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Sustained Academic Effort in Short-Duration Online Learning Environments

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Sustained Academic Effort in Short-Duration Online Learning Environments

Abstract

Academic success in Online Learning Environments (OLEs) depends on sustained effort, yet little is known about how initial motivation translates into engagement over time. In this paper we examine motivation, effort, and performance in a five-week online programme, focusing on the dynamics of a short-duration OLE. Study 1 identifies four key motivations for enrolling: novelty, flexibility, capability, and networking. Study 2 combines survey and behavioural data from active learners to show that willingness to invest effort mediates the relationship between learners' expectations and behavioural engagement, which positively affects performance. A robustness test shows that, when inactive learners are included, the effects of capability on willingness to invest effort and networking on behavioural engagement become insignificant. Study 3 analyses behavioural patterns throughout the course and demonstrates that both the amount and consistency of behavioural engagement are associated with better performance. Together, the findings suggest that initial expectations contribute to academic success primarily by fostering willingness to invest effort, while sustained and consistent engagement supports stronger learning outcomes. The study contributes to understanding learner behaviour in short-duration OLEs and highlights the importance of supporting students early to transform motivation into consistent effort and successful course completion.

Keywords: Online Learning Environments (OLEs); Self-Determination Theory (SDT); Student Effort; Academic Performance

Introduction

Despite early caution toward online learning (Carroll, 2013; Mitchell, Parlamis, and Claiborne, 2014), the use of online learning environments (OLEs) in Higher Education (HE) has grown substantially (e.g., Cheng, Xie and Collier, 2023; Lee et al., 2025; Lu, Bradlow and Hutchinson, 2022; Morgan-Thomas and Dudau, 2019; de Nito et al., 2023; Pöysä-Tarhonen, 2025; Razmerita et al., 2020; Sorokova, 2020). A wide range of OLE formats, particularly in HE now exists, including micro-courses, MOOCs, online credit modules, and full online degrees. Global e-learning revenue is forecast to rise from 167 billion USD in 2023 to 240 billion USD in 2027 (Statista, 2024), driven largely by HE online programmes. This expansion reflects the broader need for pedagogical innovation in HE education (Lacka and Wong, 2021; Mason et al., 2024).

Yet OLE programmes face ongoing challenges, particularly low success rates (Borrella, Caballero-Cabellera and Ponce-Cueto, 2022; Reich and Ruipérez-Valiente, 2019). Understanding academic performance in OLEs remains a key objective (Carranante et al., 2020; Hao and Gu, 2024). Existing research is fragmented, focusing on different phases, theories, and methodological approaches (Morgan-Thomas and Dudau, 2019; Reed et al., 2023; Razmerita et al., 2020; Whitaker, New and Ireland, 2016). Building on the notion that the amount and consistency of effort are central to online course achievement (Serravallo, 2020; van Herpen, Hilverda and Vollmann, 2025), this study maps the factors influencing student effort in different phases of a short-duration OLE programme, drawing on and integrating the fragmented strands of prior research identified above.

OLEs differ considerably in their duration, structure, and learning demands. While some programmes extend over several months or years, short-form learning experiences have become increasingly prominent as flexible mechanisms for targeted skill development (Cumberland et al., 2022). It is reasonable to expect that learners' motivations and their capacity to sustain effort vary according to the duration and structure of the learning experience. In short-duration OLEs, initial perceptions and early engagement may be particularly consequential, as learners have less time to revise their expectations or recover from early disengagement. Learners' attitudes and intentions to participate may therefore be shaped by their initial perceptions of the usefulness and ease of use of the learning environment (Wang et al., 2022). By contrast, longer online programmes require learners to sustain their participation over time, making persistence and ongoing self-regulation particularly salient to successful progression (Shaikh and Asif, 2022).

The present research focuses on a five-week online course and therefore examines the motivational and behavioural processes associated with sustaining effort within a short-duration OLE. Consequently, the findings should be interpreted primarily in relation to short-form online learning, an increasingly prominent form of provision designed to offer flexible and targeted opportunities for skill development (Varadarajan et al., 2023).

The extant literature suggests that time spent in an OLE predicts continuation or withdrawal (Bawa, 2016). Persistence requires self-motivation (Garaus, Furtmüller and Güttel, 2015; Han, DiGiacomo and Usher, 2023; Lai et al., 2024). A paradox emerges: autonomy, initially motivating (e.g. Reed et al., 2023), may later hinder sustained effort, making students more likely to disengage (Sun et al., 2019). OLEs are particularly well-suited to examining these dynamics, as they provide useful behavioural data. This enables researchers to develop insights to inform the design of more effective asynchronous learning environments (Goumaa and Anderson, 2024).

Achieving these design goals and improving academic success requires a deeper understanding of the OLE trajectory, including motivational drivers for enrolment, effort during the OLE programme and its link to performance (Carranante et al., 2020; Lacka and Wong, 2021; Morgan-Thomas and Dudau, 2019). Although effort is recognised as key to academic success, research on effort itself remains limited (Love, Love and Northcraft, 2010). To address this gap, we present three studies spanning short-duration OLE enrolment to final certification, focusing on factors that shape effort and performance.

In the following we outline the conceptual framework, discussing academic effort, performance, and motivational drivers over time, drawing on Self-Determination Theory (SDT) (Deci and Ryan, 1985). We then report three studies in the context of a five-week online programme: In Study 1 (pre-programme) we develop a structured exploration of students' initial motivational drivers to join a five-week OLE programme, identifying four key expectations: flexibility, capability, networking and novelty. These motivational drivers form the basis of Study 2 (start and during programme), which examines the mechanism through which initial expectations are translated into effort among learners who engaged with the course. Survey and observational data are used to demonstrate that initial willingness to invest effort mediates the impact of initial course expectations on the actual amount of effort during the programme, which in turn impacts performance (H1a-d, H2a-d, H3, H4). Study 3 (during programme), based on observational data, further explores participant behaviour, particularly consistency of effort amount over time and performance during the course through to final certification (H5). The findings suggest that, apart from the amount of effort, effort consistency plays an important role in student performance. We conclude with limitations and directions for future research.

Academic effort and its link to academic performance

Psychologists have long examined the active role of students in the educational process, focusing on the choices they make when engaging in learning activities (Fisher and Ford, 1998). Central to this is academic effort, defined as the energy invested in meeting academic requirements (Carbonaro, 2005; Love, Love and Northcraft, 2010), which plays a pivotal role in determining performance (Chevalier, Dolton and Lührmann, 2018). In OLE contexts, academic performance has been defined as the level of achievement attained by the student in online academic tasks or coursework (Lee, 2013). Effort reflects students' intellectual and behavioural commitment and influences their ability to master material, complete assignments, and succeed in assessments (Carbonaro, 2005; van Herpen, Hilverda and Vollmann, 2025).

Effort in educational research is commonly divided into two categories: amount of effort and type of effort (Fisher and Ford, 1998). Based on the extant literature (Kemp, 2020; Patron and Lopez, 2011), we define amount of effort in short-duration OLE contexts as the volume of study-related activity invested by a student over a given period. The type of effort concerns qualitative strategies or approaches. Although both matter, most research emphasises the amount of effort. We argue that the amount of effort is especially significant in short OLE programmes, where students must quickly self-regulate persistence in largely self-directed environments in an intense and condensed time period.

The literature suggests that maintaining a consistent amount of effort may be especially challenging in OLEs, where reduced supervision and the need for self-discipline complicate sustained engagement (Whitaker, New and Ireland, 2016). Although OLEs provide flexibility and resource access, these benefits can be undermined by superficial engagement and technological disparities, which impede consistent effort (Min and Nasir, 2020). Without sustained focus, the amount of effort decreases, potentially harming academic performance.

The conditions for academic effort

The concept of academic effort stems from psychological theories explaining human motivation and learning (Deci and Ryan, 1985; Dweck, 1986; Eccles and Wigfield, 2002). Motivation to invest sustained academic effort refers to the psychological processes that initiate and guide behaviour toward goal achievement. A prominent framework in education, Self-Determination Theory (SDT) (Deci and Ryan, 1985), posits that individuals are motivated to satisfy the basic psychological needs of autonomy, competence, and relatedness. Research shows that HE students who perceive their learning activities as aligned with these needs are more likely to invest greater academic effort (Deci and Ryan, 2000; Jang, Kim and Reeve, 2016).

Autonomy refers to experiencing self-direction and control. In HE, it emerges when students feel they have flexibility, decision-making capacity, and ownership over their learning.

Competence reflects the desire to feel capable and effective. When students view themselves as competent in their tasks, they tend to engage more deeply in their studies.

Relatedness denotes the desire to form meaningful connections. Supportive social environments, networking opportunities, and positive peer or educator relationships enhance motivation and engagement.

Research on SDT in OLEs presents mixed findings (e.g., Chen and Yang, 2010; Hsu, Wang and Levesque-Bristol, 2019; Huang et al., 2019). While OLEs may support autonomy and diverse learning styles, they also require strong self-motivation, which can contribute to failure (Chen and Yang, 2010). Similarly, although virtual communities can facilitate collaboration (Arbaugh and Benbunan-Fich, 2006), physical distance may hinder relationship-building and challenge relatedness. Consequently, many studies have focused on OLE attrition and quitting behaviour (e.g. Lu, Bradlow and Hutchinson, 2022; Reich and Ruipérez-Valiente, 2019) rather than on successful completion. To develop a clearer understanding of what drives student success, we next illustrate how SDT manifests within a short-duration OLE trajectory with respect to motivation, effort, and performance.

The short-duration OLE programme trajectory

Course duration represents an important contextual condition in online learning. In short-duration OLEs, learners make enrolment and continuation decisions within a compressed timeframe, which increases the importance of initial expectations and early motivational states. Novelty, flexibility, perceived capability, and willingness to invest effort are therefore likely to exert a strong influence on engagement because learners have limited time to revise expectations, develop habits, or recover from periods of disengagement. In contrast, longer online programmes may rely more heavily on evolving self-regulatory processes, changing life circumstances, habit formation, and the ongoing satisfaction of psychological needs. The present hypotheses are developed and tested in the context of a five-week online programme and should be interpreted as explaining motivation, effort, and performance in short-duration OLEs.

Phase 1: Pre-programme - selection and enrolment

Most studies examining initial motivational drivers to enrol in OLE programmes have been inductive (e.g. Shapiro et al., 2017; Stephani, Alvin and Riatun, 2023) and have used varied theoretical frameworks, including the Theory of Planned Behaviour, Social Cognitive Theory, and Social Exchange Theory (e.g. Razmerita et al., 2020). Here, we assess in an integrated manner how SDT principles apply to short OLE-specific contextual factors.

Flexibility permits autonomy. Flexibility has been defined as programme adaptability in time, space, and pace in OLE contexts (Beer et al., 2022). Flexibility allows students to choose when, where, and how they engage with course material (Lu, Bradlow and Hutchinson, 2022; Naidu, 2017). This aligns with autonomy — the desire to feel in control of one's actions — motivating enrolment by framing learning as a self-directed process.

Capability as a basis for competence. Students prefer programmes they believe they can succeed in (Bandura, 1977). This aligns with the concept of capability, which has been defined in OLE contexts as the perceived ability of students to use tools or learning resources effectively for academic purposes (Sonnenberg et al., 2021). Such perceived capability supports the need fulfilment for competence, the desire to feel effective. When students expect an OLE to provide adequate resources and structure, confidence in achieving their goals increases, motivating enrolment.

Networking as a pathway to relatedness. In educational contexts, networking has been defined as the extent to which students use online or platform-based connections to interact, collaborate, or exchange academic information with others (Anders 2018). Opportunities for collaboration enhance learning perceptions (Arbaugh and Benbunan-Fich, 2006) and fulfil relatedness needs. Expectations of strong community, collaborative projects, and meaningful interactions may therefore motivate students to enrol.

Novelty discovery meets innovation needs. In online learning, novelty has been defined as the extent to which the learning environment is perceived as new, unfamiliar, or innovative by the student (Jeno et al., 2019). Although novelty is not formally part of SDT, evidence shows curiosity and the desire to discover new content can motivate OLE enrolment (e.g. Chen et al., 2020; Hsu et al., 2023). Gonzalez-Cutre et al. (2016) suggest novelty may be an important addition to SDT's basic needs. Thus, innovative content, technology, or teaching methods can increase enrolment motivation.

Phase 2: Start of programme - initial willingness to invest effort

From the above discussion, we develop hypotheses linking students' expectations of basic needs satisfaction through flexibility, capability, networking, and novelty to their initial willingness to invest effort (WTIE) in short-duration OLE programmes. Based on the extant literature (Kramer et al., 2023), we define WTIE as the early readiness to devote time and energy to learning activities before sustained engagement patterns develop. From an SDT perspective, students are more willing to invest effort when they perceive that their psychological needs will be met. Expectations of flexibility, capability, networking, and novelty align with the satisfaction of autonomy, competence, and relatedness, which foster motivation.

When students believe these needs will be fulfilled, they approach the OLE with enthusiasm and a readiness to exert effort, viewing participation as meaningful and rewarding. This may positively influence their initial WTIE at the start of the programme. In a short-duration OLE, learners have limited experience with the course before engagement decisions are made. Consequently, initial expectations regarding flexibility, capability, networking, and novelty should be particularly influential determinants of WTIE. We thus hypothesise:

Hypothesis 1: Expectations towards course a) flexibility, b) capability, c) networking, and d) novelty are positively related to initial willingness to invest effort.

Phase 3: During programme - consistent academic effort and performance

Based on the SDT framework, we propose that initial WTIE mediates the relationship between expectations toward flexibility, capability, networking, and novelty (at the start of an OLE programme) and actual student effort throughout the programme, as it leads students to set goals and commit to them. Early effort may generate initial successes or learning gains, reinforcing students' beliefs in the programme's value and their ability to succeed, creating a self-reinforcing cycle of effort and performance. Students who begin with high WTIE may also be more likely to overcome obstacles and maintain effort when the programme becomes demanding. Finally, initial WTIE may translate into early participation, helping establish productive habits and routines that sustain effort throughout the programme. Because participation unfolds over only five weeks in the context of our study, learners have relatively little time for motivational adaptation. As a result, the impact of initial expectations should operate primarily through early WTIE, which should influence behavioural engagement throughout the course. We therefore hypothesise:

Hypothesis 2: The initial willingness to invest effort mediates the positive effect of expectations towards a) course flexibility, b) capability, c) networking, and d) novelty on amount of academic effort.

Based on the above SDT considerations, we further suggest that the initial motivation of WTIE is related to actual sustained academic effort over time. This relationship may be especially pronounced in short-duration courses where effort patterns are established rapidly and where few opportunities exist for later motivational recovery.

Hypothesis 3: Students' initial willingness to invest effort is positively related to amount of academic effort.

Further, in a five-week course, performance outcomes are likely to reflect recent engagement behaviours more directly than in longer programmes, where cumulative learning experiences and external influences may play a larger role. We thus suggest that students' academic effort has a positive impact on their performance in online programs:

Hypothesis 4: Students' amount of academic effort is positively linked to their academic performance.

One of the major challenges of online student performance is their ability to maintain effort throughout the long learning process. OLE programmes demand high levels of self-regulation and persistence, making consistency in the amount of effort, defined as the stability of a student's academic activity level across time (Saqr et al., 2023), a cornerstone of success (Broadbent and Poon, 2015; Han, DiGiacomo and Usher, 2023; Shi *et al*., 2024). By establishing a routine and committing to steady progress, students can overcome the challenges posed by the high degree of autonomy inherent to OLEs (Min and Nasir, 2020). Therefore, consistency in the amount of effort put into an OLE programme should enhance students' performance (Patron and Lopez, 2011). Consistency may be particularly important in short-duration OLEs because periods of disengagement represent a larger proportion of the total learning experience and leave limited time for learners to compensate through later effort. This leads us to hypothesise:

Hypothesis 5: Students' consistency in amount of academic effort is positively linked to their performance.

Methodology

Study context

The empirical setting of this study is a five-week OLE programme, delivered by a long-established French business school that holds three major international accreditations in management education (AACSB, EQUIS, and AMBA). While the institution typically operates in a selective and fee-paying higher education environment, this programme represents a deliberate extension of its teaching mission beyond its traditional student population, in line with broader objectives of knowledge diffusion and public engagement.

The programme is offered fully online and is entirely free of charge, including unrestricted access to all learning materials and the certificate of completion. The course is open to everyone without prior academic, professional, or linguistic prerequisites, and no selection occurs at entry. In line with the school's international outreach strategy, the programme is available in both French and English, enabling participation from students with diverse educational and geographical backgrounds. Its primary objective is the worldwide diffusion of knowledge related to creativity and innovation, rather than the recruitment of degree-seeking students or the monetisation of online learning. From an institutional perspective, the programme thus functions as a public-facing educational initiative rather than a revenue-generating programme.

The course is hosted on the Canvas Free-for-Teacher platform and made available through the school's online campus website. Its five-week duration aligns with the typical range for short-duration digital education offers, which generally span one week to three months (Scatton, 2024). Notably, 77% of courses on Coursera, a leading platform in this field, fall within this timeframe.

Pedagogically, the programme is autonomous and asynchronous, structured around four thematic modules combining short video lectures, quizzes, applied activities, and peer interaction via discussion forums. Participation in all activities is voluntary, with no formal sanctions or extrinsic constraints attached to course completion. However, the programme includes four quizzes at the end of each module, which must be validated to receive a certificate of completion. The programme has received EOCCS certification from EFMD Global, attesting to the quality of its pedagogical design and delivery.

Overview of studies

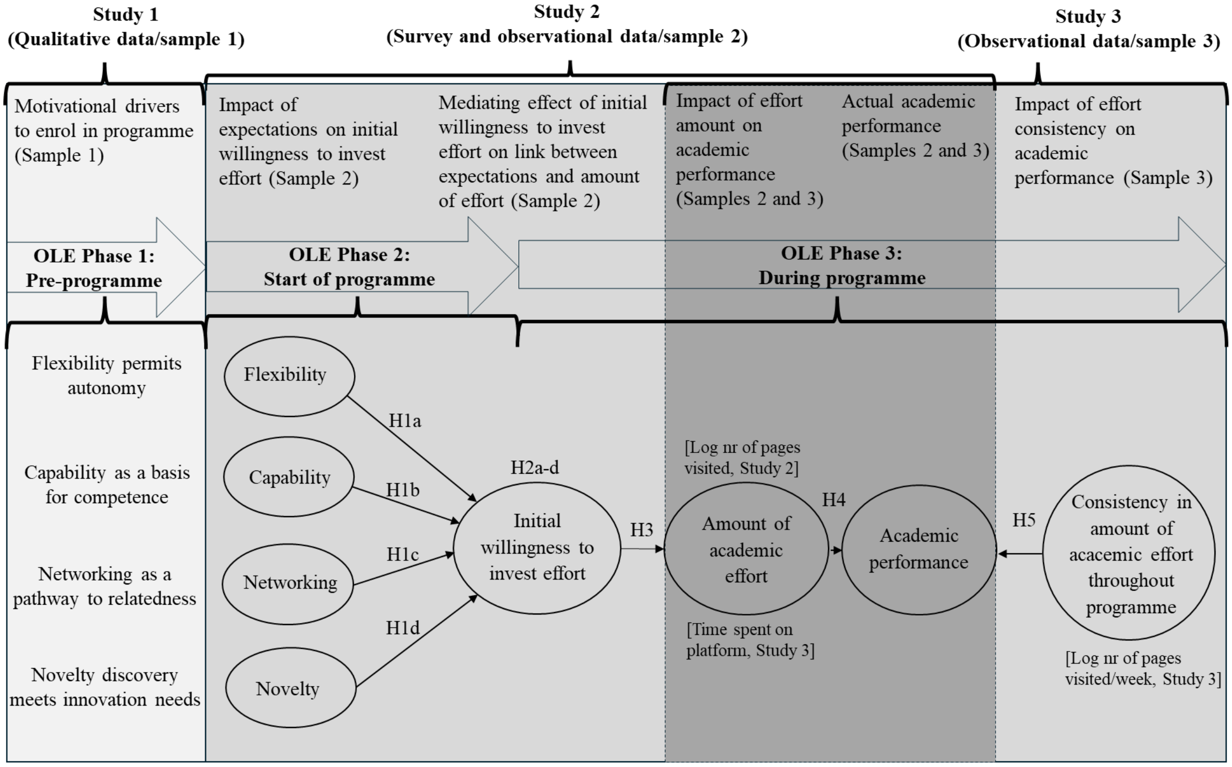
To test our hypotheses and cover the three phases of the OLE programme trajectory (as described above), we developed three consecutive studies that build on each other. They each draw on data from different programme editions and thus all have a unique sample. Table 1 provides details on the studies, linking the programme phases, type of data collected, the sample and sample size, as well as the research objectives and hypotheses addressed by each study.

Table 1. Details of studies

Study	Data	Sample size and origin	Research objectives (Hypotheses)
Study 1:			
Phase 1: Pre-programme - Selection and Enrolment	Responses to open-ended question in OLE welcome survey at registration stage	N1=575 (Data from editions 1-5)	Examine initial motivational drivers to join a short OLE before programme start.
Study 2:			
Phase 2: Start of programme - Initial expectations and willingness to invest effort	Survey data collected at the start of the OLE programme … in conjunction with …	N2=181 (Data from editions 6-8)	Assess whether initial expectations influence WTIE at the start of the programme. (H1a-d) Assess whether WTIE mediates the link between initial expectations and amount of academic effort during the programme. (H2a-d, H3)
Phase 3: During programme – amount of academic effort (proxy: total nr. of pages visited) and performance	observed behavioural data from OLE platform during the programme from the same participants		Assess the link between academic effort and actual performance during OLE programme. (H4)
Study 3:			
Phase 3: During programme – amount of academic effort (proxy: total time spent on platform), consistency of effort over time, and performance	Observed behavioural data from OLE platform during the programme	N3=671 (Data from editions 8-16)	Gain further insights into the link between amount of academic effort and performance in short-duration OLEs. Assess the link between effort consistency and performance. (H5)

Figure 1 further illustrates the methodological approach, depicting the connections between phases and variables, as well as the samples employed. In Study 1 we utilised a sample for qualitative deductive analysis, grounded in SDT, to examine initial motivational drivers for enrolment in an OLE programme (Phase 1: Pre-programme). The findings from Study 1 informed the development of a questionnaire administered in Study 2.

Figure 1. Organisation of studies and research model



In Study 2 we used a second sample for quantitative assessment, drawing on survey and observational data collected from participants at the start of the programme and throughout its duration (Phase 2 and 3: Start of programme and During programme). This study examined the relationships between students' expectations of the OLE programme and their willingness to invest effort (WTIE) at course onset, as well as students' amount of effort (proxy: total number of pages visited) and actual academic performance during the programme (H1a-d, H2a-d, H3, and H4). In Study 3 we used a third sample, drawing on observational data collected during the programme (Phase 3) to provide additional insights into the relationships between the amount of academic effort (proxy: overall time spent on platform) and student performance (H4) and the consistency in amount of academic effort and student performance (H5).

Study 1

To examine the initial motivational drivers to join a short-duration OLE programme, we adopted a qualitative deductive approach (see Creswell, 2014; Yin, 2018). This method involves empirical data collection guided by an a priori theoretical framework (Vargas-Bianchi, 2020), allowing us to examine whether patterns in the data align with theory. We used data from a questionnaire completed by participants at the OLE registration stage, one week before the programme began. Data was collected during the first five editions of the programme. The questionnaire contained open-ended questions about motivations to join, providing rich qualitative insights (Cheng, Xie and Collier, 2023). The final sample consisted of 575 usable responses: 305 (53%) men and 270 (47%) women, with broad variation in age, education, and occupational status (see Table 2).

Table 2. Socio-demographic sample profile

		Frequency	Percent
Age	19-24	100	17.4
	25-34	125	21.7
	35-44	151	26.3
	45-54	129	22.4
	55-64	61	10.6
	65+	9	1.6
	Total	575	100.0
		Frequency	**Percent**
Educational Level	no school qualification	10	1.7
	College, GCSE, Level 1/2	6	1.0
	High School, Level 3	67	11.7
	2-year Tertiary Education	77	13.4
	Bachelor	134	23.3
	Master	257	44.7
	Doctorate	24	4.2
	Total	575	100.0
		Frequency	**Percent**
Occupational Status	Full time employed	246	42.8
	Part time employed	113	19.7
	Self employed	108	18.8
	Unemployed	85	14.8
	Currently not active	14	2.4
	Retired	9	1.6
	Total	575	100.0

To code the data, we followed content-analysis guidelines by Krippendorff (2004), which require 1) clear coding instructions, 2) equally trained coders, and 3) coder independence. To meet these criteria, we developed a list of motivations, including words and terms from the extant literature (see Table 3 for examples). Following deductive coding principles, which allow data exploration based on pre-existing theoretical propositions (Crabtree and Miller, 1999), this list served as the template for coding qualitative responses regarding motivational drivers to enrol in the programme. Coders assigned one key motivation to each unit of analysis (one value per variable). If a response did not fit any of the four categories, it was labelled “other” for later discussion.

Table 3. Examples of words and terms used for coding

Motivational drivers	**Examples of words and terms used for coding**	**References**
Flexibility	Accessible; convenience; lifestyle; anywhere; anytime; variety of resources; free (to choose) - order/timing; choice; allows; makes possible; pattern; fits in; manage (schedule/pace/content)	Chiu (2022); Kuem, Khansa and Kim (2020); Ryan and Deci (2020); Shapiro *et al*. (2017), Vanslambrouck *et al.* (2018); Wu and Chen (2017); Yousef, Schroeder and Wosnitza (2015)
Capability	Can (do this); possible; difficult; know (how it works); have done it (before); worried; achieve; confident; able; will make it (to the end/certificate)	Chen *et al*. (2020); Chiu (2022); Deci and Ryan (1985); Gupta and Maurya (2022); Kuem, Khansa and Kim (2020)
Networking	meet; develop network; exchange (ideas); share; community; dialogue; connect; transmit; others; interact; group; contribution; participate; contact	Arbaugh and Benbonan-Fich (2006); Chen *et al.* (2020); Chiu (2022); Kuem, Khansa and Kim (2020); Ryan and Deci (2020); Wang *et al*. (2019); Yousef, Schroeder and Wosnitza (2015)
Novelty	curious; new (experience); discover; first (time); excited; start; fresh; unfamiliar; different; never before; change; surprise; original	Chen *et al.* (2020); Deci and Ryan (1985); Gonzalez-Cutre *et al*. (2016); Hew and Cheung (2014); Hsu, Lin and Chang (2023)

All data were independently coded by two trained researchers to enhance the reliability and validity of the findings. This procedure resulted in a strong level of inter-rater agreement (Kappa=0.811, $p<0.001$, 95% CI (0.774; 0.848)) (Sheskin, 2004). The units with divergent coding or with 'other' coding were further discussed and agreement was sought from definitions and descriptions found in the extant literature.

Results of study 1

Based on the qualitative study we observed (see Table 4) that *novelty* (28.5%) was the most prevalent motivation, followed by *flexibility*, (21.7%) *capability* (20.5%), and *networking* (9.4%). The raters also identified responses that did not fit any of the four concepts. After discussion and comparison of interpretations, it emerged that the majority of these related to what we termed *leverage* (18.8%): These respondents mentioned the usefulness of the OLE programme to achieve concrete objectives, such as an improvement in current job situation, career change or salary progression. For a few responses, no clear interpretation was found and as a result these were classified as *other* (1.0%). Please refer to Table 4 for an overview of motivation counts. There were no statistically significant differences in the distribution of motivations by gender ($\chi^2(5, n=575) = 3.922$, $p=0.561$) and respondents with different educational levels ($\chi^2(30, n=575) = 30.108$, $p = 0.460$). However, the results were statistically different between age groups ($\chi^2(25, n=575) = 62.437$, $p<.001$), and respondents with different occupational statuses ($\chi^2(25, n=575) = 56.949$, $p<.001$). In most age and occupational status groups, though, novelty was most frequently mentioned, followed by flexibility. Please refer to Table 5 for example verbatim extracts.

Table 4. Counts: Initial motivational drivers

		Frequency	Percent
Motivational drivers	Novelty	164	28.5
	Flexibility	125	21.7
	Capability	118	20.5
	Networking	54	9.4
	(Leverage	108	18.8)
	Other	6	1.0
	Total	575	100.0

Table 5. Examples of verbatim extracts

Motivation	Verbatim examples
Novelty	It's a real pleasure for me to discover this new learning experience. I'm delighted to be registered for this new course! I'd like to find out what's new and how to learn here. This is my first online programme. I recently discovered this opportunity to learn and improve, so I'm throwing myself into it. I'm happy to be able to discover a different learning format, and to test the Canvas LMS as a user, which I only know by name.
Flexibility	I'm arriving a little late here, but I can catch up, even with my completely crazy schedule. As a mother of five, it's great that I can seize the opportunity here, learn and meet deadlines without stress. I live in Switzerland, but the advantage of this course is that it knows no borders, so I can learn remotely. Currently in my final year of high school, I'm delighted that I can take part in this programme on the side to enrich my knowledge in this field.
Capability	I'm a big online programme consumer and have had very positive learning outcomes. I'm not very good with digital stuff and slightly worried that I won't manage this here. I'm confident that I can finish the programme and get the certificate. This is my first online course and I'm not sure how it works.
Networking	I'm delighted to be part of your programme. I'm looking forward to working together with you all! I'm happy to exchange ideas with others and share the learning experience. I'd be delighted to talk to you all, with such varied profiles - it can only be very interesting.
(Leverage)	I'm interested in this programme to further boost my career. On reorientation following a road accident two years ago, I'm looking for a way out through learning. I'm currently looking for a new career path and need to explore other subjects (like this course). This programme will certainly also be of great use to me in developing my professional project and improve my status.

Overall, in line with SDT, the findings from Study 1 support our suggestion that expectations towards flexibility, capability, networking, and novelty act as motivational drivers to enrol in a short-duration OLE programme. Unsurprisingly, we also found that extrinsic motivations, such as career advancement and broader professional opportunities (we group them under the term ‘leverage’), play a role in the decision to enrol in a particular OLE programme.

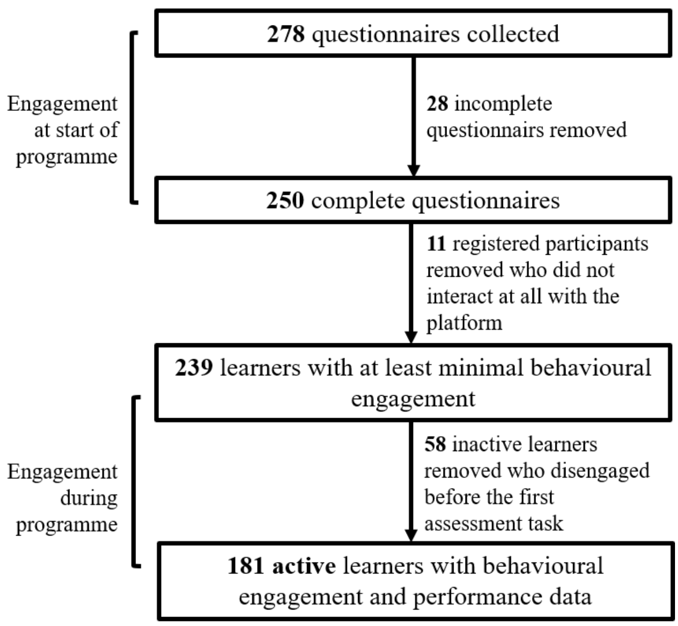
To build on this initial qualitative study, we subsequently assessed in Study 2 how these initial motivational drivers are linked to willingness to invest effort, actual academic effort and resulting performance, at the start and during the programme.

Study 2

A mixed-method approach (with survey and observational data) was used for data collection. Drawing on the extant literature and findings from Study 1, we first developed a questionnaire to assess student motivations through items designed to capture antecedents of their WTIE in the course. WTIE should not be interpreted as a direct measure of motivation. Rather, it captures the intentional component of motivation, namely students' stated readiness to devote effort at the beginning of the programme. In addition, observational data were collected from the same participants to capture their effort and their level of performance.

Data was collected during three editions of the five-week OLE programme, yielding 278 responses. Of these, 28 surveys were incomplete and therefore excluded. Another 11 respondents were excluded from the sample as they never interacted with the platform at all, i.e. they never progressed beyond course registration. Finally, we excluded 58 respondents who did not participate in any evaluation task (meaning that there was no performance data available for them), resulting in a final sample of 181 participants. This exclusion process kept out participants also referred to as "tourists", "dabblers”, “non-starters” or “samplers”, who enrol out of curiosity or with minimal intent to engage deeply (Frick et al, 2022; Kizilcec and Piech, 2013). Including them in the analysis could have introduced noise and distort the relationship between motivations and effort. Their exclusion does not imply that they are theoretically unimportant. Rather, the structural model investigates relationships among learners who generated sufficient behavioural engagement and performance data. However, the existence of this sizeable subgroup of inactive learners highlights that disengagement itself represents an important outcome requiring separate investigation. Figure 2 synthesises the data filtering and sample selection process.

Figure 2. Data filtering and sample selection



The questionnaire at the start of the programme included two items for flexibility (e.g., *"I appreciate the flexibility of organizing my own work during the course"*), three for novelty (e.g., *"It's exciting to discover a new way of learning through this course"*), three for networking (e.g., *"The course will give me the opportunity to enter a network I want to belong to"*), two reverse-coded items for capability (e.g., *"It will be a challenge for me to work on the* *program platform"*), and three for WTIE (e.g., *"I am prepared to invest all effort required to succeed in this course"*). All items were rated on a seven-point Likert scale (1=strongly disagree to 7=strongly agree). Following recommendations to mitigate common method variance, the questionnaire introduced a psychological separation between the motivation questions and the WTIE measure by including neutral questions about digital usage.

A central challenge in online learning research is distinguishing psychological effort from observable manifestations of effort. Direct measures of effort are difficult to obtain at scale because they require intrusive procedures such as observation, think-aloud protocols, or experience sampling. Consistent with prior online learning research, we therefore conceptualise effort as behavioural engagement that reflects opportunities for learning-related investment. The number of pages visited does not directly measure cognitive effort. Rather, it captures behavioural engagement, defined as the extent to which students repeatedly expose themselves to learning materials and activities. Although behavioural engagement and effort are conceptually distinct, behavioural engagement represents a necessary precondition for effort investment in asynchronous online environments. We therefore interpret page visits as an imperfect but theoretically relevant indicator of effort-related behaviour.

The logarithm of the number of pages consulted over the five weeks of the online course served as a proxy for actual effort (M=513.31; SD=324.36; Min=91; Max=1657; Ln(Number of pages): M=6.07; SD=0.58). Logarithmic transformation was applied to mitigate the bias of excessive page refreshes inflating effort estimates. The choice of this proxy was partly determined by data availability. However, such proxies are widespread in online education research (e.g., Baker et al., 2020; Godwin et al., 2021; Li et al., 2020; Riestra-González et al., 2021). Although the number of pages visited does not capture the actual effort *per se*, it reflects the extent to which students give themselves opportunities to learn and put in effort. Performance was measured by the average score obtained on the four assessment tests administered during the five weeks of the online course (M=72.89; SD=25.30). To check for robustness of our results, we also tested the research model with an additional indicator of behavioural engagement provided by the OLE platform. This addition did not significantly change the results and the conclusions. The procedure and results are detailed in the supplementary material, section 1.

To examine the data's factorial structure, we conducted principal component analyses (PCA) with Promax rotation, which confirmed the expected five underlying constructs. However, two novelty-related items were removed due to cross-loadings with flexibility. Composite reliability exceeded 0.8 for all constructs, indicating satisfactory scale reliability and internal consistency. Further confirmatory analyses using ML estimation in AMOS24 showed an acceptable model fit ($\chi^2(33)$ =48.21, p=0.042; RMSEA=0.05 [0.01; 0.08], p-close=0.461; SRMR=0.04; TLI=0.97). The average variance extracted (AVE) met the 0.5 threshold for all constructs except capability (AVE=.49). Discriminant validity was established by confirming that AVEs exceeded squared correlations between variables and that none of the HTMT ratios surpassed 0.85 (Henseler et al., 2015). The highest HTMT ratio (network-novelty) was 0.59 (see Table 6). Finally, an ex-post control for common method variance was conducted using the CFA-marker technique (Richardson, Simmering and Sturman, 2009), with three privacy concern items serving as markers. The shared variance between the marker and indicators ranged from 0.1% to 0.5%, suggesting negligible common method bias.

Table 6. Heterotrait-monotrait (HTMT) ratio of correlations

	Network	Capability	WTIE	Flexibility	Novelty
Network	1.00	0.14	0.41	0.41	0.59
Capability		1.00	0.17	0.09	0.13
WTIE			1.00	0.57	0.47
Flexibility				1.00	0.58
Novelty					1.00

Results of study 2

The research model was tested using covariance-based SEM in AMOS 30. Given our proxies for actual effort and performance, we assumed no measurement errors. Following Hair *et al*. (2019), loadings and variances for these single-indicator latent factors were set to 1 and 0, respectively. Such count-based indicators that do not measure psychological constructs are often treated as error-free because they are directly observed and not subject to interpretation. However, assuming they perfectly reflect the constructs they are intended to measure can be debatable. Therefore, to check for robustness, the model was also tested by applying Gerbing's and Anderson's (1988) recommendations for single-item measures. The results appeared insensitive to this change, both in model fit and parameter estimates (for further details, see supplementary material, section 2).

Model fit was satisfactory ($\chi^2(75)=125.57$, $p<0.001$; RMSEA=0.06 [0.04;0.08], p-close=0.159; SRMR=0.05; TLI=0.93). A screenshot of the estimated model is provided in Appendix A.

The results for active learners support H1a, H1b, and H1d, indicating a positive, significant relationship between perceived flexibility and WTIE ($\beta=0.28$, $p=0.014$), perceived capability and WTIE ($\beta=0.21$, $p=0.031$), and perceived novelty and WTIE ($\beta=0.33$, $p=0.046$). However, the relationship between networking and WTIE was positive but non-significant ($\beta=0.13$, $p=0.270$), leading to the rejection of H1c and H2c (see Table 7). Thus, only flexibility, capability and novelty influence WTIE at the onset of short-duration OLE programmes. Additionally, WTIE is positively associated with behavioural engagement ($\beta=0.24$, $p=0.023$), which, in turn, positively impacts performance ($\beta=0.45$, $p<0.001$), supporting H3 and H4.

Table 7. Coefficients of the structural models

	Research model		
Direct effects	**St. B**	**S.E.**	**p**
Flexibility → WTIE	0.28	0.116	0.014
Novelty →WTIE	0.33	0.180	0.046
Capability →WTIE	0.21	0.104	0.031
Networking →WTIE	0.13	0.096	0.270
Flexibility → Behavioural Engagement	-0.15	0.067	0.231
Novelty → Behavioural Engagement	-0.20	0.105	0.236
Capability → Behavioural Engagement	-0.10	0.055	0.304
Networking → Behavioural Engagement	0.29	0.056	0.025
WTIE → Behavioural Engagement	0.24	0.055	0.023
WTIE →Performance	-0.01	0.030	0.959
Behavioural Engagement → Performance	0.45	0.016	<0.001
Indirect effects		Bootstrap C.I. 95%	Bootstrap C.I. 90%
Flexibility →WTIE → Behavioural Engagement	0.07	[-0.01;0.24]	[0.01;0.20]
Novelty → WTIE → Behavioural Engagement	0.07	[0.01;0.26]	[0.01;0.22]
Capability → WTIE → Behavioural Engagement	0.05	[0.01;0.19]	[0.01;0.16]
Networking→ WTIE → Behavioural Engagement	0.03	[-0.01;0.15]	[-0.01;0.11]
Model adjustment to the data	$\chi^2(75)=125.57$ $p<0.001$ $\chi^2/df=1,67$ RMSEA=0.06 [0.04;0.08] p-close=0.159 SRMR=0.05 TLI=.0.93		

To analyse indirect effects, we conducted 5,000 bootstrap replications and examined 95% bias-corrected confidence intervals (Preacher and Hayes, 2008). Capability and novelty indirectly impact behavioural engagement via WTIE (capability: 0.05 [0.01; 0.19]; novelty: 0.07 [0.01; 0.26]), supporting H2b and H2d. The 95% confidence interval for flexibility's indirect effect on actual effort includes 0 (0.07 [-0.01; 0.24]), though the 90% interval does not ([0.01; 0.20]), suggesting a marginally significant effect and providing some support for H2a. Additionally, networking directly and significantly affects behavioural engagement.

For transparency and completeness, we also conducted an additional analysis including the 58 inactive learners on the programme. The findings of this analysis suggest that the core relationships in the model we report above (WTIE – behavioural engagement – performance) hold for active and inactive learners, but that the effects of capability on WTIE and networking on behavioural engagement became insignificant when inactive learners were included in the sample. (For a detailed overview of the analysis and results, see supplementary material, section 3).

Overall, the results of Study 2 support the notion that motivational factors primarily influence behavioural engagement in short-duration OLEs indirectly. By stimulating WTIE, perceived flexibility, capability, and novelty enhance the behavioural engagement of active learners, which in turn positively impacts performance. The positive link between networking and behavioural engagement in active learners suggests that initial networking motivations drive participants to visit more pages and spend more time on the platform, potentially converting this engagement into networking opportunities.

Study 2 also suggests that behavioural engagement significantly affects performance, measured through weekly quiz scores. However, this relationship remains insufficiently explored in short-duration OLE contexts. Such programmes require sustained effort over a condensed period of time, and our measures - the total pages visited for effort and the average quiz score for performance - may oversimplify this process. Therefore, we complemented our research with Study 3 in which we introduced additional measures.

Study 3

In Study 3 we kept considering behavioural engagement as a proxy for effort but we examined the relationship between effort and performance further by a) using overall time spent on the OLE platform (Godwin et al., 2021) as an alternative indicator for behavioural engagement, and b) assessing effort consistency across time and its link to academic performance (H5) (Jin, 2024). Here, consistency reflects the extent to which effort, measured by the logarithm of pages consulted, remained stable over the five weeks of the OLE programme. We used the within-participant standard deviation of pages to assess consistency of the behavioural engagement (Patron and Lopez, 2011). The variable included in the model is thus *engagement inconsistency*. We acknowledge that time spent on the OLE platform does not imply productive learning in itself. However, it captures persistence and continued behavioural engagement with learning resources. By demonstrating convergent relationships across both page-visits and time-on-platform measures, the study increases confidence that the observed findings are not artefacts of a single operationalisation.

The data was collected over nine successive editions (editions 8-16) of the OLE programme, starting with edition 8, as it was the first edition for which overall time spent on the platform was available. Our sample includes 671 participants who completed all four quizzes. We controlled for edition number, since each cohort may shape effort and performance, using nine dummies with edition 8 as the reference. We also controlled for gender, as it may impact academic effort (e.g. Workman and Heyder, 2020).

Results of study 3

The three models estimated are the following and results are reported in Table 8:

(1) Performance = $\beta_{0.1} + \beta_{1.1}$ *Amount of effort + $\beta_{2.1}$ * Effort inconsistency + u

(2) Performance = $\beta_{0.2} + \beta_{1.2}$ *Amount of effort + $\beta_{2.2}$* Effort inconsistency + $\beta_{3.2}$* Gender + u

(3) Performance = $\beta_{0.3} + \beta_{1.3}$ *Amount of effort + $\beta_{2.3}$* Effort inconsistency + $\beta_{3.3}$* Gender + $\beta_{4.3}$ * Edition9 + $\beta_{5.3}$ * Edition10 + $\beta_{6.3}$ * Edition11 + $\beta_{7.3}$ * Edition12 + $\beta_{8.3}$ * Edition13 + $\beta_{9.3}$ * Edition14 + $\beta_{10.3}$ * Edition15 + $\beta_{11.3}$ * Edition16 + u

Table 8. Results of the linear regression models explaining performance

	Model 1			Model 2			Model 3		
Variables	St. β	t-ratio	p-value	St. β	t-ratio	p-value	St. β	t-ratio	p-value
Behavioural engagement	0.16	2.99	0.003	0.16	2.99	0.003	0.15	2.74	0.006
Engagement inconsistency	-0.21	-3.88	<0.001	-0.20	-3.83	<0.001	-0.22	-3.89	<0.001
Gender (F-M)	-	-	-	0.25	2.31	0.022	0.27	2.31	0.022
Edition9-Edition8	-	-	-	-	-	-	0.18	0.86	0.390
Edition10-Edition8	-	-	-	-	-	-	0.17	0.91	0.365
Edition11-Edition8	-	-	-	-	-	-	0.07	0.38	0.705
Edition12-Edition8	-	-	-	-	-	-	0.20	1.07	0.288
Edition13-Edition8			-	-	-	-	-0.65	-2.71	0.007
Edition14-Edition8	-	-	-	-	-	-	0.03	0.15	0.877
Edition15-Edition8	-	-	-	-	-	-	0.22	1.08	0.281
Edition16-Edition8	-	-	-	-	-	-	-0.44	-1.94	0.053
F	11.7		<.001	9.67		<.001	4.55		<.001
F Change	-		-	5.32		0.022	2.49		0.012
R^2	.07			.08			.14		

Our results exhibit a consistent and robust effect of behavioural engagement (here measured as time spent on the OLE platform) on performance, even when gender and the edition of the programme are controlled ($\beta_{1.3}$ = 0.16; p=0.006), which further supports H4. Moreover, engagement inconsistency negatively affects performance ($\beta_{2.3}$ = -0.21; p<0.001), supporting H5.

Discussion

For this research we developed three consecutive studies to examine motivational antecedents and engagement patterns in short-duration OLEs. In this section we first discuss the findings of each study before we highlight the contribution to theory, implications for educational practice, as well as limitations and directions for future research.

Overall, in line with SDT, the findings from Study 1 support the notion that expectations towards flexibility, capability, networking, and novelty act as motivational drivers to enrol in short OLE programmes. Notably, novelty emerged as the predominant motivator, revealing an important extension to traditional SDT applications in online learning contexts. The prevalence of novelty-seeking suggests that online learning programmes position themselves as vehicles for intellectual exploration and personal development. The other three motivations, flexibility, capability, and networking, reveal a nuanced picture of learner needs. Flexibility reflects the reality that learners balancing work and personal responsibilities value formats accommodating time and location constraints. Capability motivation indicates a focus on self-efficacy. The lower prevalence of networking motivations suggests that learners prioritise first content and personal growth over relational benefits, indicating a need for more deliberate peer interaction design in short OLEs. The absence of significant gender and education-level differences, alongside nuanced age and occupational effects, suggests that motivation in such OLE contexts is shaped more by life stage than by static demographic traits. This implies that short OLE programmes may benefit from aligning with learners' situational contexts rather than traditional demographic categories.

Study 2 extended the qualitative findings into a quantitative examination. With regards to active learners, the positive relationships between flexibility, capability, and novelty with WTIE indicate that these motivations translate into stronger WTIE. The results including inactive learners in the sample revealed that the effect of capability on WTIE became insignificant, whereas the effect of novelty increased. The non-significant relationship between networking and WTIE challenges assumptions that social motivations uniformly drive effort. This may reflect the limited role of relational goals in mobilising academic effort in online contexts or insufficient platform affordances for meaningful interaction. Bootstrap analyses revealed significant indirect effects from capability and novelty through WTIE to behavioural engagement. This suggests that short-duration OLE design should not only appeal to intrinsic motivations but also support the formation of effort-related intentions through scaffolding and feedback. For active learners, the direct effect of networking on behavioural engagement, bypassing WTIE, reveals an alternative pathway where engagement may be driven by relational exploration rather than planned effort. It has to be cautioned, though, that this effect became insignificant when inactive learners were included in the sample. The positive relationships between WTIE and behavioural engagement and subsequent performance reinforce the importance of behavioural follow-through. The larger effect of behavioural engagement on performance compared to the effect of WTIE suggests that once a learner commits to action, the consistency and magnitude of that action matter. However, the moderate effect size between WTIE and behavioural engagement indicates that intention does not perfectly predict behaviour. This gap points to the need for environmental and structural supports that help learners sustain effort despite initial intentions, a theme that Study 3 addresses.

Study 3 enriched the findings of Study 2 by introducing temporal dynamics to examine how behavioural engagement consistency across the duration of the programme shapes outcomes. First, the positive effect of amount (in terms of time spent on the platform) on performance provides evidence that also in short OLE contexts time invested matters for learning outcomes. However, this effect, though statistically significant, is modest in magnitude, suggesting that while effort is necessary, it is not a sole determinant of performance. The finding that behavioural engagement inconsistency negatively affects performance is important: The effect size exceeds that of engagement amount itself, indicating that learners who maintain stable behavioural engagement across the OLE programme's short duration achieve better outcomes than those whose engagement fluctuates.

Contribution to theory

This research advances our understanding of effort and performance in a specific but increasingly common form of online education, short-duration OLE programmes, an area underexplored relative to cognitive ability and personality (Love, Love and Northcraft, 2010). The study contributes to the SDT literature by showing that both the amount and consistency of behavioural engagement, as proxies for effort, are associated with academic success in short-duration OLEs. The findings suggest that, in relatively brief online learning experiences, initial expectations (differing in effect size between subsequent active and inactive learners) and WTIE play an important role in shaping subsequent behavioural engagement and performance. It provides a nuanced explanation of how motivations and expectations influence sustained academic effort throughout the short OLE trajectory. First, we examine primary motivational drivers for enrolling in short-duration OLEs. Study 1 confirms that individuals are motivated by expectations linked to basic needs fulfilment: flexibility supporting autonomy, capabilities underpinning competence, networking fostering relatedness, and novelty satisfying innovation needs.

Second, we demonstrate that these motivations shape students' expectations at programme outset, influencing initial WTIE. Study 2 shows that for active learners perceived flexibility, capability, and novelty enhance willingness to invest effort, which increases behavioural engagement. Networking goals directly encourage more active platform engagement in active learners, such as visiting more pages, potentially creating meaningful connection opportunities. Study 2 also confirms that amount of effort significantly impacts academic performance.

Because the effort–performance relationship in short OLEs requiring sustained effort is underexplored, we noted that metrics such as pages visited and quiz scores may not capture the full complexity. In Study 3 we therefore analysed the role of overall time spent on the platform, as well as the consistency of behavioural engagement throughout the programme. Results support that amount of engagement in terms of overall time spent, as well as consistency of engagement over time significantly impact academic performance.

Finally, from an SDT perspective, examining how expectations of flexibility (Vanslambrouck et al., 2018), capability (Sun et al., 2019), networking (Hew, 2016), and novelty (Hsu, Lin and Shang, 2023) shape effort and performance advances understanding of psychological needs in autonomous learning contexts. Flexibility aligns with autonomy, capability with competence, networking with relatedness (Arbaugh and Benbunan-Fich, 2006), and novelty with curiosity and innovation. By linking these expectations to academic effort and performance, this research demonstrates SDT's relevance to students' short-duration OLE trajectories.

Implications for educational practice

The following recommendations are particularly relevant to short asynchronous courses where initial expectations and early engagement are likely to exert disproportionate influence. Students' expectations regarding flexibility, capability, networking, and novelty in short-duration OLEs have important implications for online education. Aligning programmes with these expectations supports psychological need satisfaction in SDT and fosters sustained effort and performance. Practically, this highlights a central lever for course designers and institutions: supporting sustained effort requires targeted intervention at entry and during the first learning cycle, so that early willingness is translated into consistent behavioural engagement over time. This can be achieved through five institutional and design levers:

Designing and communicating "credible flexibility" (autonomy with structure). Course teams should therefore provide a clear (weekly) rhythm and recommended pacing, micro-deadlines or optional checkpoints, and workload transparency (time-on-task estimates). In addition, offering diverse content formats can enhance adaptability while preserving students' sense of control. At the institutional level, course communication should present flexibility as choice within a scaffolded pathway (e.g., two routes), rather than as an unstructured self-paced experience.

Strengthening capability beliefs early through mastery support and authentic outcomes. Designers can strengthen capability perceptions by reducing ambiguity about success thanks to an onboarding module, low-stakes diagnostic quizzes and early "quick win" tasks. Regular and timely feedback can further build confidence and persistence quickly.

Designing relatedness. Designers should move beyond open discussion spaces by implementing structured peer interaction like small cohort groups or buddy systems or guided peer-review with clear prompts. This can be complemented by virtual meetups to enhance social presence.

Sustaining novelty through progressive reveal and varied media. Course teams can use progressive reveal (unlocking new content each week), weekly teasers and varied media types to renew interest. For some audiences, immersive tools may further support novelty.

Treating the first week as a high-leverage intervention point. Because WTIE mediates sustained effort, institutions should concentrate support resources at the beginning of the course with proactive onboarding messages, a clear start-here checklist, time-planning tools, and manageable introductory activities that build confidence and productive habits.

Limitations and directions for future research

The five-week duration of our empirical setting is not merely a methodological limitation but a defining boundary condition of the study. The observed relationships may differ in longer OLE programmes where learner fatigue, competing commitments, evolving goals, and cumulative self-regulation demands become increasingly salient. The findings should therefore be interpreted as evidence concerning the initial development and maintenance of effort in short-duration OLEs rather than online learning environments generally. Replicating the study in a longer OLE programme would provide deeper insights into the long-term effects of motivational drivers and effort. Longer studies also enable better assessment of knowledge retention, skill application, and overall learning effectiveness, and they more closely mirror real-world professional development, offering a fuller understanding of how students adapt to changing materials, collaborate virtually, and integrate practical concepts. Moreover, as the study is based on a single online course, it has limited external validity. Therefore, it would be worth replicating this study across other OLE programmes to determine how stable the effects of motivational drivers on WTIE and effort are in different contextual settings. For example, future studies should employ comparative designs involving longer online programmes and comparable face-to-face courses. Such designs would allow researchers to determine whether the patterns reported here reflect characteristics of online learning specifically, characteristics of short-duration courses more generally, or the interaction of both.

Another limitation is the reliance on proxies to measure amount of effort and self-reported data to assess motivational drivers. Our operationalisations capture behavioural manifestations of effort rather than effort itself. The findings should therefore be interpreted as evidence concerning effort-related engagement behaviours. Regarding the proxies for amount of effort (number of pages visited and total time spent on platform), future research could further validate or challenge our findings by employing alternative measures of effort or by triangulating data through direct protocols. Lastly, in this research, participants anticipated their behaviour based on their expectations of the programme. Future research could explore how the fulfilment of expectations influences effort and performance by surveying participants after programme completion.

Further, our research question led us to focus on more active students, meaning our findings do not apply to participants who drop out early. The exclusion of inactive learners means that the reported motivational pathways explain variation among engaged learners rather than the transition from enrolment to disengagement. The sizeable number of inactive registrants suggests that dropout and non-participation are themselves central phenomena deserving dedicated investigation. Further analysis—such as censored regression—could help explore why initial expectations and willingness to invest effort may sometimes fail to translate into actual effort and performance outcomes.

Finally, we focused here on SDT, which emphasises the basic needs of autonomy, competence, and relatedness. However, actual student effort in short-duration OLEs may also be shaped by other factors. Expectancy–Value Theory could clarify how students evaluate the benefits of effort relative to anticipated challenges, while Goal-Setting Theory might explain how structured objectives sustain engagement in self-paced settings. Future research could therefore examine cross-theoretical models in short OLE contexts.

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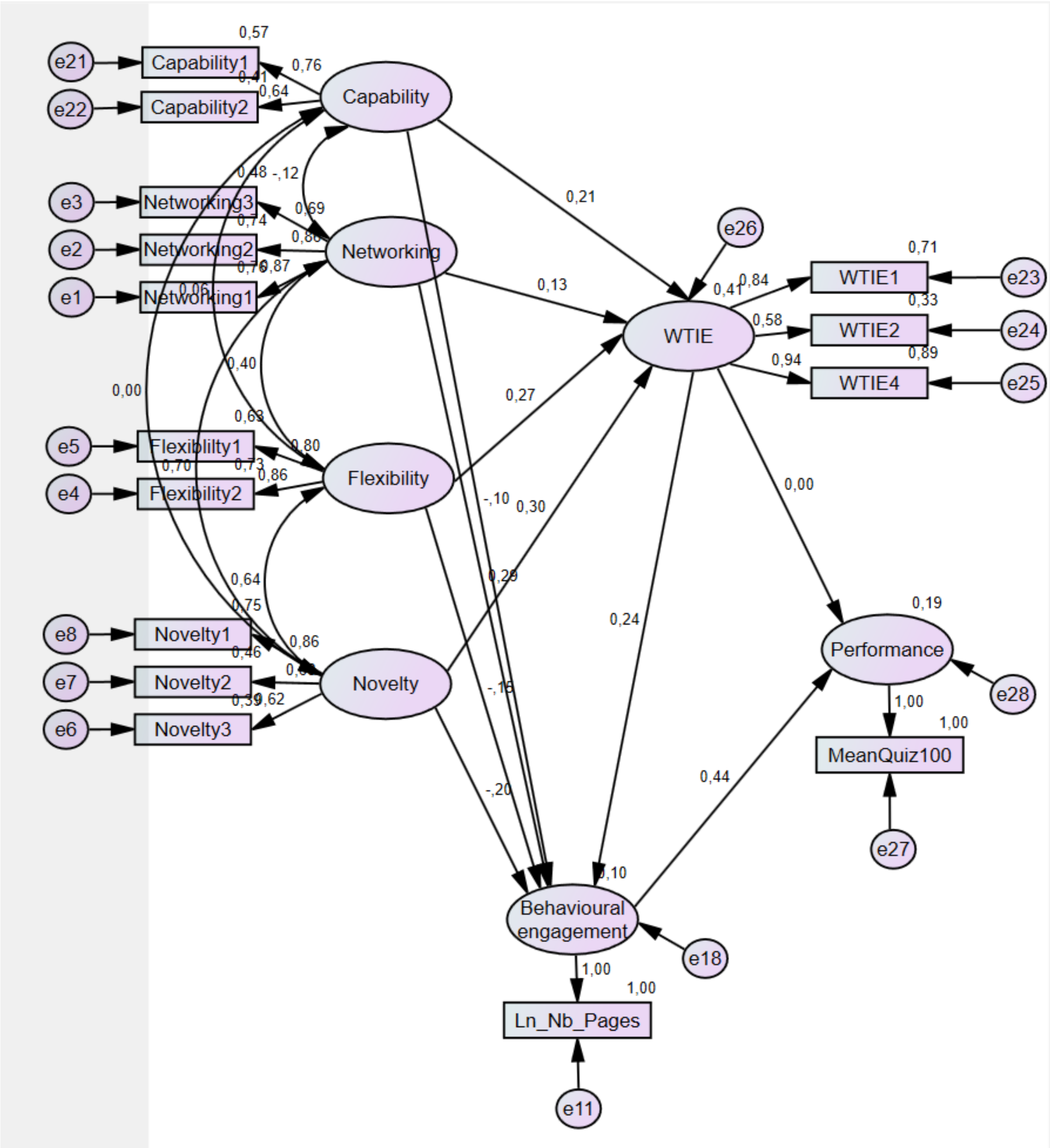
Appendix A. Screenshot of the estimated model of Study 2 in AMOS 30



Supplementary material

Section 1: Analysis using a platform-provided participation score as an additional indicator of behavioural engagement

In Canvas, the platform on which the OLE programme is offered, a weekly participation score is automatically tracked based on students' interactions in a course, such as submitting assignments or contributing to discussions. It reflects events in which a learner performs an action in the course environment. This score could be considered an interesting additional indicator to the number of pages visited. Because the platform provider does not disclose the algorithm used to construct the *participation score*, we did not include it in our model. However, it can provide an interesting input to check for the robustness of our results.

Therefore, we computed an average weekly participation score and tested an alternative model where behavioural engagement is measured with two indicators: the logarithm of the number of pages visited and this score.

Both the indicators reflect the latent construct well (St. $\lambda_{\text{Behavioural engagement}\rightarrow\text{Ln Number of pages}} = 0.76$ $p<0.001$; St. $\lambda_{\text{Behavioural engagement}\rightarrow\text{Participation score}} = 0.87$ $p<0.001$, Average Variance Extracted=0,67). Including the participation score as a second indicator does not noticeably change the model's fit to the data or the regression weights (see Table A). Some effects even increase slightly. Overall, the results provide an indication of the model's robustness.

Table A: Coefficients and adjustment of the structural model – impact of adding the participation score as a second indicator for behavioural engagement

	Research model: without the participation score as a second indicator for behavioural engagement			Research model: with the participation score as a second indicator for behavioural engagement		
Direct effects	**St. B**	**S.E.**	**p**	**St. B**	**S.E.**	**p**
Flexibility → WTIE	0.28	0.116	0.014	0.27	0.118	0.014
Novelty →WTIE	0.33	0.180	0.046	0.30	0.182	0.049
Capability →WTIE	0.21	0.104	0.031	0.21	0.106	0.030
Networking →WTIE	0.13	0.096	0.270	0.13	0.097	0.258
Flexibility → Behavioural Engagement	-0.15	0.067	0.231	-0.21	0.058	0.119
Novelty → Behavioural Engagement	-0.20	0.105	0.236	-0.31	0.090	0.110
Capability → Behavioural Engagement	-0.10	0.055	0.304	0.08	0.047	0.474
Networking → Behavioural Engagement	0.29	0.056	0.025	0.35	0.048	0.017
WTIE →Behavioural Engagement	0.24	0.055	0.023	0.31	0.047	0.010
Behavioural Engagement →Performance	0.45	0.030	<0.001	0.56	4.655	<0.001
WTIE →Performance	-0.01	0.016	0.959	-0.02	1.550	0.770
Indirect effects	**St. B**	**Bootstrap C.I. 90%**		**St. B**	**Bootstrap C.I. 90%**	
Flexibility →WTIE → Behavioural Engagement	0.07	[0.01;0.20]		0,08	[0.02;0.24]	
Novelty → WTIE → Behavioural Engagement	0.07	[0.01;0.22]		0,09	[0,02;0,27]	
Capability → WTIE → Behavioural Engagement	0.05	[0.01;0.16]		0,06	[0,02;0,18]	
Networking→ WTIE → Behavioural Engagement	0.03	[-0.01;0.11]		0,04	[0.001;0.16]	
Model adjustment to the data	$\chi^2(75)$ =125.57 p<0.001 χ^2/df=1,67 RMSEA=0.06 90%CI [0.04;0.08] p-close=0.159 SRMR=0.05 TLI=.0.93			$\chi^2(88)$ =144.40 p<0.001 χ^2/df=1,64 RMSEA = 0.06 90%CI [0.04, 0.08] p-close=0.177 SRMR = 0.05; TLI = 0.95		

Section 2. Impact of not assuming the zero-measurement error for behavioural engagement and performance

We assumed that, as count-based measures externally provided by the platform, the logarithm of the number of pages visited and the mean quiz score were error-free because they are directly observed without subjective interpretation (Hair et al. 2019). However, this assumption implies that these indicators perfectly reflect the latent construct they are supposed to measure, which is debatable.

For this reason, and as a second robustness check, we conducted a sensitivity analysis by setting different values to measurement errors and loadings. Because reliability is unknown, we followed Gerbing's and Anderson's (1988) recommendations. We set the factor loadings to 0.95*observed indicator's standard deviation and the measurement error to 0,1*the observed indicator's variance. The values used are reported in Table B:

Table B: Specified values for measurement error

		Model 1 (error-free)	Model 2
Logarithm of the number of pages - SD=0.599	Error variance	0	0.036
	Loading	1	0.569
Mean Score to the QUIZZ /100 - SD=0.253	Error variance	0	0,006
	Loading	1	0,240

The results are reported in Table C. As can be seen, they are very robust to these changes. The discrepancies in adjustment indicators and estimates are overall very small, and the conclusions are unchanged.

Table C: Coefficients and adjustment of the structural model – impact of removing the zero-measurement error assumption

	Model 1 (error-free)			Model 2		
Direct effects	**St. B**	**S.E.**	**p**	**St. B**	**S.E.**	**P**
Flexibility → WTIE	0.28	0.116	0.014	0.27	0.116	0.014
Novelty →WTIE	0.33	0.180	0.046	0.30	0.181	0.046
Capability →WTIE	0.21	0.104	0.031	0.20	0.104	0.030
Networking →WTIE	0.13	0.096	0.270	0.13	0.096	0.269
Flexibility → Behavioural engagement	-0.15	0.067	0.231	-0.15	0.118	0.227
Novelty →Behavioural engagement	-0.20	0.105	0.236	-0.21	0.184	0.242
Capability →Behavioural engagement	-0.10	0.055	0.304	-0.10	0.098	0.301
Networking →Behavioural engagement	0.29	0.056	0.025	0.29	0.098	0.032
WTIE →Behavioural engagement	0.24	0.055	0.023	0.26	0.097	0.021
Behavioural engagement →Performance	0.45	0.030	<0.001	0.48	0.079	<0.001
WTIE →Performance	-0.01	0.016	0.959	-0.01	0.067	0.877

Indirect effects	**St. B**	**Bootstrap C.I. 90%**	**St. B**	**Bootstrap C.I. 90%**
Flexibility →WTIE → Behavioural Engagement	0.07	[0.01;0.20]	0,07	[0.01;0.21]
Novelty → WTIE → Behavioural Engagement	0.07	[0.01;0.22]	0,08	[0,01;0,26]
Capability → WTIE → Behavioural Engagement	0.05	[0.01;0.16]	0,05	[0.01;0,15]
Networking→ WTIE → Behavioural Engagement	0.03	[-0.01;0.11]	0,03	[-0.01;0.14]

Model adjustment to the data	Model 1 (error-free)	Model 2
	$\chi^2(75)$ =125.57 p<0.001 χ^2/df=1,67 RMSEA=0.06 90%CI [0.04;0.08] p-close=0.159 SRMR=0.05 TLI=.0.93	$\chi^2(75)$ =126.01 p<0.001 χ^2/df=1,68 RMSEA = 0.06 90%CI [0.04, 0.08] p-close=0.153 SRMR = 0.05; TLI = 0.93

Section 3. Analysis including inactive learners

Our focus on effort and performance led us to exclude 58 participants that we labelled inactive learners. These students completed the questionnaire, engaged minimally with the course content, but then disengaged and did not take part in any assessment, meaning that their performance score is equal to zero.

To further check the robustness of our results, we estimated the model using a sample of 239 students that includes the 181 active learners and 58 inactive learners. The results are reported in Table D. They show a slight increase of novelty on WTIE, but a drop in the effect of flexibility, capability and networking on WTIE, with capability becoming non-significant. As a result, the indirect effect of capability also becomes non-significant. Moreover, the effect of networking on behavioural engagement is no longer statistically significant.

Overall, these results do not invalidate our conclusions but suggests that inactive learners have a different motivational approach that should be further explored in future research. This leads us to put the scope of certain conclusions into perspective, as they are only valid for active learners.

Table D: Coefficients and adjustment of the structural model – impact of including inactive learners in the sample

	Active learners only n=181			Active learners + inactive learners n=239		
Direct effects	**St. B**	**S.E.**	**p**	**St. B**	**S.E.**	**p**
Flexibility → WTIE	0.28	0.116	0.014	0.24	0.117	0.015
Novelty →WTIE	0.33	0.180	0.046	0.40	0.148	0.003
Capability →WTIE	0.21	0.104	0.031	0.12	0.095	0.116
Networking →WTIE	0.13	0.096	0.270	0.08	0.060	0.416
Flexibility → Behavioural engagement	-0.15	0.067	0.231	-0.02	0.086	0.855
Novelty →Behavioural engagement	-0.20	0.105	0.236	-0.12	0.110	0.422
Capability →Behavioural engagement	-0.10	0.055	0.304	-0.04	0.063	0.630
Networking →Behavioural engagement	0.29	0.056	0.025	0.15	0.067	0.187
WTIE →Behavioural engagement	0.24	0.055	0.023	0.24	0.060	0.011
Behavioural engagement → Performance	0.45	0.030	<0.001	0.72	0.021	<0.001
WTIE →Performance	-0.01	0.016	0.959	-0.00	0.014	0.954
Indirect effects	**St. B**	**Bootstrap C.I. 90%**		**St. B**	**Bootstrap C.I. 90%**	
Flexibility →WTIE → Behavioural Engagement	0.07	[0.01;0.20]		0,06	[0.01;0.15]	
Novelty → WTIE → Behavioural Engagement	0.07	[0.01;0.22]		0,10	[0.03;0.24]	
Capability → WTIE → Behavioural Engagement	0.05	[0.01;0.16]		0.03	[-0.01;0,11]	
Networking→ WTIE → Behavioural Engagement	0.03	[-0.01;0.11]		0,02	[-0.01;0.08]	
Model adjustment to the data	$\chi^2(75)=125.57$ $p<0.001$ $\chi^2/df=1,67$ RMSEA=0.06 90%CI [0.04;0.08] p-close=0.159 SRMR=0.05 TLI=.0.93			$\chi^2(75)=124.10$ $p<0.001$ $\chi^2/df=1,65$ RMSEA = 0.05 90%CI [0.03, 0.07] p-close=0.386 SRMR = 0.04; TLI = 0.96		