).

Method

In accordance with common open science practices, we provide all additional materials (i.e., coding manual, syntax, data, PRISMA20-checklist and supplemental figures and tables) online within the *Open Science Framework* (Center for Open Science, 2021): https://osf.io/wy2px/.

Literature Search and Study Selection

We identified 33,724 potentially relevant studies from electronic searches in major scientific databases (*PsycINFO*, *PsycArticles*, *PSYNDEX* and *ERIC*) and *Google Scholar* using the Boolean search term *(online learning OR online course* OR web-based learning OR e-learning OR elearning OR learning management system* OR LMS OR learning analytics) AND (achievement OR performance OR outcome)* in February 2021. We retrieved five further studies by calls for unpublished work (via mailing list of the *German Psychological Society*, *ResearchGate*, and *Twitter*). Additionally, we performed a "rolling snowball" search and identified 17 further studies by screening the reference lists of all eligible studies and by conducting forward citation tracking using *Google Scholar*. Finally, we contacted 19 corresponding authors of studies not reporting bivariate correlations and received them for three studies. We included all published or unpublished types of studies. See Figure S1 for the detailed literature search process including specifications of all sources that were searched. Subsequently, these studies were included in the analysis depending on the following inclusion criteria: (a) The study investigated a fully online or blended course in an institutional setting. (b) General online activity was measured using log data and operationalized as total login time or login frequency (i.e. number of single logins or number of days with at least one login). (c) Learning outcome was measured as course grade or course score. (d) The study consisted of a sample comprising university students. (e) The study was published between 1969 (year of the first connection of the Internet) and 2021, and (f) was written in English or German. (g) The study reported at least one correlation between general online activity and learning outcome or appropriate statistics that could be transformed into correlations. Studies were excluded if: (h) General online activity was measured as a self-report as we focused on the usefulness of log data indicators of general online activity, or (i) measured as the duration or frequency of single activities in the LMS (e.g. time spent on quizzes, number of forum postings) because these types of log data fall within different categories (such as response-related or process-related log data; see Kroehne & Goldhammer, 2018), and (j) the study had a commercial e-learning course as setting as we focused on the specific context of higher education. After applying these criteria, 41 primary studies remained (see Table S1). Study selection followed a two-stage process. First, two researchers reviewed titles and abstracts of the first 50 records and discussed disagreements about eligibility until consensus was reached. Then, one researcher screened all titles and abstracts of all studies retrieved. In cases in which eligibility was unclear, the study was considered for the second stage in form of the full-text review. A sample of full-text studies (~15%; 36/241) was independently screened by two researchers. The remaining full-text studies were screened by one researcher. Finally, the second researcher independently reviewed all included studies, and those with uncertain eligibility. Again, disagreements about eligibility were resolved through discussion.

Coding Process

We developed a standardized coding manual and data extraction sheet for the data collection process (see osf.io/wy2px/ for detailed information). The coding manual comprised eligibility criteria, guidelines for the selection of effect sizes and coding, and definitions of all outcomes and other variables for which data were sought (i.e., name and description of the respective variables, guidelines regarding the format of coding, and coding examples). For each study, we extracted all relevant effect sizes for the association between general online activity and learning outcome. Moreover, we collected data on study and sample, and online course characteristics covering especially moderator variables (i.e., course format, emphasis of discussion, course activities as part of grading, operationalization of general online activity, and publication year) and general study information.

All studies were coded twice using the coding manual and data extraction sheets by two independent raters. To evaluate the coding process, Cohen's (1960) κ for categorical variables and intraclass coefficients (ICC; Shrout & Fleiss, 1979) for continuous variables were calculated for the focal variables. Interrater reliability for the effect size was ICC = .89, 95% CI [.84, .92] and for the sample size and publication year ICC = 1, 95% CI [1, 1]. The Cohen's κ for the remaining categorical variables was .91, overall indicating strong to excellent intercoder agreement (LeBreton & Senter, 2008). All discrepancies were solved upon discussion by comparing extracted data.

Statistical Analyses

Effect size. We used Pearson product-moment correlation as effect size measure. Because transforming standardized weights from multiple linear regression analyses into correlation coefficients is problematic (Aloe, 2015), authors from studies reporting only regression weights were contacted to obtain correlations. If no correlation was available, the study was excluded from the analyses ($k = 6$). To standardize the direction of effects, we conversed effect sizes in cases where learning outcomes were conceptualized as smaller numbers indicating better achievement.

Meta-analytic model. We pooled effect sizes using a random-effects model with a restricted maximum likelihood estimator (Viechtbauer, 2010). A three-level meta-analysis was conducted to account for dependent effect sizes (Cheung, 2014), because some studies reported more than one effect size (e.g., provided correlations for both operationalizations of general online activity for a given sample). Dependencies between effect sizes derived from the same sample are acknowledged by decomposing the total random variance into two variance components: one reflecting heterogeneity of effects within samples, and the other indicating heterogeneity of effect sizes between samples (see Gnambs & Appel, 2018 for a detailed description). We calculated I^2 statistics to quantify heterogeneity in observed effect sizes (Higgins et al., 2003). Considering I^2 is not an absolute measure of heterogeneity (Borenstein et al., 2017), we additionally report the *Q*-statistics. Since the use of sample size weights performs best for estimating the random-effects variance component in meta-analytic models with correlations as effect size measures (Brannick et al., 2011), we used this weighting procedure to account for sampling error. We reported our findings focusing on the size of the effect and its confidence and prediction interval. To visualize our meta-analysis, we used a forest plot (Viechtbauer, 2010). Lastly, we conducted subgroup and meta-regression analyses to examine moderating effects on the pooled effect size (Harrer et al., 2019), given the diversity of online courses being investigated. Therefore – apart from publication year –, we categorized the included studies along dichotomous moderators: fully online vs. blended course format, instructed vs. not instructed discussion board usage, graded activities vs. no requirements, and total login time vs. login frequency as general online activity.

Sensitivity analyses. First, we used the studentized deleted residuals (Viechtbauer & Cheung, 2010) to identify extreme correlations. Additionally, we conducted sensitivity analyses that removed the identified outliers from the analyses to examine the impact of these outliers. Moreover, the robustness of the presented meta-analysis was investigated by removing two particular studies that differed in their conceptualization (i.e., Lauría et al., 2012: correlation comprised data from an entire university; and Mödritscher et al., 2013: log data from only two weeks before the examination) from the meta-analytic database and comparing the pooled effect to the pooled effect from the full database.

Publication bias. The presence of potential publication bias was investigated in two ways: First, we performed a meta-regression with the publication type as a moderator. Effect sizes from peer-reviewed sources were compared to effect sizes from other sources (i.e. theses, or conference papers). A statistically significant difference between effect sizes extracted from both sources could be a result of a distortion in the peer-reviewed research literature due to systematic suppression of (e.g. non-significant) effects. Second, we conducted a modified regression test for asymmetry by including a precision measure (i.e., 1/n) as a moderator in the meta-analytic model to account for dependent effect sizes.

Statistical software. All analyses were conducted using *R* version 4.0.4 (R Core Team, 2021). Meta-analytic models were estimated with the *metafor* package version 2.4-0 (Viechtbauer, 2010).

Results

Descriptive Statistics

The meta-analysis is based on 41 studies that were published between 1997 and 2021, predominantly as peer-reviewed articles (73%). The remaining studies appeared as theses (5%), or conference papers (22%). The database covered 69 independent samples providing 104 effect sizes, with each sample comprising between 1 and 3 effect sizes. Overall, the meta-analysis included scores from 28,986 students (range of samples' *n*s: 11 to 11,195, *Mdn* = 122). Mean age was 22.21 years, and 53.71% of the students were female, however only 11 studies reported information on age and 20 studies information on gender. The duration of the courses varied between 6 and 19 weeks (*Mdn* = 12 weeks), mainly covering one academic semester. Moreover, courses varied with respect to their format (24% fully online, 72% blended, 1% not reported separately, or 3% missing), emphasis of discussion (18% instructed use of discussion boards, 69% discussion boards available within the LMS without further instructions, 10% not mentioned, or 3% missing), and requirements (45% online activities within the LMS as part of grading, 54% none, or 1% missing). In 44% of the cases, general online activity was operationalized as total login time and in 56% as login frequency (number of single logins or number of days with at least one login).

Overall Pooled Correlation

In total, the three-level random-effects meta-analysis identified a pooled correlation of $r = .25$ $p = .003$, 95% CI [.09, .41] indicating that students who are more active online also have a better learning outcome (Figure 1). The result of the pooled correlation was robust and replicated in the separate moderator analyses (Table 1).

Overall, these findings indicate a small but statistically significant positive association between general online activity and learning outcome. Yet, the high random variance resulted in an exceedingly large prediction interval around the pooled effect, 80% PI [-.10, .59]. Hence, we conducted sensitivity analyses to examine the impact of certain studies on the prediction interval. Further, the studies showed higher between-cluster heterogeneity ($I^2 = .92$; see also Figure 1 for an illustration of the variability between samples) compared to within-cluster-heterogeneity ($I^2 = .05$), indicating pronounced unaccounted differences between samples that might be explained by moderator analyses, but negligible variability within samples (Higgins et al., 2003).

Moderator Analyses

We conducted meta-regression analyses to examine the effects of course format, emphasis of discussion, requirements, operationalization of general online activity, and publication year on the pooled effect (Table 2). On effect size level, correlations between moderators ranged from -.54 to .46, indicating negligible multicollinearity. None of the moderators was statistically significant. This result remained the same even when each moderator was examined separately (Table 1). Overall, moderator analyses showed no effect, indicating that our data do not provide evidence in favor of a moderating effect of course format, emphasis of discussion, requirements, operationalization of general online activity, or publication year on the relationship between general online activity and learning outcome.

Sensitivity Analyses

We performed sensitivity analyses to examine the robustness of our findings. In a first step, the robustness of the presented results was investigated by removing nine extreme correlations (i.e. outliers with $z > 1.96$; Viechtbauer & Cheung, 2010; Figure S2) from the database to compare this pooled effect to the original pooled effect. After we eliminated these effects from the database, the pooled effect was $r = .24$, $p < .001$. The 80% PI decreased from [-.10, 59] to [.04, .43], indicating a reduced random variance. However, the outliers did not distort the pooled effect. Similar patterns appeared for all subgroup analyses (see Table S2). Overall, the outlier analyses provided evidence for the robustness of the correlation between general online activity and learning outcome. In a second step, sensitivity analyses with respect to two studies that differ in their conceptualizations from the other included studies resulted in negligible differences: $r = .29$, $p < .001$, 80% PI [-.05, .62] (Lauría et al., 2012), and $r = .24$, $p = .011$, 80% PI [-.11, .60] (Mödritscher et al., 2013), also indicating the robustness of the present meta-analysis (see Table S3).

Publication Bias

First, the meta-regression analysis that we conducted to examine publication bias indicated no statistically significant difference between effect sizes extracted from peer-reviewed versus other sources ($\gamma = -0.06$, $SE = 0.13$, $p = .624$). Second, the modified regression test for asymmetry ($\gamma = 7.93$, $SE = 8.57$, $p = .355$) revealed no statistically significant effect for measurement precision. Overall, we did not find evidence of publication bias.

Discussion

Online courses are more important than ever (Ali, 2020), and they provide the possibility to conveniently and unobtrusively record log data (Dawson et al., 2014). Yet, it is unclear how log data contribute to explain the linkage of learning behavior to academic achievement. Although several studies have examined the association between general online activities and learning outcomes, their findings are ambiguous (e.g. Broadbent, 2016; Campbell, 2007; Gašević et al., 2016). Hence, we provided a systematic review of existing findings and investigated several potential moderators to explain ambiguity in previous literature: In a first step, we identified a small – yet statistically significant – pooled correlation of $r = .25$ between general online activity and learning outcome. This finding indicates that students who are online for a longer time (or more often) within the LMS also tend to have better course grades. This effect might seem small at first, but it remained robust across sensitivity analyses even though we used very broad indicators of general online activity. Additionally, academic success in itself is extremely complex and therefore difficult to predict (see Alyahyan & Düştegör, 2020 for a review). Comparing our results to a meta-analysis examining multiple psychological correlates of university students' academic performance (Richardson et al., 2012), log data indicators perform better in predicting academic success as compared to demographics (i.e., sex, age and socioeconomic status), and personality traits (except for conscientiousness), but perform slightly worse than prior academic performance and academic self-efficacy. The strongest correlate of all 50 measures was performance self-efficacy (r = .59). Against this background, the present analysis demonstrates the potential of log data, given that even two broad log data indicators of online learning behavior are associated with learning outcome. However, the meta-analytic model revealed high heterogeneity between studies that could not be explained by moderator analyses. Therefore, we discuss reasons why our moderator variables might have failed to explain high heterogeneity and other possible sources of variance.

Limitations of the Included Moderators

First, our potential moderator variables were restricted to broad course characteristics, which can be illustrated by the variable *course format.* The dichotomous classification of *blended* versus *fully online format* might be too coarse as there exist flowing transitions depending on the portion of content delivered online (Allen & Seaman, 2014) and the share of online elements in a certain course might be better depicted as a continuous variable rather than a dichotomous one. However, most studies on online courses only provide very superficial characteristics. Given the fact that faculties struggle with the transition to online teaching (Kebritchi et al., 2017), more evidence is needed so practitioners who design online courses are able to make informed choices to improve quality of online learning.

Second, there is a lack of information on contextual variables (e.g. instructional design, interactive tools, or synchronicity) reported in primary studies. Varying contexts and tools affect the learning process by providing different learning opportunities which are decisive for improved learning (Lust et al., 2012). The consideration of contextual factors might help explain ambiguous findings in the current literature (Gašević et al., 2016) as they enable more comprehensive moderator analyses. Our moderator analyses were limited to basic information about how the LMS was implemented. In the following, we discuss which aspects might help explain differences between settings.

Potential Other Moderators

An overall structure offered by online courses might help to reduce individual differences in online learning behavior, as it provides guidance for students to engage in the most beneficial activities at a certain point of course processing (Winne, 2004). On the individual level, instructors can help to reduce existing heterogeneity within the association between general online activity and learning outcome, as not all learners seem to benefit equally from learning opportunities (Lust et al., 2012). Learners need to be instructed how to use LMS (Kebritchi et al., 2017) to exploit the full potential of online courses. Other forms of structure are for example shares of synchronous methods and applications in online courses (e.g. teaching sessions, collaborative learning, or support and monitoring by a tutor; see Kinshuk & Chen, 2006), which provide a structured schedule for learning behavior, or any form of online assessment across the course duration to monitor students' learning progress or to provide personalized feedback (Knight, 2020), or to encourage students' engagement (Tempelaar et al., 2019). In the present literature, systematic information on the extent of structuredness of online courses is unfortunately limited. Future research might document effects of these course characteristics and their impact on learning behavior.

Another aspect of online course design comprises the incentives that are used to ensure students' participation. Apart from the extent to which participation is included in course grading, only little is known about how instructors use incentives for constant participation throughout the course. One example for these incentives is gamification – the implementation of game-design principles and elements in non-game environments (Deterding et al., 2011) – which can promote motivation (see Mora et al., 2017 for a review) for example by providing visualized immediate feedback to the learner on goal completion or on students' learning progress compared to other students. Gamification for educational purposes can be associated with an increased activity (e.g. Hamari, 2017; Huang & Hew, 2015) or general engagement in online programs (Looyestyn et al., 2017). But it remains unclear, if a game-based induced increase in online activity automatically leads to improvement in learning. If practitioners systematically provide online courses with and without different types of gamification, future research could examine differences in online learning activity and its impact on learning outcomes.

Finally, our meta-analysis was based on log data indicators that specify the extent of total login time or login frequency within LMS over an entire academic semester. Differences in the distribution of online activity across the course duration could not be considered. As distributed learning is a more efficient learning strategy than cramming before examinations for an equal amount of time (Dunn et al., 2013), future research should not only address the mere amount of activity, but also the distribution of total login time or logins in a more fine-grained way. Additionally, student's diversity and consistency of online activities might provide substantial insights in how students' activity affects learning (Lust et al., 2012).

Log Data in Educational Research

The present meta-analysis can be seen as a starting point of how log data can be used to contribute to our understanding of complex variables like academic achievement by linking course outcomes to broad log data indicators of online learning behavior. However, given the increase of online education in higher education and the recent technological development (Kebritchi et al., 2017) there undoubtedly exist more fine-grained data in research than overall participation measures comprising platform usage. One big advantage of the use of log data is that large amounts of data are easily and immediately accessible, so that learning analytics can draw on detailed and extensive log data about learners' studying activities within modern software tools (Winne, 2010). Although log data are a more accurate reflection of the quantity of media use than self-reports (Parry et al., 2021), researchers' degrees of freedom in data tracking, collection and analysis persist and thereby limiting the objectiveness of log data indicators (Avella et al., 2016). Moreover, the biggest issue is the connection with existing educational theories and the resulting necessity to consider the reliability of log data as well as its role in claims about validity based on this kind of data (Winne, 2020).

But how can learning analytics meet the vision to help improving learning and teaching by using generated data as people engage in learning? On the student-centered level, learning analytics facilitate predictive modelling of course completion (Clow, 2013). Information on student's previous educational experience and demographics, as well as data on online activity and formative and summative assessment are combined and then used to develop interventions designed to improve retention and performance. This enables early intervention systems and personalized learning, as students receive real-time feedback on their learning progress (Arnold & Pistilli, 2012). Otherwise, instructors can take advantage of learning analytics by using them to identify areas in need of improvements regarding the curriculum as well as their own performance (Avella et al., 2016). Finally, the implementation of new tools or mechanisms can be checked (Song, 2018). Multiple types of learning tools enhance the learning experience (Hathaway, 2014), but it is not always *the more, the better*. Instructors have to consider which tool, design element or multimedia will add to the learning process and which ones are distracting (Kebritchi et al., 2017).

Limitations of the Present Study and Implications for Future Research

Research on learning analytics is a promising approach for an advanced understanding of the learning process (Gašević et al., 2015). This meta-analysis provides an initial insight into the value of broad log data indicators of learning behavior. However, the present analyses come with limitations. Specifically, recent developments in meta-analytic methods suggest that it might be more adequate to model the hierarchical structure of the data by including the covariances of effect sizes derived from the same sample in the model, rather than using the default model which assumes no covariances. On a more general stance, data dependency is an important issue in meta-analytic research that is often neglected (e.g., Rodgers & Pustejovsky, 2021). While these advanced models might be even better suited to model the data structures, many issues arise not from inappropriate modeling choices, but rather from shortcomings in the primary studies. How should future research look like in order to contribute to a more advanced understanding of online learning?

While the number of studies using log data increases steadily, only few of these studies transparently describe their methodologies for data collection and cleaning, utilized measures, or analyses (Bergdahl et al., 2020). In general, learning analytics have to face challenges of heterogeneous data sources and the lack of unified vocabulary (Papamitsiou & Economides, 2014). Future meta-analyses could make use of quality assessments of primary studies, something that is already common for assessing the methodological quality of intervention effectiveness research (e.g. Valentine & Cooper, 2008). Scheffel et al. (2014) have proposed a framework of quality indicators for learning analytics earlier on. Future meta-analyses would benefit from a standardized procedure that allows to take the methodological quality of learning analytics studies into account for weighting procedures as well as the decision whether to include or exclude a primary study. However, learning analytics can benefit from a unified framework for the use of terms and definitions, operationalizations, and methodological procedures.

Another promising development to overcome central issues (i.e. data access and transparency) in meta-analyses is the open data movement (Gurevitch et al., 2018). As soon as researchers follow standards regarding an open scientific process, design standards would reduce unclearly reported methodologies, and data sharing standards would enable to directly generate effect sizes from open data (Nosek et al., 2015).

Moreover, open science practices facilitate multi-level analyses based on raw data in form of meta-analysis of *individual participant data* (IPD; e.g. Riley et al., 2010). IPD meta-analyses are considered gold standard as they prevent aggregation biases and enable to look at the impact of heterogeneity that originates from differences within studies (Kaufmann et al., 2016). Due to the COVID-19 pandemic, educational institutions were forced to shift teaching to online learning (De' et al., 2020), potentially with an increase in the usage of interactive tools (such as video conferencing tools) that could facilitate online discussions or group work, which may also lead to an increase in the quality of online courses. Hopefully, these changes will be documented in forthcoming research on online courses. Future research might comprise large collaborations and centrally coordinated data collections within online courses to benefit from the incoming data due to the digital surge so that they might gain deeper insights to improve the quality of online learning.

Apart from that, this review focused on formal higher education. However, informal learning gains more attention in the field of educational research (Zheng et al., 2019), and therefore is a promising extension. Especially the change towards online learning promotes informal learning (i.e., learner-directed and independent learning outside of formal educational contexts; Song & Bonk, 2016). However, due to the absence of external assessment within informal learning (Callanan et al., 2011), studies with an informal context could not be included in the present meta-analysis. Even though formal and informal learning lead to gains in knowledge and skills (Cerasoli et al., 2018), it is difficult to combine them in meta-analyses as their outcomes are operationalized differently since for informal learning, educational success is traditionally defined as course completion (Henderikx et al., 2017). Accordingly, it seems worthwhile to examine whether the positive association between general online activities and learning outcomes can be transferred to informal context.

Conclusion

In summary, we identified an association between broad log data indicators of general online activity and learning outcomes. Although several sensitivity analyses indicated the robustness of the present meta-analysis, the high heterogeneity between studies could not be explained by our moderator variables, which were limited to basic information on course implementation. We recommend for future research to form bigger collaborations and centrally collect data to conduct IPD meta-analyses to gain deeper insight in online learning. Learning analytics have the potential to provide more fine-grained data, but it is necessary to connect generated data to existing educational theories.

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All articles included in the meta-analysis are listed in the online supplement.

Table 1

Meta-Analysis on General Online Activity and Learning Outcome and Separate Moderator Analyses

	k_1	k_2	N	r	SE_r	95% CI	Q_M	Q	$\sigma^2_{(2)}$	$\sigma^2_{(3)}$	$I^2_{(2)}$	$I^2_{(3)}$	80% PI
Overall	104	69	28,986	.25*	.08	[.09, .41]		3960.04*	.06	<.01	.92	.05	[-.10, .59]
Course format						[-.27, .18]	0.16						
Fully online	25	20	4,816	.32*	.08	[.17, .48]		125.03*	.04	<.01	.91	<.01	[.05, .60]
Blended	75	46	12,543	.28*	.07	[.15, .41]		2919.10*	.07	<.01	.93	.04	[-.08, .63]
Discussion board usage						[-.20, .27]	0.07						
Instructed	19	14	1,077	.28*	.08	[.11, .44]		112.98*	.06	<.01	.86	<.01	[-.05, 61]
Not instructed [a]	82	52	16,475	.29*	.06	[.17, .40]		3052.80*	.06	<.01	.91	.06	[-.05, .63]
Requirements						[-.22, .20]	0.01						
Graded activities	47	35	7,673	.29*	.10	[.10, .48]		2313.94*	.10	<.01	.95	.03	[-.13, .72]
None	56	33	10,118	.28*	.05	[.19, .37]		420.52*	.03	<.01	.80	.10	[.06, .51]
General online activity						[-.29, .18]	0.21						
Total login time	46	46	11,825	.29*	.07	[.16, .40]		2320.63*	.04	.04	.49	.49	[-.09, .66]
Login frequency	58	53	24,842	.23*	.07	[.09, .37]		585.41*	.02	<.01	.81	.11	[.01, .45]
Publication year [b]						[-.03, .05]	0.23						
Older than 2017	43	31	19,860	.22*	.09	[.04, .40]		501.64*	.03	<.01	.88	.07	[-.05, 49}
Newer than 2017	61	38	9,126	.29*	.08	[.14, .44]		2495.45*	.08	<.01	.93	.05	[-.09, .67]

Note. k_1 = Number of effect sizes. k_2 = Number of samples. r = Pooled correlation. SE_r = Standard error of r. 95% CI = 95% confidence interval of r. Q = test of heterogeneity (df = k_1 - 1). Q_M = test statistic for the omnibus test of coefficients (df = 1). $\sigma^2_{(2)}$ = Random effect of r between samples. $\sigma^2_{(3)}$ = Random effect of r within samples, $I^2_{(2)}$ = Proportion of between-cluster heterogeneity. $I^2_{(3)}$ = Proportion of within-cluster heterogeneity. 80% PI = 80% prediction interval of r.

[a] Includes the categories of discussion board usage *available* and *not mentioned*. [b] For illustrative purposes, subgroup analyses are reported for older vs. newer studies based on a median split.

* $p < .05$.

Table 2

Moderator Analysis Including all Five Moderator Variables Simultaneously

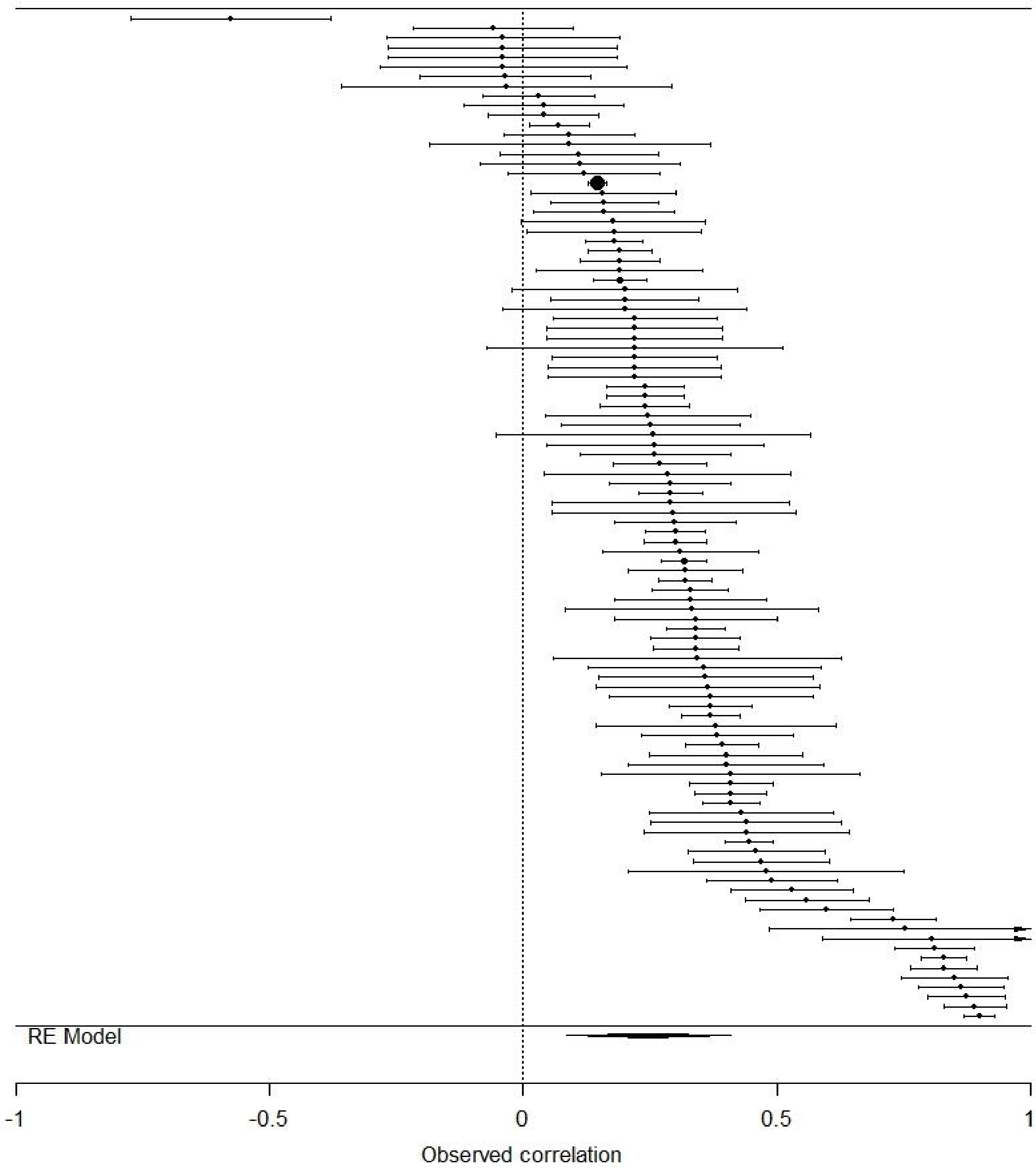
	Moderator Analysis			Correlations			
	γ	SE_{γ}	z	(1)	(2)	(3)	(4)
Intercept	-5.55	25.28	-0.22				
(1) Course format (1 = blended; 0 = fully online)	-0.07	0.13	-0.50				
(2) Discussion board usage (1 = instructed; 0 = available, not mentioned)	-0.04	0.13	-0.28	-.54			
(3) Requirements (1 = none; 0 = graded activities)	-0.03	0.10	-0.25	.12	-.27		
(4) General online activity (1 = login frequency; 0 = total login time)	0.01	0.05	0.12	-.16	.12	.12	
(5) Publication year (metric)	<0.01	0.01	0.23	.46	-.45	.12	-.28
Q_M	0.31						
$\sigma^2_{(2)}/\sigma^2_{(3)}$	0.06/<0.01						
k_1/k_2	100/66						

Note. Phi coefficients for dichotomous moderator variables and point-biserial coefficients for dichotomous and metric moderator variables on effect size level are displayed. The correlations are based on 100 to 104 effect sizes. γ = Fixed effects regression weight. SE_{γ} = Standard error of γ. Q_M = test statistic for the omnibus test of coefficients (df = 5). $\sigma^2_{(2)}$ = Random effect of r between samples. $\sigma^2_{(3)}$ = Random effect of r within samples. k_1 = Number of effect sizes. k_2 = Number of samples.

* $p < .05$

Figure 1

Forest Plot



Appendix C

Manuscript 2

Not easy to get off track: Motivational trajectories of learners completing a non-formal online course

Maria Klose

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Philipp Handschuh

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Diana Steger

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Cordula Artelt

Leibniz Institute for Educational Trajectories (LIfBi), Germany

University of Bamberg, Germany

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Abstract

Non-formal learning is becoming increasingly important in everyday life. Both the availability of open online learning opportunities and the number of participants in online courses continue to grow. Initially learners report high levels of motivation, but completion rates tend to be low. In the present study, we examined motivational trajectories of learners completing a non-formal online course. To this end, 450 learners of 49 open online courses offered by Bavarian universities completed up to three online questionnaires throughout the course. First, we used latent profile analysis to explore motivational trajectories within five subtypes of situational motivation, which resulted in four different motivational profiles. However, all profiles were characterized by remarkable stability over time, and differences only in the actual levels of the five motivational subtypes. Second, we used bivariate latent change score models to focus on differences of change in intrinsic motivation when analyzing simultaneously with situational interest. In addition, we considered self-regulation and mastery goal orientation as predictors of change in motivation. For intrinsic motivation there was only a small mean change and compensating effect from T1 to T2. We discuss the findings in the light of the fact that there are high dropout rates in non-formal online courses and offer practical advice on how to better address non-completers in future research.

Keywords: non-formal learning, online learning, situational motivation, motivational trajectories

1. Introduction

Education across the lifespan in itself is constantly changing, thereby leading to the redefinition of learning environments. Technological advancements transform the access to and delivery of learning resources (i.e., via Internet by mobile technologies or computers; Cox, 2013). Whether in formal, non-formal or informal settings, learning in general is shifting – either proportionally or completely – from face-to-face to online environments. More specifically for non-formal learning, the growing availability of online learning resources has altered the individual's learning as it provides more flexibility for learners who can freely choose what, when or where they learn (Song & Bonk, 2016). Therefore, more and more people quite naturally engage in online learning beyond institutional settings (for Germany, see e.g. Autorengruppe Bildungsberichterstattung, 2020), which emphasizes the rising importance of non-formal (online) learning as an integral part of lifelong learning. Consequently, non-formal learning promotes lifelong learning for economic progress and development, personal development and fulfilment, as well as social inclusiveness, democratic understanding and activity (Aspin & Chapman, 2000).

Despite the increasing popularity of non-formal online courses like *Massive Open Online Courses* (MOOCs), completion rates of these courses are rather low (on average less than 10%; Jordan, 2014), although learners are initially highly motivated (de Barba et al., 2016). Therefore, the question arises how the motivation of the participants changes throughout the duration of the course. In the formal context, motivational trajectories are well-described longitudinally (e.g., Corpus et al., 2009; Gottfried et al., 2001; Kyndt et al., 2015). Contrarily, in the non-formal context motivation is usually surveyed only once – either at the beginning or at the end of a course (de Barba et al., 2016; Maya-Jariego et al., 2020; Romero-Frías et al., 2023). Accordingly, with only single measurements of motivation at hand, little is known about the motivational trajectories in non-formal online courses. Although non-formal learning is deemed valuable in everyday life and recognized as a plausible alternative to formal education (Werquin, 2010), it is still not as well understood. To this end, we wanted to examine motivation in non-formal online courses longitudinally to investigate which learners do benefit from this important type of learning and scrutinize potential psychological influencing factors for initial motivation as well as for motivational trajectories.

1.1 Learning Motivation as a Dynamic Concept

Motivation manifests at different levels of generality within the individual (Vallerand, 1997), typically categorized as either global (trait) or situational (dynamic state). As we are particularly interested in how motivation fluctuates in response to the current learning environment (Guay et al., 2000), we focus on motivation as a dynamic state (i.e. *situational motivation*). More specifically, we use the conceptualization of situational motivation based on the framework of Self-Determination Theory (Ryan & Deci, 2000, 2017), as it distinguishes between different types of motivation on a continuum of experienced relative autonomy during task engagement (Ryan et al., 2022). These types of motivation differ in their impact on learning behavior, depending on the different contexts of learning (Chen & Jang, 2010). *Amotivation* marks the extreme end of the self-determination continuum, and is characterized by a lack of intention to act. Moving along the continuum, *external regulation* (i.e., behaviors that are performed because of external demands or rewards), *introjected regulation* (i.e., behaviors that are performed to avoid guilt or attain ego enhancement), and *identified regulation* (i.e., behaviors that are performed to achieve a certain goal, and are experienced as personally important) represent increasingly autonomous forms of extrinsic motivation. These types of motivation have in common that performing an activity primarily pursues the goal of attaining some separable outcome. *Intrinsic motivation*, which is situated at the opposite end of the continuum, embodies behaviors driven by interest, enjoyment, and inherent satisfaction, and that are experienced as fully volitional. Unlike extrinsically motivated behaviors, intrinsically motivated behaviors are performed for their own sake, because pleasure and satisfaction are derived from their performance (Deci et al., 1991).

Although the different types of motivation can be described along a continuum, Self-Determination Theory also acknowledges that intentional behaviors often stem from multiple motivations (Ryan & Deci, 2020).

In formal learning contexts, typical trends in students' motivational change are well-documented (see Corpus et al., 2020 for an overview). Over time, students show a decline in autonomous types of motivation (i.e., intrinsic motivation and identified regulation), and at the same time an increase in controlled types of motivation (i.e., introjected and external regulation). These average patterns are found consistently for elementary school, high school and college students, and also described for shorter time periods (e.g. first year of college; Corpus et al., 2020), as well as for longer time periods of several years (e.g., spanning the time from childhood through adolescence; Gottfried et al., 2007). However, these results may not directly apply to non-formal contexts. Formal education, which is structured and guided by instructors within a graded, performance-oriented system (Schwier & Seaton, 2013), may facilitate extrinsic types of motivation. Conversely, non-formal education varies greatly in terms of structuredness and usually comprises less controlled learning activities, ultimately requiring learners to be more self-directed, but also enabling intrinsic motivation. Yet, it is important not to confuse non-formal with informal learning. Informal learning is characterized by its unorganized and unintentional nature (e.g. incidental experiences like browsing the news), whereas non-formal learning (e.g. participating in open online courses) is intentional, involves organized learning objectives, and is initiated by the individual (Werquin, 2010). In contrast to formal courses, non-formal online courses usually offer flexible learning paths and goals, including the freedom of choice in when, how, and how long participants can learn (Cha & So, 2020). Additionally, it is usually possible to terminate the course prematurely without negative consequences. Therefore, non-formal learners experience autonomy during the whole learning process, highlighting the importance of the presence of intrinsic motivation to self-direct their own learning (Song & Bonk, 2016). As intrinsic motivation is essential for non-formal learning by empowering individuals to control their learning and sustain their engagement, we will mainly focus on this motivational subtype in the present paper.

1.2 Covariates of Intrinsic (Online) Learning Motivation

Non-formal online learning environments attract diverse learners with different learning goals and intentions (Moore & Wang, 2021), suggesting potential variability in the initial levels and trajectories of intrinsic motivation. This raises questions of potential predictors of individual differences in motivation (Corpus et al., 2020). Therefore, we investigated three personal characteristics that are closely related to situational intrinsic motivation, as they promote individuals' autonomy which increases intrinsic motivation (Deci & Ryan, 1987), namely situational interest, self-regulation, and mastery goal orientation. To obtain a more comprehensive understanding of the motivational processes underlying learning behavior, we discuss in the following the complementary contributions of each construct related to intrinsic motivation.

First, *interest* is often mistakenly used interchangeably with intrinsic motivation (Renninger & Hidi, 2022). While situational intrinsic motivation focuses on the "why" of behavior (Guay et al., 2000), interest centers on the content of learning (i.e., always related to specific objects; Schiefele, 2009). Analogous to motivation, interest can be viewed as both a trait and a state (individual interest vs. situational interest; see Hidi & Renninger, 2006). To examine the reciprocal dynamics with intrinsic situational motivation, we focus on the state perspective of interest. In non-formal online courses, situational interest supports the autonomy in learning, as individuals are allowed to choose course topics that align with their interests and preferences, and therefore facilitate intrinsic motivation (Krapp & Prenzel, 2011). When courses are perceived as personally relevant and associated with positive affect (i.e., components of situational interest), individuals are intrinsically motivated to learn more about the subject (Schiefele, 2009).

Second, self-regulation is vital for self-directed learning within online courses, as individuals are more likely to achieve their learning goals if they are able to adaptively regulate their own learning (Azevedo, 2005). More specifically, self-regulated learning strategies include *time management strategies* (i.e., scheduling, planning, and managing the personal study time), *effort management*, and *attention management,* which can be grouped as *internal resource management strategies* (i.e., self-management activities to organize learning activities; Wild & Schiefele, 1994). Non-formal online settings lack external guidance (e.g., no instructors monitoring the learning process) and grades as incentives, necessitating learners to independently manage their learning behavior, thereby promoting autonomy in learning (Dever et al., 2020). Consequently, the effective use of internal resource management strategies becomes crucial for handling high levels of autonomy inherent in these settings (Biwer et al., 2021), and is therefore essential for facilitating intrinsically motivated behavior by empowering learners to take ownership of their learning process.

Lastly, *mastery goal orientation*, a key aspect of the individuals' global motivational orientation (Spinath et al., 2012), emphasizes competence development, skill improvement, and task mastery. Individuals with high mastery goal orientation value the learning process itself (Ames & Archer, 1988). Numerous studies have consistently found evidence that mastery goals facilitate intrinsic motivation (e.g., Elliot & Church, 1997; Elliot & Murayama, 2008; Heyman & Dweck, 1992), or even predict changes in intrinsic motivation (Spinath & Steinmayr, 2012). Mastery-oriented individuals prioritize personal growth and skill development, are more likely to actively seek out opportunities to learn, fostering autonomy in learning by engaging in self-directed learning activities. Therefore, mastery goals promote the experience of intrinsic motivation on any task that allows for learning progress (Spinath & Steinmayr, 2012), especially in a non-formal online context where external rewards are limited.

1.3 The Present Study

In summary, the present study has two objectives: First, we want to investigate motivational trajectories in non-formal online courses to find out to what extent individuals differ in terms of their initial levels of intrinsic motivation and their motivational trajectories over the period of the course. Accordingly, we model change of intrinsic motivation over the course of learning as a latent change score model, which allows to investigate individual differences in motivational change. Second, we want to extend the latent change score model to examine potential influencing factors. As described above, we expect intrinsic motivation to be positively related to situational interest (*Hypothesis 1*), self-regulation (*Hypothesis 2*), and mastery goal orientation (*Hypothesis 3*). These relations should apply, on the one hand, to initial levels of intrinsic motivation, and on the other hand, change in intrinsic motivation over time. With respect to the reciprocal relationship of the situation-specific constructs, we expect situational interest to be positively related to intrinsic situational motivation when measured at the same time.

2. Methods

In accordance with common open science practices, we provide all additional materials (i.e., codebook, syntax, data, and supplemental figures and tables) online within the Open Science Framework (Center for Open Science, 2024): https://osf.io/pdfq8/. The hypotheses, study design, and analysis plan were preregistered. Deviations from the preregistration are mentioned at the respective parts in the manuscript.

2.1 Design and Participants

Data collection took place from October 2021 to June 2022 and was implemented within 51 open online courses offered by German, more specifically, Bavarian universities (OPEN vhb; Virtuelle Hochschule Bayern, 2023). Learners that were interested in participating in the study were asked to fill out online questionnaires at three time points throughout the course: Links to the online surveys were placed on the first page after course enrollment (T1), on the course page after 50% of the lessons (T2), and on the last page of a course (T3). At each time point, all course participants were invited to voluntarily participate in the respective online survey, but participation in the first survey was necessary to participate in T2 and/or T3. All courses in our sample were non-formal, fully online, taught in German and they covered various course topics from different fields (e.g. STEM, health science, social sciences and humanities, economics). The courses were freely accessible for anyone and could be started and worked on at any time. More specifically, they followed a self-paced format (i.e., all course materials were available from the beginning and there were no deadlines). The scope of the courses varied with respect to estimated processing time (9 to 60 hours) and number of course chapters (3 to 16). Each course included several formative assessments (e.g. multiple-choice quizzes, cloze tests, or matching tasks) distributed throughout the course that could be attempted multiple times and were needed to receive a certificate of participation with the required percentage of correct test answers per course varying between 50% and 100%.

For the present study, we considered all cases eligible for the analyses if the subject: a) participated at least in the initial survey, b) had any information on our dependent variable, and c) reached the threshold of correct test answers to earn a certificate of participation (i.e., course completion). Learners were allowed to take part in the survey for each course they attended. A total of 470 cases fulfilled these criteria, of which 450 (95.7%) were included in the final analyses and consisted of 425 unique subjects (see Table S1 for dropout at the different stages of data cleaning; $n = 25$ were in the data set multiple times, but within different courses). 71.1% of the sample were female (28.4% male, and 0.5% diverse or no response). The average age was 36 years ($SD = 14.10$) with a good coverage across the life span (range [16; 77], see Figure S1 for the distribution). The majority of participants had an academic background as educational degrees were made up as follows: 48.9% university degree, 35.6% secondary school degree qualifying for university (i.e., academic-track: *Gymnasium* or *Fach-/Berufsoberschule*), 10.2% middle secondary school degree (i.e., intermediate-track: *Realschule*), 2.4% lower secondary school degree (i.e., vocational-track: *Hauptschule*), and 2.9% others (i.e., no degree, other school degree, still in school, or no response). Regarding the current professional situation, the sample was composed as follows: 57.6% employed, 23.6% school/university students, 5.8% apprentices, 3.8% retired and 9.2% others (i.e., seeking employment, unemployed or no response). All participants stated that they were fluent in German. The distribution of sociodemographic variables of our sample are typical for non-formal education in Germany, where participation is more likely for young adults and people with a high level of education (Kruppe & Baumann, 2019). However, the composition of the sample also reflects the general pattern of participation in non-formal learning as lifelong learning, as adults before the retirement age (50-64 years), and even older adults (> 65 years) participated as well (see Bilger & Strauß, 2022 for continuing education behavior in Germany). The most frequently given reason for enrollment was *general interest in course topic* (89%), the least frequently given reason was *to take it with colleagues/friends* (6%), and the most balanced agreed to was *to earn a certificate* (59%; see Table S2 for percentage of agreement for all 14 queried enrollment intentions). For a more detailed outline of the study design, Table S3 displays descriptive information for courses and participants by course.

Table 1 shows an overview of all three surveys including placement, contents, and number of participants per time point. Due to the nature of our longitudinal study design, we do not have the full sample at all time points, resulting in fewer participants at T2 (n = 286, 63.6% retention) and T3 (n = 307, 68.2% retention) compared to T1 (N = 450). As participants could voluntarily choose at any time point to take part in a survey, sample sizes fluctuate over time. Figure S2 illustrates the pattern of participation across the three time points. In contrast to the statements made in the preregistration, we decided to use the achievement of the certificate as an inclusion criterion for our analyses instead of complete participation at all three time points, since the sample is already a selective sample from the outset (i.e., only completers) and a complete data set is only available for a fraction of the sample (n = 234) limiting the statistical power of our analyses and the robustness due to attrition.

Table 1

Overview of the surveys.

	T1	T2	T3
Sample size	N = 450	n = 286	n = 307
Survey placement	First page	Page after 50% of lessons	Last page
Survey contents	Situational Motivation Situational Interest Self-regulation Socio-demographics [a] Enrollment intentions	Situational Motivation Situational Interest Mastery goal orientation	Situational Motivation Situational Interest

Note. The measures we used for our analyses are part of a larger data collection (see Table S4 for all included survey contents and the actual order of data collection).

[a] Socio-demographic information on age, gender, educational degree, job status, and command of the German language.

2.2 Measures

As participation in the study was voluntary, we wanted to keep the requirements for participants low. Therefore, we kept the survey as parsimonious as possible, so that participants would be encouraged to take part in all three time points. Accordingly, we selected for the predictor variables particular subscales from established questionnaires, which we assume are the most relevant in a non-formal, self-determined online learning context.

2.2.1 Enrollment Intentions (T1)

We adapted the Online Learning Enrollment Intentions (OLEI) scale (Kizilcec & Schneider, 2015) to the context of non-formal learning and translated it into German to assess the learners' reasons for enrolling in the respective open online course. The adapted scale included 14 statements (e.g., "general interest in course topic", "to improve general education", "relevant to job, or to school/ degree program", see Table S2 for all statements and percentage of agreement). For each statement, participants were asked to indicate whether the respective intention applied as a reason for enrolling in a yes/no-format.

2.2.2 Situational Motivation (T1, T2, and T3)

We used the 20-item version of the Situational Motivation Scale (SIMS; Guay et al., 2000) as adapted by Gillet, Vallerand, Lafrenière, and Bureau (2013) and translated into German by Knörzer, Brünken, and Park (2016) to assess the subjects' situational motivation towards participating in the online course on a 7-point Likert scale (1 = "Does not apply at all" and 7 = "Applies completely") at each time point. The adapted version measures five types of motivation: *intrinsic motivation* (e.g., "Because this activity is fun", α_{T1} = .82, α_{T2} = .90, and α_{T3} = .88), *identified regulation* (e.g., "Because I am doing it for my own good", α_{T1} = .80, α_{T2} = .76, and α_{T3} = .75), *introjected regulation* (e.g., "Because I would feel bad not doing it", α_{T1} = .77, α_{T2} = .79, and α_{T3} = .86), *external regulation* (e.g., "Because I am supposed to do it", α_{T1} = .78, α_{T2} = .80, and α_{T3} = .84), and *amotivation* (e.g., "I do this activity but I am not sure if it is worth it", α_{T1} = .81, α_{T2} = .81, and α_{T3} = .87). Each subscale consisted of four items and referred to the current motivation to engage in a task (i.e., course processing) and demonstrated acceptable to good internal consistency (i.e., Cronbach's alpha > .70, or >.80) at each time point.

2.2.3 Situational Interest (T1, T2, and T3)

To measure the cognitive and affective component of situational interest with regard to the subjects' current interest in the course topic at each time point, we drew on two subscales (i.e., *maintained value* and *maintained feeling*) from the Situational Interest Survey (SIS; Linnenbrink-Garcia et al., 2010). We used the items from Grund et al. (2019) who had translated and adapted the original items into German. Additionally, we adjusted the items to our non-formal learning context. *Maintained value* refers to the perceived personal relevance and was assessed with six items (e.g. "I think the course topic is useful for me to know.", $\alpha_{T1} = .81$, $\alpha_{T2} = .79$, and $\alpha_{T3} = .84$). *Maintained feeling* refers to the positive affect and was assessed with four items (e.g. "The course topic fascinates me.", $\alpha_{T1} = .86$, $\alpha_{T2} = .86$, and $\alpha_{T3} = .87$). Both subscales were rated on a 7-point Likert scale (1 = "Do not agree at all" and 7 = "Fully agree").

2.2.4 Self-Regulation (T1)

We used *internal resource management strategies* from the short-version of Learning Strategies of University Students (LIST-K; Klingsieck, 2018) to assess self-regulation. Participants rated how often they were using internal resource management strategies while learning on a 5-point Likert scale (1 = "Very rare" and 5 = "Very often"). The scale contains three subscales with three items each: *time management* (e.g. "When I study, I stick to a certain schedule", $\alpha = .87$), *attention management* (e.g. "When I study, I am easily distracted", reversed, $\alpha = .88$), and *effort management* (e.g. "I don't give up, even if the material is very difficult or complex", $\alpha = .49$).

2.2.5 Mastery Goal Orientation (T2)

Mastery goal orientation was assessed at the second time point using the subscale *learning goals* from the Scales for the Assessment of Learning and Achievement Motivation (SELLMO; Spinath et al., 2012) referring to participants' general mastery goal orientation towards learning. We adapted the item stem to "For me, learning is about…" and participants rated eight statements covering mastery goals (e.g. "…understanding complicated contents") on a 5-point Likert scale (1 = "Not true at all" and 7 = "Completely correct"). Cronbach's alpha was acceptable ($\alpha = .74$).

2.3 Statistical Analyses

2.3.1 Missing Data, Score Computation, and Aggregate Scores

For analyses on manifest level, we computed scale scores in form of average mean scores based on subscales from the questionnaires and used pairwise complete observations to account for missingness. Where necessary, we recoded reversed items.

For analyses on latent level, we used *Full Information Maximum Likelihood* (FIML) to account for missingness, and computed aggregates to use as indicators in the measurement models as follows: For the dependent variable we used the distinct subscale (i.e., *intrinsic motivation*) with items as indicators, other than preregistered aggregated motivation indices (*autonomous* summing intrinsic motivation and identified regulation), as this index showed suboptimal model fit. For the predictor variables, we used item parcels as indicators to reduce model complexity (see T. D. Little et al., 2002 for rationale and applied parceling techniques). As mastery goal orientation is a unidimensional construct, we used the *Item-to-Construct Balance* approach to build three parcels out of eight items that are equally balanced with respect to factor loadings. For the multidimensional constructs, we used the *domain-representative* approach for building parcels that are reliable unique facets of the multiple dimensions (i.e., item sets from the combination of items from different facets). More specifically, we built three parcels each for self-regulation (one item each for attention, effort, and time management) and situational interest (balanced combination of items from maintained feeling and maintained value).

2.3.2 Latent Profile Analysis

In addition to our preregistered analyses, we explored motivational profiles of all subtypes of situational motivation to capture and compare the multidimensional nature of motivation in a descriptive manner (J. Howard et al., 2016). To achieve a parsimonious representation of structures (Woo et al., 2018), we conducted a *latent profile analysis* (LPA) to identify latent subpopulations (M. C. Howard & Hoffman, 2018) based on all five subscales of situational motivation across all three time points. We assume that there may be differences in the levels of situational motivation due to different underlying enrollment intentions or varying course requirements. To determine the number of valid subgroups, we examined a series of LPA models with one to five profiles. We compared the model fit of the five profile solutions regarding error messages (especially in terms of convergence), relative fit information criteria (i.e., Akaike Information Criterion [AIC], Bayesian Information Criteria [BIC], and sample size-adjusted BIC), the confidence with which individuals have been classified, likelihood ratio tests to quantify specific model comparisons, and profile size (Spurk et al., 2020). To select the best fitting profile solution, models were considered appropriate if: (a) they do not result in convergence problems, (b) values for information criteria are lower (i.e., AIC, BIC, and sample size-adjusted BIC), (c) values for measures of uncertainty are higher (e.g. entropy), (d) the likelihood ratio test is significant (e.g. bootstrap likelihood ratio test [BLRT]), and (e) each class is large enough to be considered meaningful (Woo et al., 2018). To initially describe how different subtypes of motivation evolve per-person over time, we plotted individual trajectories of *intrinsic motivation*, *identified regulation*, *introjected regulation*, *external regulation*, and *amotivation* for each subject grouped by the detected class solution of the LPA in form of spaghetti plots.

2.3.3 Measurement Models and Tests of Longitudinal Measurement Invariance

We estimated measurement models using *confirmatory factor analysis* (CFA) to test for unidimensionality of the scales on the basis of fit indices. Following Hu and Bentler (1999), fit indices were considered as indicators of good model fit for *Comparative Fit Index* (CFI) > .95, *Root Mean Square Error of Approximation* (RMSEA) < .06, and *Standardized Root Mean Square Residual* (SRMR) < .08. We tested longitudinal measurement variance of *intrinsic motivation* step-by-step in a series of measurement models in which factor loadings and intercepts were subsequently constrained to be equal across time points (T. D. Little et al., 2007). We assume measurement invariance across time points for consecutive model comparisons resulting in a difference in CFI < .01 (Cheung & Rensvold, 2002).

2.3.4 Latent Change Score Models

To examine change in motivation over time, we estimated *latent change score* (LCS) models. LCS models are a specific class of *structural equation models* (SEM) for longitudinal data modeling to capture interindividual differences in intraindividual change (McArdle, 2009). In order to compute additional correlations between initial values and change between *intrinsic motivation* and *situational interest*, we estimated bivariate LCS models. We used *cluster-robust standard errors* (CR-*SE*s; McNeish et al., 2017) to account for the clustered structure of our data (i.e., participants are nested in courses). Moreover, the same indicators at different time points were allowed to correlate in all models. To examine correlations of initial intrinsic motivation and predict change, we included self-regulation and mastery goal orientation in addition to situational interest as predictors to the LCS model. Furthermore, we examined the course variable *estimated course processing time* (i.e., proxy for different course durations) and *days between T1 and T3* (to consider different time intervals for different individuals as a possible reason for interindividual differences in intraindividual change; Steyer et al., 1997) as control variables. Initially we preregistered latent growth curve analyses in our analysis plan, but changed it to LCS models after methodological consultation, because LCS models provide more flexibility in modeling different change patterns or in handling missing data.

2.3.5 Sensitivity Analyses

We conducted several sensitivity analyses to check the robustness of our results by comparing results from respective subsamples to the full analysis sample ($N = 450$): First, we computed a complete record analysis as an alternative approach to handle missing data (Lee et al., 2021) resulting in an analysis sample of $n = 193$. Second, we considered repeated participation in the study from the same subject within different courses by keeping only the first record of a subject and consequently removing *n* = 25 cases. Third, we controlled for careless responding by conducting a repetitive pattern analysis for situational motivation using an iterative algorithm to detect repetitive sequences of values to compute a score for which higher values indicate a higher likelihood of repetitive patterns (R package responsePatterns; Řiháček & Gottfried, 2021), and by excluding observations with pattern scores above the 90th percentile (*n* = 41). Lastly, we excluded cases from participants that answered all surveys at the same day (*n* = 216) to check whether answering the questionnaires on situational motivation in a very short time leads to a bias in the stability of motivational trajectories.

Additionally, we conducted comparative analyses for the motivational subtype *external regulation* (see Appendix in the online supplemental materials), since the distinction between intrinsic and extrinsic motivation is of traditional interest in educational research to determine influences of different types of motivation on the learning process (Hayenga & Corpus, 2010).

2.3.6 Statistical Software

All analyses were conducted using *R* version 4.3.1 (R Core Team, 2023). Confirmatory factor analyses and LCS models were estimated using the *lavaan* package version 0.6.16 (Rosseel, 2012). LPA were conducted using the *tidyLPA* package 1.1.0 (Rosenberg et al., 2018) drawing on the package *MplusAutomation,* which requires an installed Mplus software (version 8; Muthén & Muthén, 1998-2017).

3. Results

3.1 Descriptive Statistics

Descriptive statistics and correlations for all scales are summarized in Table 2. On average, mean values of intrinsic motivation and identified regulation were higher than mean values of introjected regulation, external regulation, and amotivation. For all motivational subtypes, there were no major changes in mean values over time. Repeated measures over time were highly positively correlated. As expected, intrinsic motivation and identified regulation as autonomous motivational subtypes were positively correlated with one another, and at the same time negatively correlated with external regulation and amotivation. Unexpectedly, instead of a negative correlation, introjected regulation was not correlated with intrinsic motivation at all and even slightly positively correlated with identified regulation. Regarding the less self-determined motivational subtypes, amotivation, external regulation, and introjected regulation were also positively correlated with one another.

3.2 Latent Profile Analysis

After comparing solutions with one to five profiles for LPA, we opted for the four-class solution, as this model had the best fit while not resulting in convergence problems (see Table S5 for details on the decision process for profile identification). Figure 1 displays the four-class solution of the profiles based on the subscales of situational motivation across all three time points. Overall, all four classes had relatively stable trajectories (T1 – T3) within the different subtypes of situational motivation. The classes differ mainly in their pattern of levels on the different subtypes. The first class was the smallest (n = 27) and had the lowest mean values for *intrinsic motivation* and *identified regulation*, and the highest for *external regulation* and *amotivation*, which is why we labeled it *controlled type*. The second class (n = 126) had rather high mean values for *intrinsic motivation* and *identified regulation*, and moderate mean values for *introjected regulation* and *external regulation*. Accordingly, we chose the label *moderate type* for this class. The third class (n = 101) had even higher mean values for *intrinsic motivation* and *identified regulation*, but also the highest mean values for *introjected regulation*, and moderate mean values for *external regulation*. To emphasize the uniquely high levels of *introjected regulation*, we labeled the class *introjected type*. The fourth and biggest class (n = 196) had similar high mean values for *intrinsic motivation* and *identified regulation*, but also the lowest mean values for *introjected regulation*, *external* *regulation*, and *amotivation*. This pattern is prototypical for autonomous motivation, hence we labeled the class *autonomous type*. Figure S3 illustrates the individual trajectories for *intrinsic motivation*, *identified regulation*, *introjected regulation*, *external regulation*, and *amotivation* grouped by the four-class solution of the LPA. Table S6 displays the descriptive statistics of the total sample compared to the subsamples that arose from four-class solution of the LPA to depict potential differences between learners from different motivational profiles.

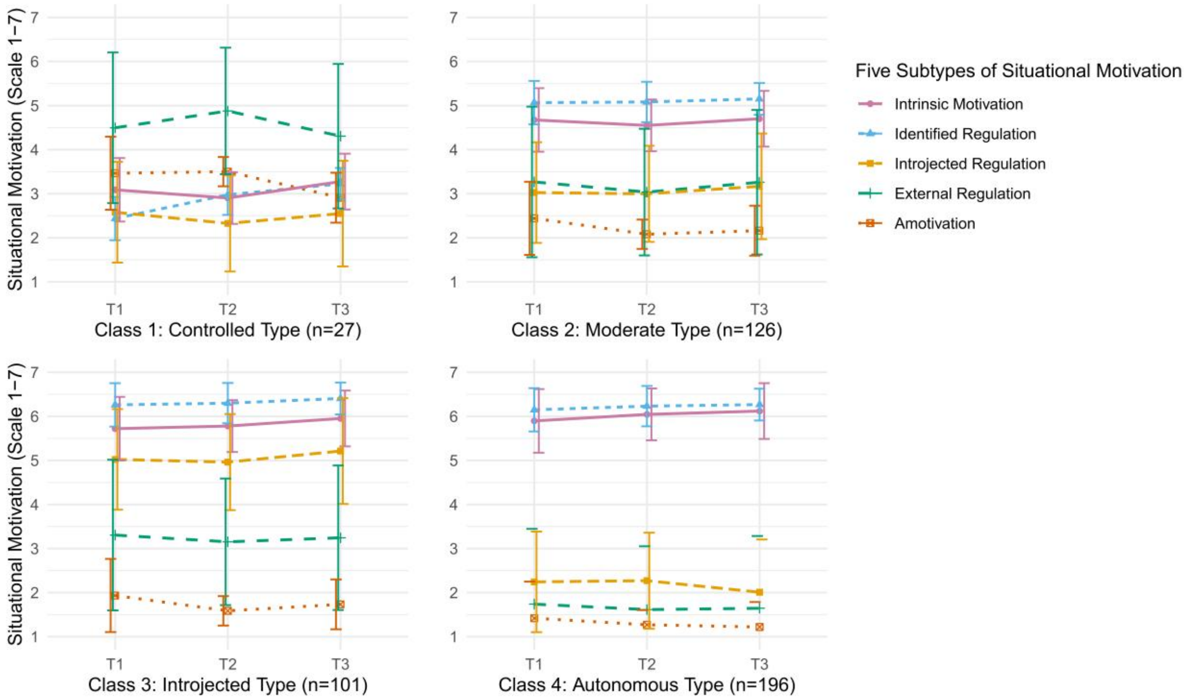

Figure 1. Four-class solution of profiles based on the subscales of situational motivation across all three time points. $N = 450$. Cluster means and standard deviations for each subtype of situational motivation are displayed.

Table 2

Descriptive statistics and correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Situational Motivation																									
1 T1 IN	-																								
2 T2 IN	**.61**	-																							
3 T3 IN	**.62**	**.85**	-																						
4 T1 ID	**.71**	**.54**	**.51**	-																					
5 T2 ID	**.54**	**.68**	**.64**	**.74**	-																				
6 T3 ID	**.56**	**.68**	**.72**	**.73**	**.83**	-																			
7 T1 IJ	.05	<.01	.02	**.20**	**.17**	**.16**	-																		
8 T2 IJ	-.04	.01	.04	**.14**	**.18**	**.15**	**.77**	-																	
9 T3 IJ	-.02	-.03	.02	.12	**.14**	**.17**	**.80**	**.85**	-																
10 T1 EX	**-.33**	**-.26**	**-.27**	**-.33**	**-.31**	**-.30**	**.37**	**.28**	**.35**	-															
11 T2 EX	**-.40**	**-.32**	**-.32**	**-.34**	**-.30**	**-.36**	**.35**	**.34**	**.37**	**.82**	-														
12 T3 EX	**-.35**	**-.33**	**-.33**	**-.29**	**-.33**	**-.32**	**.32**	**.30**	**.41**	**.84**	**.89**	-													
13 T1 AM	**-.45**	**-.37**	**-.33**	**-.40**	**-.42**	**-.32**	**.22**	.12	**.23**	**.46**	**.37**	**.42**	-												
14 T2 AM	**-.40**	**-.53**	**-.51**	**-.42**	**-.51**	**-.52**	**.11**	.09	**.16**	**.38**	**.42**	**.47**	**.53**	-											
15 T3 AM	**-.31**	**-.47**	**-.42**	**-.32**	**-.51**	**-.47**	**.20**	.09	**.27**	**.45**	**.42**	**.51**	**.62**	**.76**	-										
Situational Interest																									
16 T1 MF	**.67**	**.57**	**.57**	**.63**	**.52**	**.52**	<.01	-.01	-.10	**-.35**	**-.36**	**-.37**	**-.53**	**-.47**	**-.49**	-									
17 T2 MF	**.54**	**.73**	**.77**	**.49**	**.58**	**.62**	.02	.06	-.03	**-.26**	**-.35**	**-.37**	**-.41**	**-.60**	**-.57**	**.73**	-								
18 T3 MF	**.47**	**.66**	**.74**	**.44**	**.54**	**.64**	-.01	.02	-.04	**-.25**	**-.27**	**-.32**	**-.42**	**-.62**	**-.57**	**.67**	**.87**	-							
19 T1 MV	**.54**	**.34**	**.35**	**.63**	**.47**	**.46**	.07	.01	-.07	**-.26**	**-.23**	**-.24**	**-.47**	**-.40**	**-.42**	**.75**	**.50**	**.48**	-						
20 T2 MV	**.30**	**.41**	**.46**	**.44**	**.54**	**.55**	.08	.05	-.05	**-.17**	**-.20**	**-.25**	**-.37**	**-.50**	**-.53**	**.48**	**.59**	**.60**	**.66**	-					
21 T3 MV	**.30**	**.45**	**.54**	**.36**	**.51**	**.57**	-.02	-.05	-.05	**-.22**	**-.21**	**-.23**	**-.33**	**-.52**	**-.51**	**.44**	**.58**	**.71**	**.57**	**.82**	-				
Self-Regulation																									
22 AT	**.17**	**.23**	**.26**	**.12**	.10	**.16**	**-.11**	**-.18**	-.08	**-.22**	**-.20**	**-.17**	**-.32**	**-.18**	**-.17**	**.20**	**.19**	**.24**	.08	.08	.11	-			
23 EF	**.19**	**.16**	**.19**	**.27**	**.16**	**.27**	**.23**	.03	**.18**	.01	.06	.11	**-.19**	-.05	-.08	**.24**	.09	**.17**	**.31**	**.16**	**.26**	**.32**	-		
24 TI	.01	.10	.11	.05	.07	.04	**.17**	.10	**.17**	**.18**	**.13**	**.17**	**.10**	-.03	.11	.08	.05	.08	.04	.06	.07	**.23**	**.26**	-	
Goal Orientation																									
25 MGO	**.33**	**.36**	**.39**	**.31**	**.40**	**.37**	.08	.06	.09	-.09	**-.14**	**-.14**	**-.24**	**-.27**	**-.22**	**.36**	**.41**	**.31**	**.27**	**.32**	**.27**	**.20**	**.22**	.07	-
n	446	274	283	448	274	282	441	272	282	445	271	283	442	271	282	444	274	283	444	274	283	442	441	440	274
M	5.34	5.53	5.58	5.65	5.86	5.86	3.13	3.01	3.09	2.70	2.38	2.57	1.95	1.60	1.67	5.80	5.93	5.95	5.83	6.06	6.03	3.47	3.92	2.70	4.43
SD	1.15	1.10	1.13	1.18	1.01	0.99	1.53	1.49	1.68	1.58	1.49	1.56	1.08	0.76	0.90	1.09	0.94	0.95	0.95	0.77	0.83	0.89	0.73	1.08	0.45
α	.82	.90	.88	.80	.76	.75	.77	.79	.86	.78	.80	.84	.81	.81	.87	.86	.86	.87	.81	.79	.84	.88	.49	.87	.74

Note. $N = 450$. **Bolded** correlation coefficients are significant at $p < .05$. For Situational Motivation: IN = Intrinsic Motivation; ID = Identified Regulation; IJ = Introjected Regulation; EX = External Regulation; AM = Amotivation. For Situational Interest: MF = Maintained Feeling; MV = Maintained Value. For Self-Regulation: AT = Attention Management; EF = Effort Management; TI = Time Management. For Goal Orientation: MGO = Mastery Goal Orientation. α = Cronach's alpha.

3.3 Measurement Models and Longitudinal Measurement Invariance

The measurement models of *intrinsic motivation* for all three time points are listed in Table 3. Since our predictor variables (i.e., situational interest, self-regulation, and mastery goal orientation) each consisted of three parcels as indicators, their models were exactly identified (i.e., CFI = 1.00; RMSEA < .001; SRMR < .001) and therefore not reported in Table 3. For *intrinsic motivation*, CFI and SRMR fit indices were above the aforementioned cut-off criteria indicating good model fit. Yet, the RMSEA values of the measurement models were mostly insufficient. As RMSEA tends to be over-sensitive for models with low degrees of freedom (Kenny et al., 2015), we decided to retain these model solutions rather than exclude items from scales that consists of only four items anyway.

Table 3

Measurement models of *intrinsic motivation* for all time points.

N	Time	*n(items)*	χ^2	*df*	*p*	CFI	RMSEA[90% CI]	SRMR	ω
446	1	4	2.102	2	.350	1.00	.011 [<.001; .063]	.016	.82
274	2	4	4.764	2	.092	.992	.071 [<.001; .146]	.013	.91
283	3	4	7.809	2	.020	.978	.101 [.036; .177]	.017	.88

Note. CFI = Comparative Fit Index. RMSEA = Root Mean Square Error of Approximation. SRMR = Standardized Root Mean Square Residual. ω = McDonald's Omega.

Longitudinal measurement invariance testing for *intrinsic motivation* are outlined in Table 4. As consecutive model comparisons resulted in a difference in CFI <.01, scalar measurement invariance across time points is given and therefore, latent means and correlations across time can be interpreted (van de Schoot et al., 2012). Constraints on measurement parameters (i.e., equal factor loadings, intercepts, and residual variances across time points) were used in all subsequent analyses accordingly.

Table 4

Longitudinal measurement invariance testing for *intrinsic motivation*.

Model	χ^2	*df*	$\Delta\chi^2$ (*df*)	*p*	CFI	ΔCFI	RMSEA	ΔRMSEA
Intrinsic motivation								
1. Configural	20.811	6			.992		.086	
2. Metric	32.191	12	11.38 (6)	.077	.989	.003	.071	.015
3. Scalar	45.837	18	13.65 (6)	.034	.985	.004	.068	.003

Note. *N* = 446. CFI = Comparative Fit Index. RMSEA = Root Mean Square Error of Approximation. Configural = loadings, intercepts, residuals are freely estimated; means are set to 0. Metric = intercepts, residuals are freely estimated, means are set to 0. Scalar = residuals are freely estimated, factor mean at one time point is set to 0. Differences in the model fit refer to consecutive models (e.g., metric – configural).

3.4 Bivariate Latent Change Score Models

The bivariate LCS model of *intrinsic motivation* and *situational interest* (see Figure 2) provided acceptable model fit ($N = 450$; $\chi^2 = 446.036$; $df = 189$; $p < .001$; CFI = .943; RMSEA = .055; SRMR = .053). From T1 to T2, there was statistically significant change in both *intrinsic motivation* ($\sigma^2 = .841$, $p < .001$) and *situational interest* ($\sigma^2 = .672$, $p < .001$), and from T2 to T3, there was statistically significant change only in *situational interest* ($\sigma^2 = .995$, $p = .001$), but not for *intrinsic motivation* ($\sigma^2 = .726$, $p = .323$). Compensating effects (i.e., negative regression coefficients for initial level and growth) were found for both constructs (*intrinsic motivation*: $\beta = -.470$, $p = .002$; *situational interest*: $\beta = -.608$, $p = .001$). Cross-domain effects were not statistically significant, but initial levels and changes score at the same time point were positively correlated (T1: $\rho = .736$, $p < .001$; T2: $\rho = .730$, $p < .001$; T3: $\rho = .676$, $p = .018$).

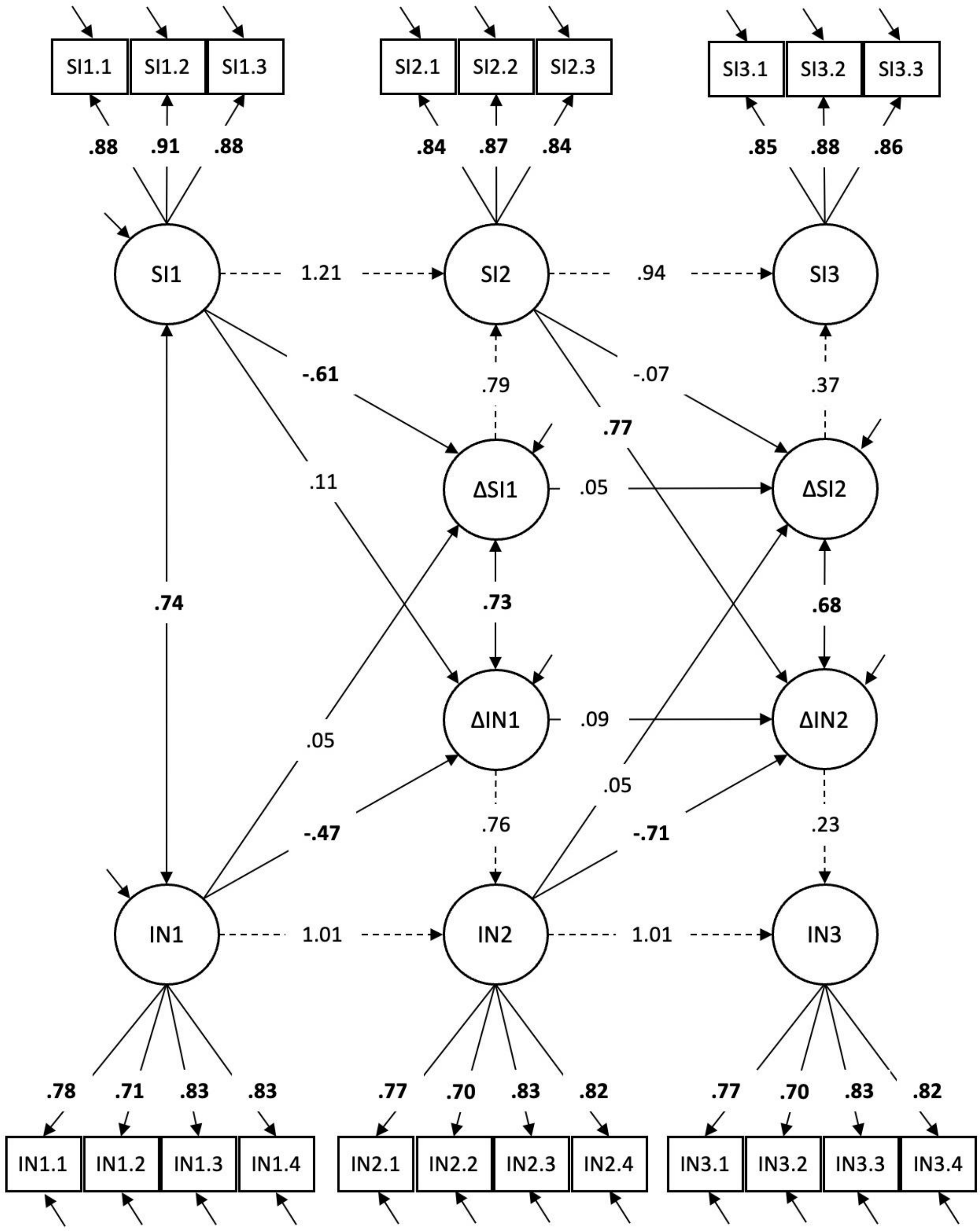

Figure 2. Bivariate LCS model of *intrinsic motivation* and *situational interest*. *Note*. $N = 450$; $\chi^2 = 446.036$; $df = 189$; $p = <.001$; CFI = .943; RMSEA = .055; SRMR = .053; all residual correlations between the same indicators at different time points were omitted for the sake of clarity. Dashed lines indicate paths with unstandardized parameters set to 1. Statistically significant model parameters are printed in **bold** ($p < .05$).

3.5 Correlates of Initial Intrinsic Motivation and Predicting Change

We added several predictors to the bivariate LCS models in order to (a) investigate the correlations with initial *intrinsic motivation*, and (b) predict change in *intrinsic motivation*. The respective results are listed in Table 5. As there is no statistically significant change in *intrinsic motivation* from T2 to T3, we only summarize interpretable results for associations with change in *intrinsic motivation* from T1 to T2. Initial *intrinsic motivation* was positively correlated with initial *situational interest* ($\rho = .736$, $p < .001$), *self-regulation* ($\rho = .201$, $p = .003$), and *mastery goal orientation* ($\rho = .435$, $p < .001$). The only statistically significant effect for predicting change in *intrinsic motivation* was *self-regulation* ($\beta = .199$, $p = .029$), indicating that a higher self-regulation at T1 was associated with a positive change in intrinsic motivation. With respect to the control variables, neither estimated course processing time nor days between T1 and T3 had statistically significant effects for predicting change or correlates with initial levels of motivation.

Table 5

Correlates of initial *intrinsic motivation* and predicting change in bivariate LCS models.

	ΔIN1			IN1	
	β	*SE*	*p*	*r*	*p*
Situational interest (T1)	.092	.177	.571	**.736**	<.001
Self-regulation	**.199**	.092	.029	**.201**	.003
Mastery goal orientation	.019	.145	.860	**.435**	<.001
Estimated course processing time	.042	.005	.371	-.101	.154
Days between T3 and T1	.020	.002	.822	.108	.135

Note. $N = 450$. The regression coefficients are standardized and displayed for change in intrinsic motivation (ΔIN1) from T1 to T2. Correlation coefficients relate to initial levels (T1) of intrinsic motivation (IN1). Statistically significant effects were marked in bold type ($p < .05$). Estimated course processing time, and days between T3 and T1 were included in the full model as control variables.

3.6 Sensitivity Analyses

The results of our sensitivity analyses for the bivariate LCS models of *intrinsic motivation* and *situational interest* are summarized in Table S7. Complete case analyses (n = 193), considering repeated participation within different courses (n = 425), controlling for careless responding (n = 409), and analyses without subjects that answered all surveys at the same day (n = 234) resulted in negligible deterioration in model fit (ΔCFI < .01) in comparison to the full model. Overall, sensitivity analyses provided evidence for the robustness of our results.

4. Discussion

Non-formal learning is becoming increasingly popular in the course of digitalization, as the introduction of new technologies makes it possible to provide education that is accessible to all learners online (Wong et al., 2021). As a result, its position as a key aspect of lifelong learning strengthens, highlighting the importance of acquiring knowledge, skills and competences outside the realm of formal education (Colardyn & Bjornavold, 2004). At the same time, non-formal online learning is criticized for its high dropout rates (Huang et al., 2023). In the accompanying scientific discourse, motivation seems to play a crucial role for learners' retention (see Badali et al., 2022 for a systematic review), yet little is known about its trajectory limiting the in-depth understanding of how individuals do benefit from non-formal education. Therefore, with the present study we answered the questions (1) "How does intrinsic motivation change over time for learners completing a non-formal online course?", and (2) "Can we predict differences in these changes?" by examining change in association with a set of theoretically related variables.

4.1 Motivational Trajectories in Non-Formal Online Courses

4.1.1 Individual Patterns of the Motivational Subtypes

Across all participants, we found mainly stable motivational trajectories on a manifest level, with high levels for intrinsic motivation and identified regulation, and in contrast moderate to low levels for introjected regulation, external regulation, and amotivation, suggesting that for learners completing a non-formal online course, autonomous types of motivation might play a greater role since these courses provide freedom of choice in form of self-determined learning (Ryan & Deci, 2017). To gain insights into interindividual differences of learners, which is crucial for a deeper understanding of learners' behaviors and motivations in non-formal online courses (Barthakur et al., 2021), we used LPA to determine whether there exist subgroups in our sample of completers that are distinguishable based on different patterns within the five motivational subtypes. In summary, all four classes shared a common feature. Across all four profiles, the five subtypes of situational motivation exhibited minimal average change across the three time points, suggesting a notable stability of situational motivation among completers of non-formal online courses. However, the classes differ in their levels of the subtypes of situational motivation, and fittingly, also in their pattern of agreement to certain enrollment intentions (extrinsic vs. intrinsic intentions) in line with self-determination theory (Ryan et al., 2022). Most of the learners were assigned to the *autonomous type*, characterized by the highest levels of autonomous subtypes of situational motivation (i.e., intrinsic motivation and identified regulation) and at the same time low levels for the other subtypes. Participants that were assigned to the autonomous type also almost unanimously agreed to the intrinsic enrollment intentions that reflected self-determined behavior best (e.g., *general interest*, or *for fun or as challenge*). Similarly, the *introjected type* had also high levels of autonomous motivation, but moderate levels of external regulation, and, across all classes, the highest levels of introjected regulation. This pattern was also reflected in the enrollment intentions, as there was a high agreement to intrinsic intentions, but simultaneously agreement to extrinsic intentions like *earn a certificate*, or *for career change*, referring to multiple underlying motives. In comparison, the *moderate type* showed less pronounced levels of autonomous motivation and instead, moderate levels of controlled types of motivation (i.e., introjected and external regulation) and most often agreed to external intentions like *recommended by employer* and *offered by prestigious professor* compared to the other classes, indicating the influences of controlled behavior. Finally, the smallest class, the *controlled type*, is characterized by the lowest levels of autonomous motivation, and the highest levels for external regulation and even amotivation. This class was primarily motivated by external intentions like *earn a certificate* and *relevant to job, or school/ degree program*, and had by far the lowest agreement to intrinsic intentions, mirroring the prototypical non-self-determined behavior. Taken together, the diversity of non-formal online learners completing a course can be described by their different patterns of motivational trajectories in combination with their initial enrollment intentions. Previous research found that different enrollment intentions can lead to different learning outcomes like grades or dropout in non-formal online courses (Chaker et al., 2022). With the present study, we can add to the existing literature as analogously, different enrollment intentions are associated with different motivational profiles as potential underlying mechanism for different learning outcomes.

However, our findings regarding non-formal learning do not align with prior research on motivational change in the formal learning context (e.g., Corpus et al., 2009; Gottfried et al., 2001; Kyndt et al., 2015), suggesting that motivation develops differently in the non-formal context. Unlike the robust literature on motivational change in formal education detecting average pattern of loss in the more autonomous types of motivation and growth in controlled types of motivation (Corpus et al., 2020), we found a notable stability for all five motivational subtypes over time in the non-formal setting. Thereby, on average, levels of intrinsic motivation and identified regulation were quite high, and levels of introjected regulation, external regulation and amotivation were moderate to low, pointing to the autonomous nature of non-formal online learning (e.g., Song & Bonk, 2016) and supporting our decision to focus on intrinsic motivation. Even when looking at motivational change in more detail by considering the four-class solution of the LPA, there is no subpopulation in our sample of completers of non-formal online courses that matches the pattern previous literature reported for formal settings. Therefore, it is worthwhile to investigate motivational trajectories complementary in non-formal contexts, since the results from the formal setting cannot simply be transferred.

4.1.2 Trajectory of Intrinsic Motivation

In addition, we examined change in intrinsic motivation with a bivariate LCS model comprising intrinsic motivation in a simultaneous analysis with situational interest. However, based on the presented descriptive analyses it becomes clear that the trajectory of intrinsic motivation seems to be quite stable over time and therefore, there is not much variance in change to explain. Nevertheless, there is on average a statistically significant change in intrinsic motivation from T1 to T2 in form of a compensating effect, which suggests, growth in intrinsic motivation was larger for learners with lower initial intrinsic motivation levels. However, this may be indicative of a ceiling effect, as a large proportion of the sample had already high initial levels of intrinsic motivation from the beginning and were unable to achieve further growth.

In the same vein, our results contradict the assumption that (situational) motivation is variable over time (Guay et al., 2000)—at least at first glance. However, despite the supposed stability of the results, we would not assume that motivation is always so stable, but rather that the design of the present study was not suitable to portray the variability, since we are analyzing a very specific, self-selected sample—namely those learners who have managed to maintain their initial level of motivation in order to complete the course, and in addition, also have participated in voluntary surveys.

4.2 Correlates of Initial Intrinsic Motivation and Prediction of Change

To answer the second question and consistent with our hypotheses, we found positive correlations of initial intrinsic motivation with initial situational interest, self-regulation and mastery goal orientation. These findings are in line with the existing literature on motivation in the formal context, suggesting a positive relation of intrinsic motivation with interest (e.g., Schiefele, 2009), self-regulation (e.g., Pintrich & De Groot, 1990), and mastery goal orientation (e.g., Spinath et al., 2012). Moreover, there was also a strong positive relation of situational interest with intrinsic situational motivation when measured at the same time (see Figure 2), reaffirming the closely intertwined relation of both constructs often reported in previous research (Hidi, 2000; Reeve, 1989; Schiefele, 2009). With regard to the prediction of change in intrinsic motivation, on the other hand, only one of the hypotheses could be confirmed. Self-regulation was the only statistically significant predictor for change in intrinsic motivation, indicating that a higher self-regulation was related to growth in intrinsic motivation and thus, emphasizing that self-regulation seems to be a key factor for retention (Reparaz et al., 2020). However, there might be no relation between situational interest and mastery goal orientation with change in intrinsic motivation due to the methodological artifact that there were ceiling effects for both covariates and thus variance was missing that would be needed for a meaningful prediction. Interestingly, course duration (i.e. estimated processing time) as a control variable was not related to intrinsic motivation (neither initial level nor change; see Table 5). Whereas existing literature generally suggest a negative correlation between course length and persistence (Jordan, 2014), within the scope of our specific sample consisting of course completers there seem to be no negative impacts of course duration for motivation, indicating that learners that have committed to course completion cannot be demotivated even by longer courses.

4.3 Limitations of the Present Study and Implications for Future Research

First, one common challenge for longitudinal studies is the risk of bias due to dropout of study participants (R. J. A. Little, 1995), which leads to lower sample sizes for later time points, thus making it necessary to employ statistical methods to deal with missing data. Besides the attrition of participants from T1 to T3, our sample consists solely of course completers and thus analyses and interpretation of results are restricted to a special portion of learners: those who committed to course completion. For example, due to the voluntary nature of non-formal online course offerings, there is quite a number of learners that either did not want to complete the course in the first place and failed mastering the course material, or had mastered it without demonstrating that accomplishment via formative assessments implemented within the course (DeBoer et al., 2014). Therefore, in the non-formal context, it is useful to redefine course success, as course completion is not the only main objective for all learners and dropout should not be simply equated with not receiving a certificate (Henderikx et al., 2017). These participants appear to have a different attitude towards non-formal courses and therefore could not simply be included in the analyses on motivational trajectories—especially not those that dropped out right after the beginning, since these dropouts may be systematic and therefore potentially characterized by different motivational patterns as compared to completers. Consequently, it is important for future research to examine if there underlies a systematic difference, for example in initial motivation, enrollment intentions or other personal characteristics, between learners completing versus dropping out of a non-formal online course.

Furthermore, a fundamental consideration in examining change is the number and distribution of time points. Regarding costs and logistical constraints, we have decided on three time points, which are evenly distributed over the entire course including the absolute starting and ending point to capture as much as possible of the learning process. Of course, it is arguable that more time points are always better, as more waves of data allow more flexible statistical models with less restrictive assumptions (e.g. nonlinear growth; Singer & Willett, 2003). Additionally, as non-formal online courses permit highly flexible learning, perhaps a more flexible way of surveying is a worthwhile approach to better measure fluctuations in motivation. One possibility to meet these requirements is ambulatory assessment—that is methods to study people in their natural environment to gather ecologically valid data such as self-report (Trull & Ebner-Priemer, 2013). Especially for affective-motivational development, ambulatory assessment is a promising method, as it leads to a deeper understanding of motivational development processes (Hoppmann & Riediger, 2009). Therefore, future research could apply for example Ecological Momentary Assessments (i.e., repeated, frequent assessments in people's daily life; Wrzus & Neubauer, 2023) to capture real-time states of motivation, even if non-formal learning appear scarcely in real-life to study within-person effects as wells as within-person dynamics in more detail (e.g. nonlinear trajectories to identify particular time periods when changes in motivation may be more or less dramatic to inform possible interventions or course design decisions). This approach might also make it possible to detect the tipping point of motivation in non-formal online courses in order to differentiate between course completers and dropouts—all indicating that they were initially highly motivated.

Moreover, our original study design envisaged that participants who did not take part in the following surveys after 28 days (as long as the final survey at the end of a course has not been answered yet) were contacted by e-mail with the request to fill out a follow-up survey if they discontinued working on the course. Thereby, we wanted to learn more about the actual reasons for dropping out of the course in order to be able to distinguish whether a decline in motivation or external factors like lack of time, technical issues or life events were decisive (see Shapiro et al., 2017 for common challenges and barriers). Unfortunately, hardly anyone took part in the follow-up survey. In order to make informed course design decisions, future research should further examine the underlying motives for course dropout as a course redesign with motivational interventions is only useful if there are motivational barriers. For instance, participants that “learn on demand” and quit a course once they had accessed the desired learning material, are satisfied with their learning even without course completion (Zheng et al., 2015). Alternatively, participants enroll out of sheer curiosity and soon drop out which is possible due to open and free access (Bezerra & da Silva, 2017), or they may lack a clear understanding of the course requirements, leading to unrealistic expectations about the course difficulty or their ability to complete it (Onah et al., 2014). Considering the extremely low response rate of the follow-up survey, if ambulatory assessment is used in future research and motivation is collected app-based, one could also synchronize the follow-up survey with the app to prevent survey noncompliance due to potential pitfalls like forgetting to check the emails, survey was identified as junk-mail, or email address was entered incorrectly.

Finally, 51 different online courses with a variety of topics were investigated, which ensured a certain heterogeneity. Yet, all analyses were conducted with data from one specific learning platform, guaranteeing a certain level of comparability and course quality, as for example all courses were designed by university professors. Although we examined online courses of varying content and duration, thus enhancing external validity, this approach might increase the influence of extraneous factors (i.e., additional, but construct irrelevant variance in the data). Moreover, albeit the sample composition is typical for non-formal education in Germany (i.e., very large age range of participants; Bilger & Strauß, 2022; but predominantly young adults with a high educational background; Kruppe & Baumann, 2019), it is unclear if our results would replicate in other populations or online learning platforms as structural differences between courses, for example time dependent learning schedules, or absence of a certificate, or various reasons for enrolling in non-formal courses might influence motivational trajectories. Therefore, future research requires examining motivational trajectories in further non-formal online courses to verify if the observed patterns are consistent across different settings.

5. Conclusion

In contrast to previous findings from formal learning contexts, all subtypes of situational motivation showed remarkable stability over the period of non-formal online courses. Individuals differ mainly in their level of the five subtypes of situational motivation, resulting in four profiles of motivational trajectories. The majority of learners completing a non-formal online course showed high values for intrinsic motivation and identified regulation and low values for introjected regulation, external regulation, and amotivation over time which emphasizes the importance of autonomous motivation in non-formal online learning. However, for the few learners for whom there was a significant change in intrinsic motivation, self-regulation played an important role in predicting change. Yet, the present study examined only learners that have completed a non-formal online course. Given the generally high dropout rates from non-formal online courses, future research should a) implement a more close-meshed survey of situational motivation to identify potential tipping points in e.g. intrinsic motivation, b) reach out for course dropouts to investigate their underlying reasons for discontinuing the course, and c) investigate if completers differ systematically from dropouts.

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Appendix D

Manuscript 3

Embracing the challenge: Predicting self-testing in non-formal online courses using machine learning

Maria Klose

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Philipp Handschuh

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Diana Steger

Leibniz Institute for Educational Trajectories (LIfBi), Germany

Cordula Artelt

Leibniz Institute for Educational Trajectories (LIfBi), Germany

University of Bamberg, Germany

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Abstract

Technology-driven advancements have made adaptive and interactive learning techniques more accessible. Online courses increasingly integrate self-tests that offer automated and immediate feedback. Self-tests can help learners to identify knowledge gaps and to reinforce their retention and comprehension. However, not all learners readily use self-tests, raising the question of which factors may impact learners' engagement with self-tests. The present study focused on non-formal education, covering 45 online courses offered by Bavarian universities. Analyses were based on a sample of $N = 1{,}261$ participants aged 16 to 84 years. We used a machine learning approach to predict learners' engagement with self-tests and to identify important influencing factors. Therefore, we included 50 predictor variables in an elastic net regression to explore the role of learner- and course-related characteristics. The predictor variables were drawn from self-report, process, and meta data. Overall, learners differed substantially in their self-testing behavior. The prediction model explained 11% of the variance in learners' engagement with self-tests. Despite the model's modest explanatory power, the analysis identified potentially relevant predictors. The two most important predictor variables were learner commitment and the intention to obtain a confirmation of participation. Accordingly, course designers might implement extrinsic incentives—such as confirmations of participation—as a potentially useful strategy to encourage learners' engagement with self-tests. From a methodological perspective, the study highlights the importance of using appropriate statistical methods—such as machine learning algorithms—to understand complex learning behaviors.

Keywords: online learning, technology-enhanced learning, lifelong learning, self-testing, machine learning

1. Introduction

In the age of digitalization, education is undergoing a rapid transformation, offering new opportunities for lifelong learning (Mozelius et al., 2024). Technology-enhanced learning facilitates access to formal, informal, and non-formal education across the lifespan (Jaldemark et al., 2021). Among these, non-formal online courses enable learners to easily access organized learning materials, but without formal accreditation (Schwier & Seaton, 2013). These courses typically lack external control, for example by instructors or graded performance-based systems. Thus, greater demands are placed on learners' self-regulation skills (Kizilcec et al., 2017), which include goal setting, strategy use, progress monitoring, and time management (Zimmerman, 2002). In general, one effective learning technique to autonomously monitor and regulate the learning process is the engagement with self-tests (i.e., completing tests as a no-stakes practice and on one's own; Dunlosky et al., 2013). However, although it is known that self-tests are powerful tools to improve learning performance in both formal and non-formal learning contexts (Rowland, 2014), not all learners readily engage in self-testing, as it might be seen as a tedious necessity (Dunlosky et al., 2013). With the present study, we aim to better understand which learners persist in engaging with self-tests within non-formal online courses, which can be regarded as prototypical self-regulated learning environments.

1.1 Self-Tests as Formative Assessments in Non-Formal Online Courses

Self-tests are a form of formative assessment, which accompany the learning process and support learning by providing immediate feedback on the correct solutions (e.g., Dolin et al., 2018; Wiliam & Black, 1996). Unfortunately, self-testing can be perceived negatively, as many learners mistakenly equate self-tests with high-stakes summative assessments, which are often seen as tools for judgment rather than learning (Dunlosky et al., 2013), as summative assessments are used for the purpose of grading or certification, and are given mid-term or at the end of a course (e.g., Bloom et al., 1971; Dixson & Worrell, 2016). Consequently, learners shy away from self-testing as a learning technique and tend to use less effective learning techniques (e.g., passive review methods like rereading and highlighting) that require less time and effort, because they misinterpret the mental effort of self-testing as a sign of poor learning (Kirk-Johnson et al., 2019).

Learners' perceptions of self-testing as an inefficient technique stand in contrast to extensive evidence demonstrating its robust effectiveness in promoting long-term retention across numerous studies in formal learning contexts (e.g., Adesope et al., 2017; and Yang et al., 2021). Importantly, comparable effects of self-testing have also been observed in non-formal learning environments, indicating that its effectiveness is not confined to institutional settings (Rowland, 2014). Tests do not only assess knowledge to identify which course content has or has not been understood, but they also directly enhance learning by initiating retrieval processes when learners are taking tests (i.e., *testing effect*; Karpicke, 2017). Therefore, the benefits of testing for learning are manifold (Roediger et al., 2011). For example, testing identifies gaps in knowledge, improves transfer of knowledge to new contexts, and triggers active retrieval which fosters later retention.

Despite these well-documented benefits, self-tests may also entail unintended negative side effects, such as false memory effects. Especially in the case of recognition tests (e.g., multiple-choice tests, true/false statements, matching exercises), the correct answer is presented along with distractors that provide wrong statements or erroneous information. This might ultimately lead to the acquisition of false knowledge (Marsh et al., 2007) if learners memorize the wrong answer. This so-called *negative suggestion effect* (Roediger & Karpicke, 2006) can be diminished by providing corrective feedback (Kang et al., 2007). It might be even eliminated if learners receive the feedback promptly after taking the test (Roediger & Karpicke, 2006), provided that they learn from the feedback and understand the principles underlying their errors. Therefore, it is not only important for learners to receive immediate feedback, but also to interact with the feedback to correct their errors to overcome potential negative effects of testing (i.e., cognitive engagement).

In general, learning engagement is commonly conceptualized across three interrelated dimensions: affective, behavioral, and cognitive engagement (Bond et al., 2020). *Affective engagement* includes aspects like interest and a positive attitude towards learning, *behavioral engagement* encompasses participation and involvement in learning activities, and *cognitive engagement* involves self-regulation and investment in learning (Appleton et al., 2008; Fredricks et al., 2004). Our learning behavior of interest, engagement with self-tests, goes beyond learners participating in the learning process by taking the self-tests (i.e., behavioral engagement; Fredricks et al., 2004). Learners must not only participate in self-tests, but rather invest sustained effort in using self-testing as a self-regulated learning technique over time to achieve mastery of the learning material (Lawson & Lawson, 2013).

1.2 Who Engages with Self-Tests and Under What Conditions?

A substantial body of research has already examined whether the effectiveness of testing as a learning technique is moderated by interindividual differences, concluding that testing is beneficial for all learners irrespective of, for example, personality traits or working memory capacity (Bertilsson et al., 2021), cognitive ability (Jonsson et al., 2021), age (Pastötter & Bäuml, 2019), and motivational or emotional dispositions (Glaser & Richter, 2023). Apart from learner characteristics, testing has proven effective across different learning environments (Rivers, 2021)—including content areas, education levels (Agarwal et al., 2021), and study settings (Adesope et al., 2017). Together, these findings underscore the robustness of self-testing as a learning technique that benefits a wide range of learners across diverse contexts.

However, to benefit from the testing effect, learners must first engage in self-testing. Accordingly, our focus is not on evaluating whether engaging with self-tests improves course performance, but rather on examining whether learners utilize self-tests as a learning technique at all, including the persistence in interacting with corrective feedback until tests are answered correctly as a proxy for cognitive engagement. In the context of the present study, the key question is how learners can be encouraged to adopt self-testing as a learning technique by identifying relevant predictors for the engagement with self-tests. Given the ongoing debate about which learners engage in self-testing, a comprehensive approach that considers both learner and course characteristics, along with multiple data sources, is essential (Carpenter, 2023).

In the process of self-regulated learning, learners are free to choose to use self-testing as a learning technique (Pintrich, 2000). Prior research has shown that this choice is associated with various learner characteristics, including socio-demographic factors, cognitive, and non-cognitive aspects (e.g., Bertilsson et al., 2024; Fellman et al., 2020). In particular, motivation plays a central role: learners who are more motivated to engage in learning activities are also more likely to use self-tests (Bertilsson et al., 2024), emphasizing the importance of context-specific motivational factors for the engagement with self-tests. Beyond motivation, learners' interest in the learning task (Zepeda et al., 2020) and their ability to employ self-regulation strategies to maintain effort regulation towards self-testing (De Bruin et al., 2023) are further prerequisites for continued engagement. Moreover, learning behavior and engagement levels are influenced by the initial reasons for enrolling in a voluntary (online) course (Kizilcec & Schneider, 2015), which can also impact the adoption of self-testing as a learning technique. Overall, these findings suggest that a variety of learner characteristics are associated with engagement with self-tests, which is why the joint investigation of all of the aforementioned characteristics may adequately depict the complex interrelations.

In addition to learner characteristics, contextual aspects of the learning environment that influence learners' engagement with self-tests must also be considered (Zepeda et al., 2020). Research on the testing effect has primarily been conducted in formal learning contexts (i.e., in the classroom or in standardized laboratory experiments; e.g. Adesope et al., 2017; Yang et al., 2021). Consequently, there is limited research on the effects of different learning contexts. Understanding the impact of contextual variables like course characteristics becomes even more crucial when investigating authentic, real-life learning scenarios, especially since non-formal online courses vary greatly in their course design (Maya-Jariego et al., 2020). For instance, course duration can influence perceived workload and, in turn, learners' sustained engagement (Eriksson et al., 2017; Goopio & Cheung, 2021), especially since such courses are typically taken in participants' leisure time.

1.3 The Present Study

Not all learners take advantage of self-tests as a learning opportunity (Carpenter et al., 2022). Especially in a non-formal online learning context, learners have to decide for themselves whether to invest effort in the voluntary option of self-testing. Thus, it is crucial to understand which learners are willing to commit to self-testing and under which conditions they persist until they can answer the tests correctly. Accordingly, in the present study, we aim to predict the learners' engagement with self-tests in non-formal online courses.

However, one's willingness to engage with self-tests potentially hinges on a variety of different factors. Drawing on the conclusion from a recent review on effective learning with retrieval practice (Carpenter et al., 2022), we investigated learners' engagement with self-tests a) within a real (online) learning scenario, b) based on a comprehensive dataset that simultaneously covers learner- and course-related characteristics, and c) using multiple data sources. Thereby we want to explore potential factors that may impact learners' engagement with self-tests, providing potential strategies to make self-testing more accessible to a broader range of learners. As we draw on a large number of predictor variables, we use a machine learning approach to appropriately model the extent to which learners engage with self-tests as a learning technique throughout an online course.

2. Methods

Following common open science practices, all supplemental study materials (i.e., codebook, syntax, data, and supplemental figures and tables) are available online within the Open Science Framework (Center for Open Science, 2025): https://osf.io/5za3d/.

2.1 Design and Participants

The present study was part of a larger research project with a longitudinal design. For the current analyses, we rely on cross-sectional questionnaire data only, which was collected at the first assessment (for more detailed information see Klose et al., 2024). These data were collected between October 2021 and April 2022 via an online survey implemented within 45 non-formal online courses offered by German, particularly Bavarian, universities (OPEN vhb; Virtuelle Hochschule Bayern, 2025). Data collection was conducted in accordance with the ethical guidelines established by the German Society for Online Research, the declaration of Helsinki, and the General Data Protection Regulation (GDPR). After course enrollment, a link to the survey was provided on the first page, allowing learners to participate voluntarily. Participants actively approved their involvement by agreeing to take part, and their anonymity was fully guaranteed. Ethical approval was not required under local legislation. Participants answered questions on socio-demographic information, enrollment intentions (*OLEI* Scale; Kizilcec & Schneider, 2015), situational motivation (*SIMS*; Guay et al., 2000), situational interest (*SIS*; Linnenbrink-Garcia et al., 2010), and self-regulation (*LIST-K*; Klingsieck, 2018). Table S1 provides a comprehensive overview of the survey content compilation, detailing the specific subscales utilized, any adaptations made, the number of items, and the response format. The online courses were available to anyone interested at no cost, following a self-paced format (i.e., enrollment at any time, with all course materials available from the outset, and no set deadlines). Moreover, the courses were taught in German and covered a broad range of subjects, for example social sciences and humanities, science, technology, engineering, and mathematics (STEM), health science, and economics. Each course included self-testing opportunities that were required for learners to receive a confirmation of participation, which could be downloaded at the end of the course. However, this document is no official certification or degree but simply verifies attendance. The required percentage of correct test answers per course ranged from 50% to 100% (M = 77%; SD = 13%). In addition, the courses' length varied with respect to the estimated time needed to complete the course (Range 9 to 60 hours; M = 18.88; SD = 9.38), and its number of chapters (Range 3 to 16; M = 7.49; SD = 2.75) and lessons (Range 11 to 143; M = 56.70; SD = 27.44).

The online survey resulted in a total of 1,307 cases, of which 1,126 (96.5%) were included in the final analyses and consisted of 1,205 unique subjects (95.6%; learners were allowed to participate in the survey for each course they attended, so that multiple participation in the study was possible if they were enrolled in several courses). No sample-size-dependent stopping rule for data collection was specified beforehand, as the planned analyses require comparatively large sample sizes for stable estimations. Using machine learning algorithms, issues of underpower are generally more discussed than issues of overpower, since limited sample sizes are for example problematic for pattern recognition (Vabalas et al., 2019). Generally, our current sample size falls within the range of sample sizes reported by studies using comparable methods (e.g., Greenwood et al., 2020; Wang et al., 2024). Table S2 displays the detailed data cleaning procedure and the participant dropout at different stages due to missing data or validation checks. In the final sample, 68.0% of the participants reported being female (30.9% male, and 1.1% nonbinary or non-response). The average age was 37.0 years (*SD* = 14.30, range 16 to 84 years), encompassing all age groups from older adolescents to adults of retirement age (> 65 years; see Figure S1 for the age distribution). The sample predominantly consists of individuals with academic backgrounds: 47.8% had an university degree, 34.1% had a secondary school degree qualifying for university (i.e., academic-track: *Gymnasium* or *Fach-/Berufsoberschule*), 10.4% had a middle secondary school degree (i.e., intermediate-track: *Realschule*), 2.6% had a lower secondary school degree (i.e., vocational-track: *Hauptschule*), and 5.1% had a different educational background (i.e., no degree, other school degree, still in school, or non-response). In terms of the current employment status of the sample, the distribution was as follows: 58.1% were employed, 23.6% were school/university students, 4.3% were apprentices, 5.0% were retired and 9.0% had a different employment status (i.e., seeking employment, unemployed, or non-response). All participants were fluent in German. While our sample is not representative of a broader population, its socio-demographic composition is consistent with those observed in other studies on non-formal education in Germany. In particular, participation often skews towards younger adults and individuals with higher levels of education (Kruppe & Baumann, 2019). The presence of older participants (ages 50-64 and above) also reflects broader trends in lifelong learning participation (see Bilger & Strauß, 2022 for continuing education behavior in Germany). Table S3 provides descriptive information on courses and participants separately by course to provide an overview over the hierarchical data structure (i.e., learners nested in courses).

2.2 Measures

The present study followed an exploratory, data-driven, machine learning approach (Yarkoni & Westfall, 2017) and therefore included a broad set of predictor variables across different data types to maximize the opportunity for detecting relevant patterns (Breiman, 2001). To predict learners' engagement with self-tests, three types of data were considered: *meta data* that was coded from openly available course information as course-related characteristics, as well as *process data* from the online survey, and *questionnaire data* (i.e., self-report scales from the online survey) as learner-related characteristics. While not all predictors were derived from theory, their inclusion was justified by their plausible relationship to the dependent variable. Concerns such as multicollinearity or overfitting were addressed by the choice of appropriate statistical modeling techniques. Table S1 summarizes all 50 variables used as predictors with a detailed description of each variable including descriptive statistics. For categorical variables, the category of interest is specified for dummy-coding. For each subscale, Cronbach's alpha is indicated as a measure of internal consistency.

We operationalized learners' engagement with self-tests using the percentage of correct test answers, derived from log data transmitted by the *Virtuelle Hochschule Bayern* (*vhb)*, the provider of the non-formal online courses. This percentage reflects the correct test answers recorded throughout the course, regardless of the frequency of learners' test attempts (i.e., the proportion of self-tests that learners answered correctly at least once). Consequently, learners with no correct test answers included those who did not take the self-test option at all, as well as those who took the tests but answered incorrectly. Since these tests were designed as formative assessments—characterized by no-stakes testing situations, immediate feedback on performance, and unlimited test attempts—we argue that the percentage of correct test answers serves as a proxy for the learners' cognitive engagement (i.e., investing effort until a part of mastery of learning content is achieved). It does not, however, reflect actual course performance, as learners' proficiency goes beyond the percentage of correct test answers (Abbakumov et al., 2020). Each course offered at least three self-tests (M = 26; SD = 32; max. = 179), that were distributed throughout the course to accompany the learning process. The tests covered a variety of formats, including multiple-choice quizzes, matching tasks, true/false statements, and fill-in-the-blank exercises, all designed to capture course material without requiring prior knowledge. While participation in the self-tests was voluntary, completion of a certain portion of the self-tests was a requirement for confirmation of participation.

2.3 Statistical Analyses

2.3.1 Score Computation and Missing Data

We aggregated scales using mean scores for each subscale of the questionnaires. Where necessary, we recoded reversed items before aggregation. Overall, the amount of missing data for metric predictors was small, with a maximum missingness of 7.5% per variable and an average missingness of 2.9% across all variables. Given this low level of missingness, we imputed missing values for metric predictors using the *k*-nearest neighbor algorithm, which is considered a robust and sensitive method for missing value estimation for data sets with less than 10% missing entries (Troyanskaya et al., 2001). All metric predictor variables were standardized before entered in the machine learning models.

For categorical variables, we applied dummy coding to include them in the analyses as dichotomous predictors using one category of interest as specified in Table S1. Missing data was coded as 0 and therefore grouped together with all other categories and treated as a reference category. The amount of missing data for dichotomous predictors was slightly higher with an average missingness of 5.3%. The variables with the largest proportion of missingness were enrollment intentions with a maximum missingness of 25.1% for the statement "course offered by prestigious professor". Out of 14 enrollment intentions, 12 fall below the rule-of-thumb limit of maximum 10% missingness. We decided to include all dichotomous predictors in the final analyses because we treated missing data the same as disagreement (i.e., treated as reference category) since almost all missing data were due to the deliberate decision to choose the "no answer" option rather than dropping out of the survey.

2.3.2 Elastic Net Regression

To predict the engagement with self-tests, we used elastic net regression—a statistical method that builds a prediction model while automatically reducing the influence of less important variables. Elastic net regression is a shrinkage and variable selection method (Zou & Hastie, 2005) which combines ridge regression (Hoerl & Kennard, 2000) and LASSO regression (i.e., least absolute shrinkage and selection operator; Tibshirani, 1996) as forms of regularization to avoid overfitting. Since ridge regression cannot produce a parsimonious model, and lasso regression cannot handle correlated predictor variables, elastic net regression creates a useful compromise via the regularization parameters λ and α (Zou & Hastie, 2005): λ controls the overall strength of penalty applied to the model, and α determines the mix between ridge and lasso penalties (see Helwig, 2017 for more details). This combination allows elastic net regression to handle correlated predictors by shrinking coefficients of correlated predictors towards each other, and less important coefficients towards 0 (ridge), while still achieving a sparse prediction model solution through variable selection (lasso) at the same time (Friedman et al., 2010).

To ensure unbiased model evaluation, we split the full dataset into 80% of the courses for training and 20% of the courses for independent testing of the prediction model. Given the hierarchical structure of our data (i.e., learners nested in courses), we employed a blocked cross-validation approach (Roberts et al., 2017) to prevent bias in performance estimates (Pargent et al., 2023). Consequently, all observations belonging to one online course were assigned either to the training set or the test set (i.e., blocked resampling). The consideration of the aforementioned multilevel structure in our analyses was supported by an intraclass correlation coefficient (ICC) for a null multilevel model, as the estimated ICC =.13 indicated variance between courses (arbitrary rule of thumb ICC > .05; see Hayes, 2006). Moreover, for model training, we used ten-fold cross-validation to estimate the prediction error by training and testing the prediction model on different samples of data (Yarkoni & Westfall, 2017). We applied a tune length of 21 to tune the model with respect to the regularization parameters λ and α for the elastic net regression (Helwig, 2017), resulting in 21 combinations of λ and α to identify the combination that best balanced model simplicity and accuracy. To obtain a stable and reliable prediction model, and to quantify the prediction accuracy, we repeated this procedure of cross-validation, training, and testing 100 times. To evaluate the performance of the models, we used explained variance (R^2), the *Root Mean Squared Error* (RMSE), and the *Mean Absolute Error* (MAE) as indices of model fit. To interpret the direction of each predictor variable's effect on learners' engagement with self-tests, we report the respective coefficients for the model with the best tuning parameter λ.

2.3.3 Variable Importance

To answer the question as to which learner or course characteristics are more suitable for predicting learners' engagement with self-tests, we calculated the average variable importance for all predictor variables in the test sample across all 100 iterations. The values range between 0 and 100, and reflect a transformation of the absolute weights in the linear regression (Grömping, 2009).

2.3.4 Sensitivity Analyses

We conducted several sensitivity analyses to check the robustness of our results by contrasting the main model with modified models which varied with respect to methodological approaches, and sample or predictor variable restrictions. For all sensitivity analyses, we compared prediction accuracy and the ten most important predictor variables to examine whether there are differences between models.

2.3.5 Statistical Software

All analyses were conducted using *R*-version 4.4.1 (R Core Team, 2025). The *caret* package version 6.0.94 (Kuhn, 2008) was used for the *k*-nearest neighbor imputation and as an interface for modeling and prediction. The *glmnet* package version 4.1.8 (Friedman et al., 2010) was used for elastic net regression.

3. Results

3.1 Descriptive Statistics

The distribution of the logged percentage of correct test answers (M = 0.39, SD = 0.42, Range [0; 1]) is characterized by a strong tendency to extremes (see Figure S2). 36.3% of the subjects did not answer a single test item correctly[1]. In contrast, 17.2% of the subjects answered all test questions of a course correctly and thus worked through the course completely. As self-testing was linked to receiving a confirmation of participation, 403 learners (32.0%) met the threshold required for this confirmation. Among these, ten learners completed a course that required a perfect score (100%). However, for courses with a lower threshold, achieving the confirmation of participation did not discourage further self-testing, as 98.2% of learners (386 out of 393) continued using self-tests even after meeting the requirement. Additionally, descriptive statistics and correlations for all scales are summarized in Table S4. A correlation matrix of all 50 predictor variables is displayed in Table E1.

3.2 Elastic Net Regression

The means and standard deviations of the prediction accuracy (R^2) across 100 random splits of the total sample into training and test sets are displayed in Figure 1. Overfit of the resulting prediction model is indicated by a difference between training and test sets. Overall, the degree of overfitting was high (ΔR^2 = .10), and 11% of the variance in the engagement with self-tests could be explained by learner and course characteristics. To further evaluate the prediction model, the average *RMSE* for the train set was .38 compared to .40 for the test set, and the

[1] This includes participants that a) did not participate in the self-tests, and b) that participated in the self-tests but did not answer any questions correctly.

average *MAE* for the train set was .33 compared to .35 for the test set. The best tuning parameters in our elastic net regression were α = .19 and λ = .03. Table S1 shows the coefficients for each predictor variable for the model with the best tuning parameter λ.

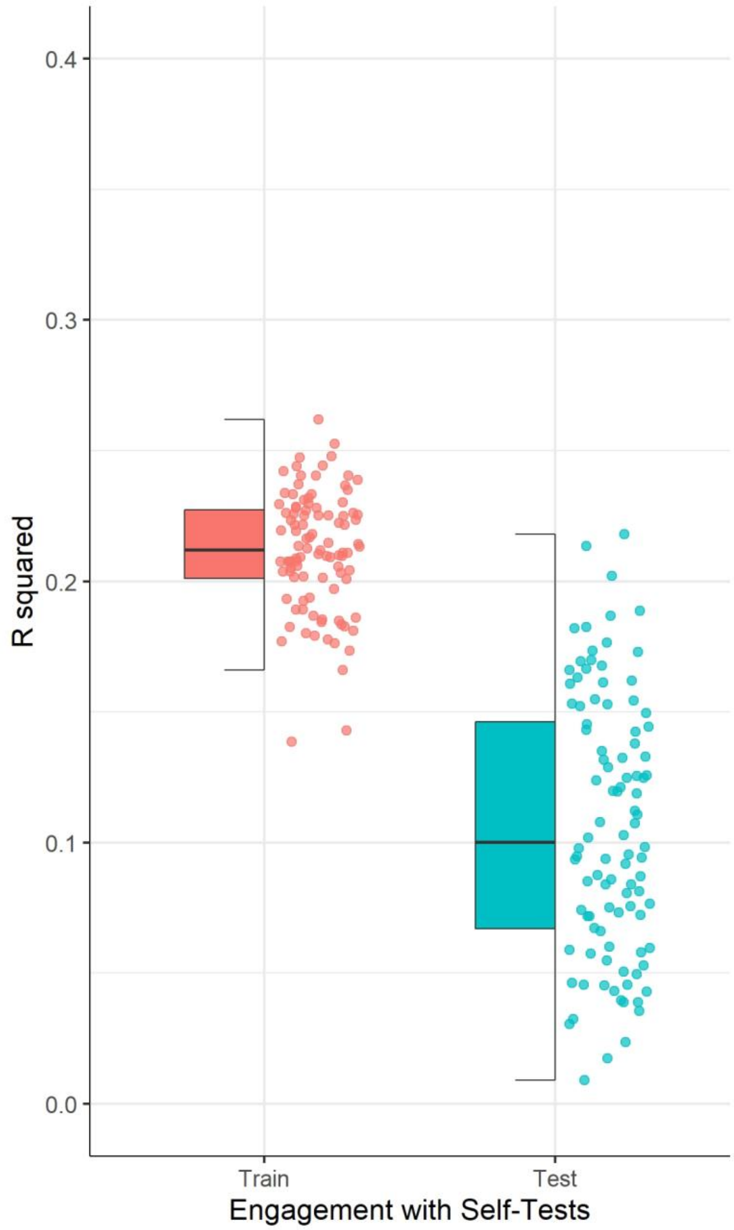

Fig. 1. Accuracy predicting the engagement with self-tests based on learner and course characteristics. *N* = 1,261. Left side: The boxplot reflects the interquartile range, the solid line represents the median, and the whiskers represent the minimum/maximum values within 1.5 time the interquartile range. Right side: Jittered point plot of all 100 values for the average R^2.

3.3 Important Variables in Predicting the Engagement with Self-Tests

Figure 2 shows the ten learner and course characteristics with the largest average variable importance for predicting the engagement with self-tests (see Table S1 for the variable importance estimates of all predictor variables). In the following, we will give an overview of the major findings for each data type: First, the most important variable for predicting the engagement with self-tests in terms of process data was the distinction whether a learner participated in our survey once within a single course or multiple times within different courses, which might be an indicator of overall commitment or general learning motivation. Second, in terms of self-report data, learners' enrollment intentions, particularly their intention to receive a confirmation of participation, are especially important for predicting their engagement with self-tests, as they make up four out of ten of the most important variables, thereby highlighting the importance of underlying motivations and external incentives. Lastly, in terms of course characteristics, the course type (i.e., specific area of expertise versus key qualifications/ entry-level courses) is the most important variable. However, course type is not consistently among the ten most important variables across sensitivity analyses.

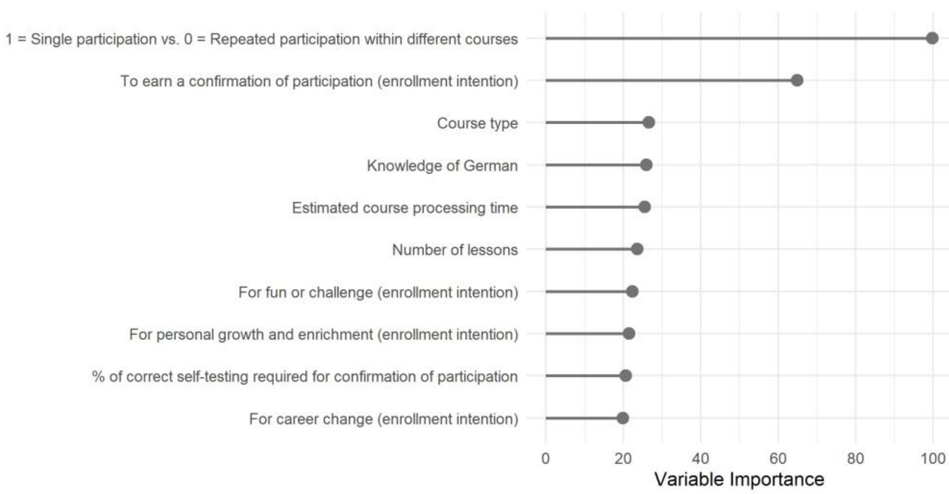

Fig. 2. The ten predictor variables with the largest average variable importance for predicting the engagement with self-tests.

3.4 Sensitivity Analyses

Sensitivity analyses were conducted to check whether our findings remain consistent under adjustments to the 1) methodological approach, 2) sample composition, and 3) predictor variable selection. Table 1 compares the prediction accuracy of our main model—an elastic net regression of the full analysis sample using blocked resampling—with the prediction accuracy of the modified models. Further, Table S5 summarizes the comparison of the ten most important variables for the prediction of learners' engagement with self-tests across sensitivity analyses.

3.4.1 Prediction Accuracy

First, we examined the impact of different methodological approaches. To evaluate the impact of resampling approach, we contrasted our main model with an elastic net regression that used simple balanced data splitting based on the outcome instead of blocked resampling (model 1a), which neglects the hierarchical structure of the data. This approach explained more variance and showed less overfitting. In contrast, both, an ordinary multiple linear regression using blocked resampling (model 1b), and a complete case analysis as an alternative approach to handle missing data (Lee et al., 2021; model 1c), explained less variance and resulted in higher overfitting. While neglecting the hierarchical structure of the data might lead to an overestimation of predictive power, the KNN imputation allowed us to retain more information compared to complete case analysis (N = 1,261 vs. N = 731) and yielded plausible model estimates. Overall, the results support the appropriateness of our methodological decisions regarding data splitting, model selection, and handling of missing data.

Second, we investigated the effects of different sample compositions by comparing elastic net regressions using blocked resampling for the following subsamples: without cases of multiple participation from the same subject to control for data dependencies (model 2a), containing only learners that have completed at least one test to control for early course dropouts (model 2b), and comprising learners who completed more tests than required for the confirmation of participation (model 2c). Generally, all tested sample restrictions resulted in negligible differences in prediction accuracy as compared to the main model. The most noticeable, albeit small, difference was observed in the subsample of learners who completed more tests than required for the confirmation of participation.

Third, we examined the impact of the variable selection by removing the predictor variable "Intention to earn a confirmation of participation" from the model (model 3) to control for potential masking effects, as completing self-tests were a prerequisite for receiving a confirmation of participation. This also resulted in negligible differences in prediction accuracy as compared to the main model. Taken together, subgroup analyses and the removal of a potential masking predictor variable provided evidence for the robustness of our results.

3.4.2 Important Predictors

Important variables for predicting learners' engagement with self-tests are rather similar across models except for those for the subsample of learners who completed more tests than required for the confirmation of participation (model 2c; see Figure S3). In this case, other predictors were more important compared to those from the main model. However, the resulting different patterns must be interpreted with caution, since the restriction to this highly selective and probably more homogenous subsample leads to severe variance restrictions. When omitting the intention to earn a confirmation of participation as predictor variable, multiple course participation remained by far the most important variable and the other important variables hardly differed from the main model. Hence, the intention to earn a confirmation of participation did not seem to mask effects of the other predictors

Table 1

Sensitivity analyses for the elastic net regression of the full analysis sample using blocked resampling.

		Train set			Test set			ΔTrain-Test		
	N	R^2	*RMSE*	*MAE*	R^2	*RMSE*	*MAE*	Δ R^2	Δ *RMSE*	Δ *MAE*
Main Model										
Elastic Net Regression (Blocked Resampling)	1,261	**.21**	.38	.33	**.11**	.40	.35	**.10**	.02	.02
1) Methodological Approaches										
1a) Elastic Net Regression (Balanced Data Splitting)	1,261	**.21**	.38	.33	**.15**	.40	.34	**.06**	.02	.01
Δ Main Model		<.01	<.01	<.01	.04	<.01	-.01	-.04	<.01	-.01
1b) Linear Regression (Blocked Resampling)	1,261	**.23**	.37	.32	**.09**	.43	.35	**.14**	.06	.03
Δ Main Model		.02	-.01	-.01	-.02	.03	<.01	.04	.04	.01
1c) Complete Case Analysis	734	**.22**	.38	.34	**.09**	.42	.36	**.13**	.04	.02
Δ Main Model		.01	<.01	.01	-.02	.02	.01	.03	.02	<.01
2) Sample Restrictions										
2a) Unique participation	1,205	**.20**	.38	.33	**.09**	.40	.35	**.11**	.02	.02
Δ Main Model		-.01	<.01	<.01	-.02	<.01	<.01	.01	<.01	<.01
2b) At least 1 test completed	803	**.26**	.33	.29	**.12**	.39	.32	**.14**	.06	.03
Δ Main Model		.05	-.05	-.04	.01	-.01	-.03	.04	.04	.01
2c) More tests completed than required for a cop	386	**.28**	.06	.04	**.15**	.07	.05	**.13**	.01	.01
Δ Main Model		.07	-.32	-.29	.04	-.33	-.30	.03	-.01	-.01
3) Predictor Variable Restriction										
Without “intention to obtain a cop”	1,261	**.19**	.38	.34	**.09**	.41	.36	**.10**	.03	.02
Δ Main Model		-.02	<.01	.01	-.02	.01	.01	<.01	.01	<.01

Note. ΔTrain-Test = Difference between train and test set. *RMSE* = Root Mean Squared Error. *MAE* = Mean Absolute Error. Other Δs = Difference between main model and modified model. “intention to obtain a cop” = “Intention to obtain a confirmation of participation”.

4. Discussion

The rise of online learning opportunities is continuously reshaping the educational landscape, offering learners greater flexibility in choosing when, where, and how to learn (Cha & So, 2020). However, this increase in autonomy also raises the demand for self-regulation (Biwer et al., 2021). Accordingly, learners must take responsibility for their own learning and make informed decisions about which learning techniques to employ (Rivers, 2021). Self-testing can be seen as an effective learning technique (e.g., Carpenter, 2023; Dunlosky et al., 2013; Fiorella & Mayer, 2016). Testing not only allows learners to track their progress, but also promotes active, effortful processing that enhances comprehension and retention. This so-called testing effect is achieved when learners either confirm their understanding by providing correct answers or learn from corrective feedback after making errors (Roediger & Karpicke, 2006). However, while self-testing promotes learning through intensive engagement with the learning material, it also makes learning more effortful (Bjork & Bjork, 2014). Therefore, in a non-formal online learning environment—characterized by its autonomy and lack of external incentives—embracing the challenge of engaging with self-tests until some degree of mastery is achieved seems crucial. To this end, we aimed to predict learners' engagement with self-tests in an authentic learning context. We focused on self-regulated learning using the percentage of correct test answers as a proxy for cognitive engagement. To identify potential predictors, we juxtaposed self-reported learner characteristics (e.g., demographic information, self-regulation, or enrollment intentions), process data from the online survey (e.g., indicators of repetitive response patterns, number of missings within the survey), and course characteristics (e.g., length, content).

4.1 Predicting the Engagement with Self-Tests in Non-Formal Online Courses

As expected, not all learners engaged with self-tests to the same extent. While a portion of learners (17.2%) fully exploited all available self-test opportunities, a considerable share (36.3%) did not answer a single test item correctly. The remaining 46.5% of learners varied in their engagement with self-tests, evenly distributed between these two extremes. This finding points to substantial individual differences in learners' engagement with self-tests in non-formal online courses, raising the question of which learner and course characteristics might explain this variability. To tackle this issue, we applied a machine learning approach to identify important variables to predict the engagement with self-tests. Given the context of empirical social science research, the predictive power of our model was acceptable ($R^2 = .11$; Ozili, 2023), offering initial insights and capturing potentially important predictors. However, the large proportion of unexplained variance highlights the complexity of predicting the engagement with self-tests. This is typical for complex human behavior within the learning process, suggesting that there is substantial room for improvement and a need for exploring other predictor variables. At the same time, the most important predictor variables of the present study need to be interpreted with caution given the modest explanatory power of the model.

Nevertheless, the main result of our prediction model was accompanied by two major findings with respect to the applied method: First, even though a R^2 of .11 is on the lower end of the spectrum for explained variance, the elastic net regression still outperforms an ordinary multiple linear regression which justifies the application of the rather complex procedure and highlights the importance of appropriate statistical techniques when examining complex phenomena such as learning behavior. Second, sensitivity analyses emphasized the importance of the implementation of the appropriate data splitting approach, as a non-observance of the hierarchical data structure can quickly lead to biased (i.e., overly-optimistic) prediction models. This is of particular importance in the context of educational research, as nested data structures are usually the case when studying learners from different courses (e.g., students nested in classes, classes nested in schools, and schools nested in school districts; Dedrick et al., 2009).

4.2 Important Variables for Predicting the Engagement with Self-Tests

Across all main and sensitivity analyses, two predictor variables proved to be particularly important: (1) whether a learner participated in our survey once within a single course or multiple times within different courses, and (2) whether they intended to enroll in order to receive a confirmation of participation. First, participating in multiple courses might indicate that an individual is motivated to learn and committed to the course. These individuals use not only multiple courses as learning opportunities, but they also participate in a study on the same topic multiple times, which might be an indicator for the general motivation to contribute to research as well. This behavior appears to reflect a more serious engagement with the course content overall—including the self-tests. This interpretation aligns with previous findings highlighting the importance of commitment for self-regulated learning in self-paced online learning environments (Kim et al., 2021). Additionally, this finding demonstrates the usefulness of directly observable behavior indicators rather than the use of self-reports to assess learning commitment. It highlights the potential of log data to gain more insight into learning behavior in general (e.g., Klose et al., 2022; Steger et al., 2021). From a practical perspective, fostering commitment to the course (e.g., through gamification elements like badges; Hamari, 2017) might support learners to engage with self-tests as a learning technique (see Rahman et al., 2018 for an overview of frequently used gamification elements). Such elements can help create a more motivating and interactive learning environment that stimulates active participation and enhances potential learning outcomes (Saleem et al., 2022).

Second, the intention to enroll in order to receive a confirmation of participation was a strong predictor of engagement with self-tests. In our study, successful participation in self-tests was necessary to receive such confirmation. Therefore, the offered self-testing opportunities that were intended to have formative value were simultaneously used as a summative judgement of the learner's achievement for course progress (Wiliam & Black, 1996). Interestingly, despite the granted autonomy within non-formal online courses, extrinsic incentives like a confirmation of participation motivate learners to engage with self-tests. Importantly, these incentives did not appear to undermine intrinsic motivation. Most learners continued to engage with self-tests despite reaching the required threshold for a confirmation. This finding is consistent with previous research on non-formal online courses, suggesting that learners' intention to earn a confirmation of participation is associated with more active course engagement, such as watching more videos, participating in discussion forums, and, most importantly, taking more tests (Kizilcec & Schneider, 2015). Therefore, course designers could consider offering a confirmation of participation as a way to promote engagement with self-tests. Perhaps a more fine-grained incentive structure with intermediate learning goals through a badge system could lead to an even more pronounced engagement within the course (Ortega-Arranz et al., 2019) and accordingly to an increase in the engagement with self-tests and enhanced long-term retention and understanding by promoting deeper cognitive processing of the course material.

Apart from these two key predictors, it is particularly remarkable that enrollment intentions in general play a central role for the prediction of the engagement with self-tests. Across models, enrollment intentions consistently make up four out of ten (or even eight out of 20) of the most important variables. This may reflect the diversity of learner goals within non-formal online courses (Moore & Wang, 2021) that have a strong influence on, for example, course completion. Consequently, the longer that learners keep up with the course the greater the likelihood of answering correctly the implemented tests. At the same time, successful learning within non-formal online courses might not look the same for all individuals (Henderikx et al., 2017): Depending on different enrollment intentions and learning goals, individuals might not seek to complete a whole course or master a complete topic, but rather seek very specialized bits of information. Accordingly, "finishing" a course might not be indicative of successful learning behavior for all participants and other learning behavior (such as taking only parts of the course or dropping out early) might be expedient for some individuals (DeBoer et al., 2014). Therefore, future research should consider the enrollment intentions of the learners as a potential explanatory variable within non-formal online courses.

Moreover, regarding course characteristics, we found a consistent pattern of important predictor variables across the different models: estimated course completion time and the total number of lessons consistently contributed to predicting the engagement with self-tests. Therefore, shorter courses seem to be positively linked to learners' engagement with self-tests. Additionally, the threshold for the percentage of correct self-tests required for a confirmation of participation appears to be a relevant factor in predicting engagement. This may also point to the usefulness of including extrinsic incentives in the design of non-formal online courses.

Finally, socio-demographic variables such as age or gender, did not predict the engagement with self-tests. This finding suggests that the ability to embrace challenging learning techniques such as engaging with self-tests is accessible to a diverse range of learners, reinforcing the inclusive potential of non-formal learning for lifelong learning (Werquin, 2010).

4.3 Limitations of the Present Study and Implications for Future Research

In light of the present results, a few limitations must be mentioned: First, since 89% of the variance in learners' engagement with self-tests remains unexplained, the question arises as to which other variables might be incrementally predictive. Our examined learner- and course-related characteristics seem not to be sufficient to map out engaging with self-tests in non-formal online courses. One big advantage of online learning environments is the possibility to automatically track information on learning behavior via log data from learners' interactions with the online platform (Gašević et al., 2016). Accordingly, both very general information on the behavioral learning engagement (such as number of logins, or time spent on the course platform), as well as more fine-grained information on which type of learning materials the course participants interact with (for example texts, videos, or discussion boards) might be indicative for the engagement with self-tests (compare with You, 2016 for an overview of the usefulness of log data for the prediction of learning achievement).

Second, in addition to the potential benefits of further studies including log data retrieved from learning platforms, other established psychological constructs might also contribute to a deeper understanding of the engagement with self-tests as a learning technique. The individual perception of the test context might also play an important role. For example with respect to the engagement with self-tests, participants might be driven by performance goals (i.e., either motivated to demonstrate competence, or to avoid showing incompetence) or mastery goals (i.e., seeing the formative assessment as a part of the learning process itself; Elliot & Murayama, 2008). Moreover, learners might associate self-tests with high-stakes summative assessments as a means of evaluating performance instead of an effective learning technique (Dunlosky et al., 2013). This misperception can trigger feelings of (test) anxiety and stress leading to an increase in worry, self-doubt, and interfering thoughts (Weissgerber & Reinhard, 2018), as learners may experience the pressure to perform well, or a fear of failure, as self-tests may expose gaps in their knowledge. This potential negative tendency in the perception of tests is particularly important as learners that are at general risk for these types of learning-related fears might benefit from less structured learning environments that are usually less performance-oriented which might circumvent the negative effects (Bledsoe & Baskin, 2014). In summary, both the investigation of log data as direct indicators of learning behavior, as well as the investigation of other learning-related psychological constructs might contribute further to our understanding of learners' engagement with self-tests and thereby help educators to create learning environments that are beneficial for a larger audience of learners.

Third, future research might also investigate different operationalizations of cognitive engagement with self-tests. The percentage of correct self-tests is only an approximation of such a complex phenomenon. For example, the log data used in the present study cannot distinguish between learners that simply do not engage much with the course content in general (and potentially drop out early), and learners that work through the course and only shy away from the actual engagement with self-tests. This distinction might help to gain more insight into specific characteristics that might influence learners' decision to accept the extra effort that these learning techniques entail. It remains uncertain to what extent our findings can be generalized to other conceptualizations of learning engagement or different test conditions. Other log data—such as the total number of completed tests, or number of test attempts—could provide deeper insights into learners' *behavioral* engagement with self-tests. These information could help to make the distinction more clearly between the quantity of self-testing (i.e., behavioral engagement) and the cognitive effort learners put into mastering these tests (i.e., cognitive engagement). For instance, the total number of test attempts might reveal other patterns, as some learners might answer correctly in a single attempt (e.g., due to prior knowledge), while others might make numerous attempts without answering correctly, yet still participating in self-testing. In this example, the person with multiple test attempts would have shown greater behavioral engagement but still not achieved cognitive engagement.

Fourth, regarding the study design, another potential limitation is the high dropout rate after the initial survey. In the present study, data from a subsequent second and third survey could not be considered in the present analysis, due to large proportions of missing data for these measurement occasions. Especially since our surveys included many motivational variables that are very likely to be related to study dropout, imputation of these variables seemed not a valid option (i.e., missing not at random; MNAR; Donders et al., 2006) This goes along with the observation that our self-report scales at the first measurement occasion did not show much variance, as potentially at the beginning of the course all participants were at least somewhat interested in the course and motivated to start learning. However, with the lack of variance in the initial self-reports, these measures also failed to predict differences in the engagement with self-tests throughout the course. While we additionally aimed to follow-up on participants who dropped out of the study by contacting participants that did not respond to our regularly scheduled surveys after 28 days, the response rate to the follow-up was poor, with only 36 participants (of 1,098 contacted individuals) responding. This points to the dilemma that although research within real-life based learning environments is demanded, these setups usually create considerably complex data due to the less controlled environment and more heterogeneous sample. On a more general stance, the increase of ecological validity of these data comes with losses in internal validity since potential confounding variables or certain biases cannot be ruled out. Future study designs might explore new approaches to gain more information, especially on those participants that drop out over time, for example by using more tight-knit sampling designs in the tradition of ecological momentary assessments (Shiffman et al., 2008).

Lastly, the results of the present study might be interpreted with caution, as all analyzed data stem from one specific learning platform. Although the courses varied in certain characteristics such as content and length, they met the same quality standards in terms of course design (e.g., developed by university professors, delivered via the same platform interface). However, unobserved confounders like course reputation, course subject, or perceived difficulty may have influenced learners' engagement with self-tests but were not captured by the presented course characteristics. As not only the participants but also online courses themselves can be very heterogeneous, for example regarding structure or (pedagogical) design (Maya-Jariego et al., 2020), future research might investigate structural differences between courses like course quality, presence of an instructor, time dependent learning schedules, or absence of a confirmation of participation on the engagement with self-tests across different settings. A systematic investigation of course characteristics seems also advisable, as our analyses indicated that the hierarchical structure of the data needs to be taken into account—highlighting that, despite our relatively homogeneous selection of courses, findings cannot be fully generalized from one course to another. Furthermore, the courses also attracted a specific group of participants, resulting in a sample that relies heavily on learners with higher educational backgrounds. Given that the individuals' ability to self-regulate their learning might be confounded with their prior education, it is unclear to what extent the results can be generalized to the general population.

5. Conclusion

In non-formal online courses, a considerable variability in the engagement with self-tests among learners exists, highlighting the importance of learner commitment and extrinsic motivations such as confirmations of participation on this behavior. The application of machine learning models—despite their moderate predictive power—revealed valuable insights and outperformed traditional analytical approaches. Taken together, our results underscored the importance of appropriate analytical techniques for our understanding of complex learning behaviors. Our findings suggested potential practical implications for course designers, including the incorporation of confirmations of participation and more nuanced incentive structures to enhance engagement with self-tests. Course designers might also ensure that course length remains manageable. Additionally, the lack of influence from socio-demographic variables on the engagement with self-tests reinforces the inclusivity of non-formal learning environments, supporting their potential for lifelong learning across various life stages. Regarding the theory on the effectiveness of testing for learning, theoretical models should take into account that there might be entry barriers for learners to accept these challenges, and that the testing environment is crucial because learners need to be committed to the learning opportunity in the first place. Future research should continue to explore additional predictors and refine methods to capture the intricate dynamics of learner behavior, ultimately contributing to the development of more effective and personalized educational experiences. In summary, this study enhances our theoretical understanding of learners' self-regulation by shifting the focus from the effectiveness of self-testing to the question of who engages with self-tests in voluntary settings. Moreover, it offers practical guidance on designing online courses that could encourage the wider use of self-testing as a learning technique, such as the implementation of extrinsic incentives like confirmations of participation. Overall, the study advances our understanding of learner engagement in non-formal online courses and provides concrete recommendations for course design to encourage the use of self-tests.

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