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Date of secondary publication: 29.07.2024

Version of Record (Published Version), Article

Persistent identifier: urn:nbn:de:bvb:473-irb-968882

Primary publication

Klose, Maria; Handschuh, Philipp; Steger, Diana; Artelt, Cordula (2024): „Not easy to get off track : Motivational trajectories of learners completing a non-formal online course". In: Computers in Human Behavior, Vol. 159, October 2024, 108322, pp. 1-13, Amsterdam [u.a.]: Elsevier Science, doi: 10.1016/j.chb.2024.108322.

Computers in Human Behavior 159 (2024) 108322

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

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

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ARTICLE INFO

Handling Editor: Min Jou

Keywords:
Non-formal learning
Online learning
Situational motivation
Motivational trajectories

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.

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

☆ We have no known conflict of interest to disclose. The article was preregistered at https://osf.io/f648g. Supplemental materials, syntax, and data are available online at the Center for Open Science, 2024 (https://osf.io/pdfq8/?view_only=080eb795e5954599baffa8561d46d777).

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https://doi.org/10.1016/j.chb.2024.108322
Received 8 November 2023; Received in revised form 2 May 2024; Accepted 29 May 2024
Available online 3 June 2024

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 (9–60 h) and number of course chapters (3–16). 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 Fig. 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. Fig. 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

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	Situational Motivation Situational Interest	Situational Motivation Situational Interest
	Self-regulation	Mastery goal orientation	
	Socio-demographics [a] Enrollment intentions		

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.

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.

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 et al. (2013) and translated into German by Knörzer et al. (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.", α_{T1} = .81, α_{T2} = .79, and α_{T3} = .84). *Maintained feeling* refers to the positive affect and was assessed with four items (e.g. "The course topic fascinates me.", α_{T1} = .86, α_{T2} = .86, and α_{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", α = .87), *attention management* (e.g. "When I study, I am easily distracted", reversed, α = .88), and *effort management* (e.g. "I don't give up, even if the material is very difficult or complex", α = .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 (α = .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 response Patterns; 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). Fig. 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*. Fig. 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.

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 = Cronbach's alpha.

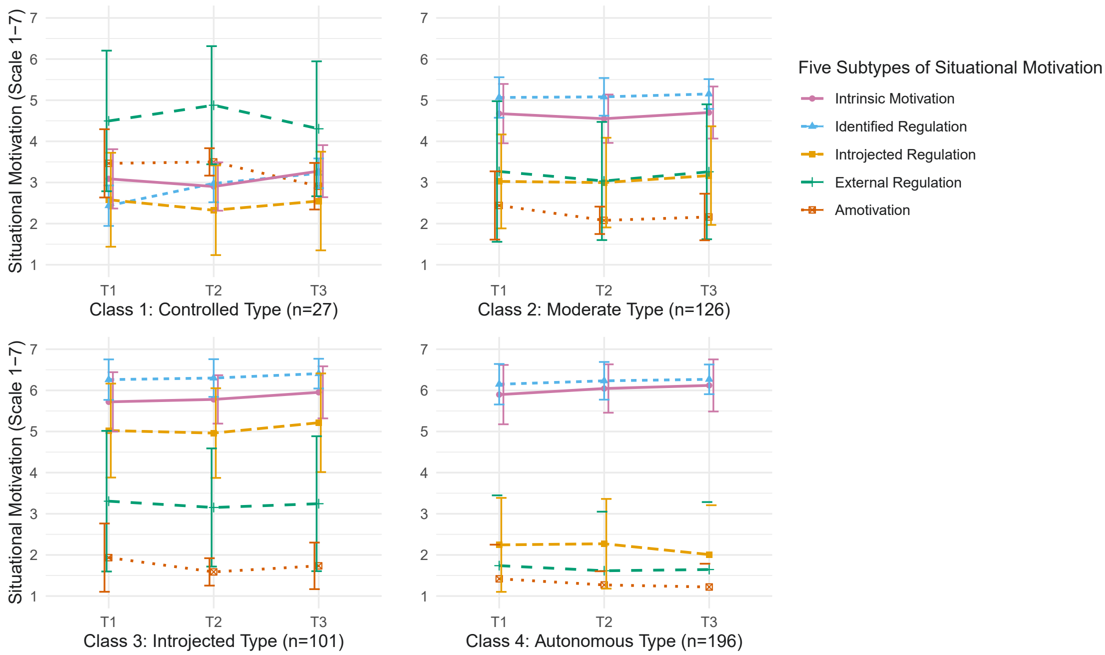

Fig. 1. Four-class solution of profiles based on the subscales of situational motivation across all three time points. $N = 450$. Cluster means and standard deviations for each subtype of situational motivation are displayed.

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.

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.

3.4. Bivariate latent change score models

The bivariate LCS model of *intrinsic motivation* and *situational interest* (see Fig. 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: $\rho = .676$, $p = .018$).

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 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.

Table 4
Longitudinal measurement invariance testing for *intrinsic motivation*.

Model	χ^2	*df*	$\Delta\chi^2$ (*df*)	*p*	CFI	ΔCFI	RMSEA	ΔRMSEA
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).

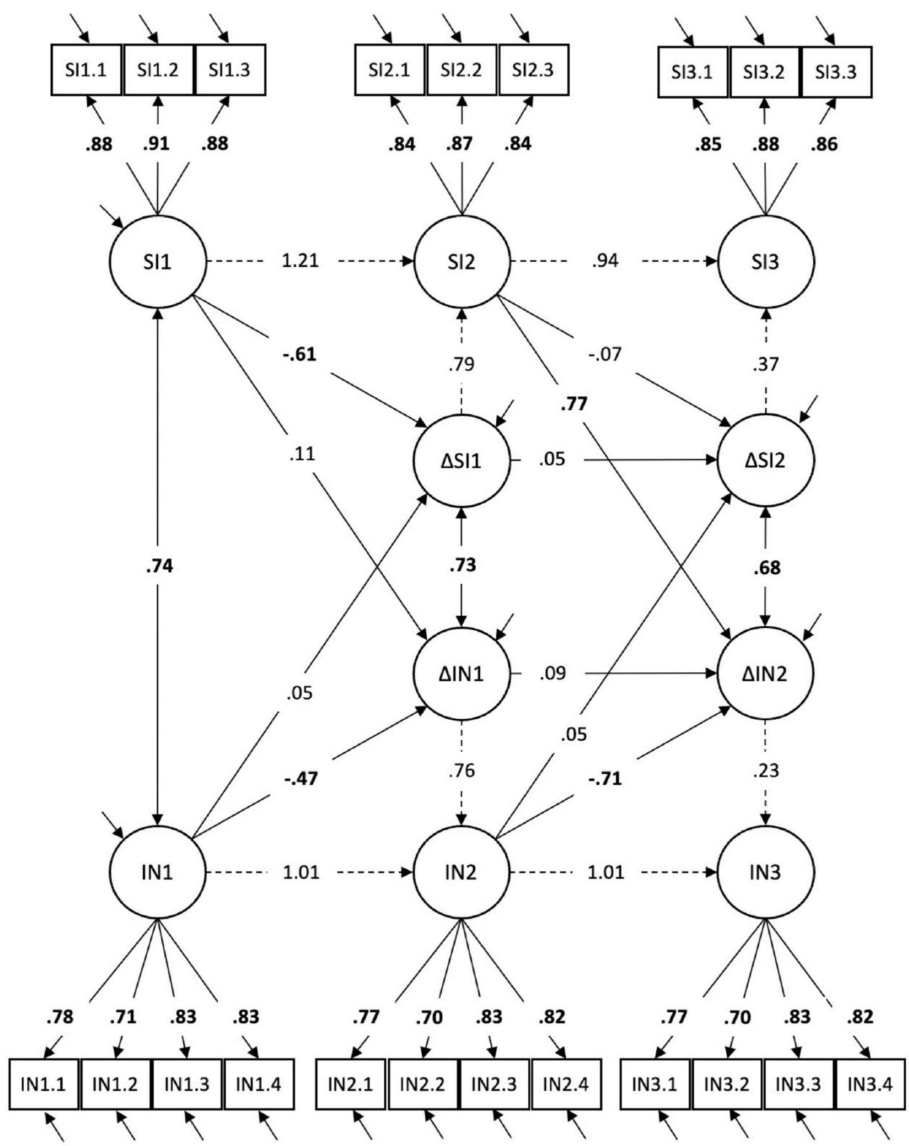

Fig. 2. Bivariate LCS model of *intrinsic motivation* and *situational interest*. *Note.* $N = 450$; $\chi^2 = 446.036$; $df = 189$; $p = <.001$; CFI = .943; RMSEA = .055; SRMR = .053; all residual correlations between the same indicators at different time points were omitted for the sake of clarity.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

3.6. 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

Table 5
Correlates of initial *intrinsic motivation* and predicting change in bivariate LCS models.

	ΔIN1			IN1	
	β	*SE*	*p*	ρ	*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.

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 Fig. 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.

CRediT authorship contribution statement

Maria Klose: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Philipp Handschuh:** Writing – review & editing, Supervision, Project administration, Investigation, Data curation, Conceptualization. **Diana Steger:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Cordula Artelt:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared a link to the data and code in the manuscript

Acknowledgements

We would like to thank Timo Gnambs for his insightful feedback on our analyses, which greatly contributed to the improvement of this work.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2024.108322.

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