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How do online learning intentions lead to learning outcomes? The mediating effect of the autotelic dimension of flow in a MOOC

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Abstract

We focus on the predictors of persistence and achievement in online learning by studying the students' learning intentions and their psychological states during learning activities. Flow/autotelic experience is a powerful predictor of engagement in MOOCs and online learning in general and relates to the deep involvement and sense of absorption during learning activities. Both theory and empirical evidence propose that predictors of flow in an educational setting include the need for belonging to a group of learners. Using path analyses and structural equation modeling, we verify the causal links between social intentions, autotelic experience and MOOC learning outcomes such as final grade and dropout. Using the Online Learning Enrollment Intentions (OLEI) scale, we find that in total six OLEI items predict MOOC success and dropout, with flow as a mediating effect. In two models, we verify "Autotelic experience" as a mediator between enrollment intentions and MOOC final grade and dropout. Our results highlight socially driven intentions as major factors to be considered in online learning environments. We draw theoretical and practical implications for MOOC design, considering explicit communication about the provided learning environment and tools towards a socially shared learning experience.

1. Introduction

Research on MOOCs and their audiences places great emphasis on ways of engaging the participants in online activities. For instance attention has been paid to the phenomenon of dropout in MOOCs, even if it is commonly accepted that, in this specific case, it is important to be mindful with one's definition of dropout (Chaker and Bachelet, 2020), since these massive online courses, by definition, do not obey the classical academic form (Kizilcec, Piech and Schneider, 2013). As Kizilcec and Schneider (2015) put it: "Many learners interact with these courses in ways that would not be considered 'successful' with respect to instructor-defined criteria of success".

In this perspective, previous work has attempted to take into account the learning intentions for dropout rate measurement (Chaker and Bachelet, 2020). It is therefore necessary to study online learning behavior and academic performance through a situated approach, by focusing on the reasons motivating people to enroll in the course. In their study, Kizilcec and Schneider (2015) show that some of the enrollment intentions predict subsequent behaviors. For example, "Meet new people" and "Take with others" intentions predict more than 50% of forum posting, whereas "Obtain a certificate" predicts 80% of homework completed – but does not specifically predict obtaining the certificate (Kizilcec and Schneider, 2015, p. 14). The other items in the inventory have so far not been correlated to indicators of achievement. These findings

suggest that further work is needed to explore which other factors enrollment intentions might correlate to, and, more specifically, to check whether indirect stronger links could be drawn with learning outcomes, by analyzing participants' psychological states as mediating variables at play during the learning process.

As explained by Guo, Xiao, Van Toorn, Lai and Seo (2016, p. 279): "the challenge for online learning is to create an environment that engages students in ways that will maintain their high involvement, interest, and commitment throughout the duration of their learning". As such, the flow theory framework describes optimal experience during which people are deeply motivated to persist in their activities. Introduced by Csikszentmihalyi in 1975, flow is a state of fulfillment linked to the deep involvement and sense of absorption that people experience when faced with demanding tasks and when they perceive that their skills allow them to meet these challenges. In an educational setting, the state of flow is reached when at no time learning or understanding is interrupted by any concern about how to achieve the task at hand, nor by external disruptive elements. This psychological state is regarded as a form of optimal experience, leading to the - ultimate - autotelic state: to engage in an activity for its own sake (Csikszentmihalyi, 1990). Indeed, research shows that people experiencing flow online are more likely to be motivated to take on additional activities and achieve positive results (Finneran and Zhang, 2005). Moreover, flow is found to be a strong predictor of learning outcomes (Lee, 2010; Guo et al., 2016; Rodríguez-Ardura and Meseguer-Artola, 2016; Liao, 2006; Mulik, Srivastava, Yajnik and Taras, 2019; Zhao, Wang and Sun, 2020), especially in MOOCs (Antonaci, Peter, Klemke, Bruysten, Stracke and Specht, 2017; Heutte, Kaplan, Fenouillet, Caron and Rosselle, 2014b; Heutte, Fenouillet,

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Kaplan, Martin-Krumm and Bachelet, 2016b; Lu, Wang and Lu, 2019; Mulik et al., 2019; Zhao et al., 2020).

The flow model in computer-mediated environments proposed by Hoffman and Novak (1996) adds the concept of telepresence among the premises of flow. Zhao et al. (2020) also show that the perceived sociability enabled by the MOOC environment predicts the occurrence of social presence, and in turn the state of flow reached during the MOOC activities. In her study, Liao (2006) found that the perceived interactivity of the online learning environment participates to the prediction of Flow. Relatedness and need for belonging constitute one of the basic psychological needs (Deci and Ryan, 2008), while human optimal experience and functioning relates to the satisfaction of the basic needs for competence, autonomy, and relatedness (Deci and Vansteenkiste, 2004; Schüler, Brandstätter and Sheldon, 2013). For Osterman (2000), this need for relatedness is the need to experience belongingness or the sense of community during learning. The fulfilment of this basic need affects psychological development and the overall experience of well-being (Ryan, 1995). As a consequence, it is not surprising to find within the Online Learning Enrollment Intentions (OLEI) inventory proposed by Kizilcec and Schneider (2015) two items that relate to social needs: “Take with others” and “Meet new friends”, which predict socialization and interaction behaviors. Therefore, when looking for potential mediating variables between enrollment intentions and learning outcomes, it seems relevant to investigate whether these two socially-driven learning intentions could be linked with flow. How to explain the gap between learning intentions and learning outcomes in online learning settings, such as MOOCs? Evidently, individual factors (Fellman, Lincke and Jonsson, 2020; Hong, Cao, Liu, Tai and Zhao, 2021) and contextual and social determinants (Goglio and Parigi, 2018; Rizvi, Rienties, Rogaten and Kizilcec, 2022) participate in explaining non-achievement. Psychological states, such as well-being, are also important determinants in adult online learning settings (Devey, Connaughton, Nance, Chambers and Hased, 2020; Sen, Prybutok and Prybutok, 2022), especially since the COVID-19 pandemic (Walters, Simkiss, Snowden and Gray, 2021).

In this study, we chose to focus on the flow determinants (namely learning intentions) and flow learning outcomes (MOOC success and dropout), as flow relates to optimal experience, i.e. autotelic experience, during the learning phase (Csikszentmihalyi and Csikszentmihalyi, 1992), and as such is one of the most powerful predictor of individual engagement in learning activities. As found in many studies, the flow dimensions display high interaction effects with other psychosocial constructs such as optimal motivation (Deci and Ryan, 2008), self-regulated learning (Kim and Seo, 2013), perceived self-efficacy (Rodríguez-Sánchez, Salanova, Cifre and Schaufeli, 2011), achievement goals (Rheinberg and Engeser, 2012) and self-determination (Kowal and Fortier, 1999; Bakker and van Woerkom, 2017). As such, we believe flow could provide an interesting path to follow for studying “what happens” between the initial intentions set at the beginning

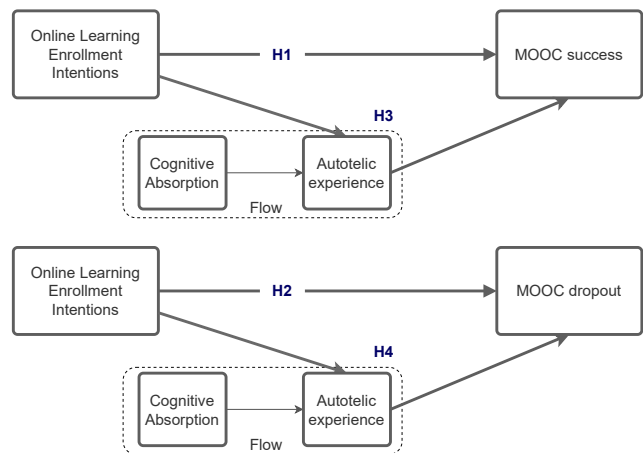


Figure 1: The four relationship hypotheses in the two predicted models in terms of success (B, top) and dropout (D, bottom)

of an online course and learning outcomes, by studying if flow/optimal experience acts as a mediator between learning intentions; and learning outcomes such as MOOC success and dropout. Although other variables could be considered, “retention and completion/dropout” and “performance/outcome” are the only two research topics in the top 10 established by Zhu, Sari and Lee (2020) in their recent systematic review that can be considered as learning outcomes.

2. Research questions and hypotheses

Building on this theoretical framework, we propose to verify two models predicting the causal path between initial enrollment intentions, the flow state during the educational activities, and MOOC performance, in terms of success (model B) and retention (or, seen conversely, dropout) (model D), as shown by the predicted models (cf. Figure 1), with four hypotheses introduced below.

2.1. Learning intentions in MOOCs

MOOCs provide options for learners with various needs and interests (Chang, Hung and Lin, 2015). MOOCs’ flexible, open and informal learning context, can attract applicants from different backgrounds and different motivations. For instance, learners’ intentions can “range from achieving tangible results at the end of the course such as acquiring expertise in a particular field of competence (with a long-term commitment) to developing personal contacts through active involvement in the discussion forums” (Bulger, Bright and Cobo, 2015), cited by Maya-Jariego, Holgado, González-Tinoco, Castaño-Muñoz and Punie (2020). Similarly, Hew and Cheung (2014) sum up four reasons why learners enroll in a MOOC: to learn about a certain topic, to experience taking a complete online course along with thousands of other people, for the personal challenge and with the motive of earning as many course certificates as possible. In another study led from one course, Liu, Kang and McKelroy (2015) found that participants enrolled essentially by personal in-

terest, because of topic relevance with their job, for future career possibilities, by curiosity, for course materials and to earn a certificate. Therefore, although the listed intentions vary somehow, research results agree on their diversity. Moreover, identifying these intentions has a direct practical impact, as Maya-Jariego et al. (2020) show that the evaluation of MOOC learning motivation and intentions can help identify different profiles in terms of competencies, self-efficacy and satisfaction with learning experiences. In other words, it is possible to establish a causal path between enrollment intentions and behavior - as psychosocial constructs - during the learning process in a MOOC context. For Kizilcec and Schneider (2015), MOOC registrants' motivation assessment can indeed provide a "lens" for understanding their behavior during learning.

However, the reasoned action approach (Fishbein and Ajzen, 2011) shows that intention does not necessarily lead to a subsequent behavior: many factors may influence the process of acting out these intentions. These factors include contextual obstacles (Drachsler and Kalz, 2016; Ruipérez-Valiente, Staubitz, Jenner, Halawa, Zhang, Despujol, Maldonado-Mahauad, Montoro, Pfeffer, Rohloff, Lane, Turro, Li, Pérez-Sanagustín and Reich, 2022), extrinsic or intrinsic motivation, self-determination (Deci and Ryan, 2002), self-regulation (Pintrich, 2003), achievement goals (Ames, 1992), self-perceived efficacy (Bandura, 1984) or flow (Csikszentmihalyi, 1997), and they impact the engagement and persistence in an educational activity. Thus, the initial goal to reach the end of an online course will have a better chance of being translated into an effective commitment if the subject experiences one or more of these psychological states. Moreover, Henderikx and colleagues tried to study and classify the main barriers between the learning goals set at the beginning of the MOOC and actual achievements (Henderikx, Kreijns and Kalz, 2018a,b; Henderikx, Kreijns, Muñoz and Kalz, 2019). They found that social context can constitute a barrier towards MOOC achievement: "the impersonal feel of learning, lack of interaction, no collaboration, no interaction and feelings of isolation" (Henderikx et al., 2019, p. 10). In a similar way, trying to implement a peer recommender to break these feelings of isolation, Labarthe, Bachelet, Bouchet and Yacef (2016a) showed that the mere fact of seeing peers to communicate while attending to a MOOC had a positive impact on retention, even when no real social interaction actually happened.

Building on literature review on learning intentions and flow in online learning contexts, we can formulate the following research question: RQ1: do learning intentions directly predict MOOC learning outcomes, such as performance and dropout?

To verify if intentions may lead to learning outcomes, regardless of "what happens" during the learning activities, we propose the following two hypotheses, to confirm previous research about potential direct links between enrollment intentions and learning achievements: *H1: Learning intentions predict MOOC performance* and *H2: Learning intentions predict MOOC dropout*.

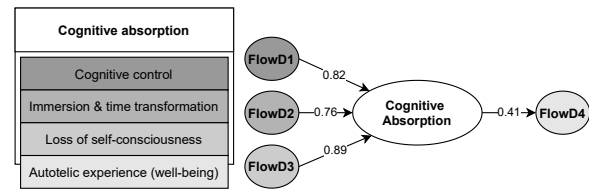


Figure 2: Left: The Flow model in education; Right: The Flow in educational context, both from Heutte et al. (2016b)

2.2. Flow in Education

Building on previous research (Heutte, Fenouillet, Boniwell, Martin-Krumm and Csikszentmihalyi, 2014a; Heutte et al., 2016b), Heutte, Fenouillet, Martin-Krumm, Gute, Raes, Gute, Bachelet and Csikszentmihalyi (2021) proposes that the autotelic experience is a specific feature of adult learning, especially in the context of self-directed lifelong learning, which correspond to the majority of people registering to most MOOCs (e.g. Ho, Chuang, Reich, Coleman, Whitehill, Northcutt, Williams, Hansen, Lopez and Petersen (2015) found 40 to 47% of participants to be older than 30). As flow often occurs when there is a perception of an optimal balance between personal skills and the demands of the task (Heutte et al., 2016b), its framework is then specifically designed to be put into practice in educational settings.

The EduFlow-2 scale (Heutte et al., 2021) is specifically designed for the study of the autotelic experience in an educational setting. The authors model a flow measurement tool inspired by Csikszentmihályi's works on the flow concept, which he describes in different stages, among them: concentration, task control, time absorption and autotelic experience (Guo, Klein, Ro and Rossin, 2007) (cf. Figure 2 left).

EduFlow-2 is a twelve-item scale that has been validated in several educational contexts and measures four dimensions of Flow (Heutte et al., 2021) :

1. FlowD1: Cognitive control — concentration and immersion in the task.
2. FlowD2: Time transformation — alteration in the perception of time, sometimes leading to a lengthened duration of immersion in the task.
3. FlowD3: Loss of self-consciousness — lack of self-concern related to an increase in importance of the psycho-social dimension of learning.
4. FlowD4: Autotelic experience — well-being during task performance resulting from purpose in the task itself that enhances persistence and the desire to engage in the activity again.

Building from the definition given from Agarwal and Karahanna (2000), Heutte et al. (2014a, p. 167) defines Cognitive Absorption (CA) as "a state of deep engagement focused on the will to understand with, as without, the use of digital technologies". This state is linked to an episode of total attention (optimal learning experience) absorbing

the cognitive resources and enabling a very high concentration sequence, where the learning is exclusively focused on understanding. Therefore, CA is an exclusive, extreme and calming focus linked to a state of total concentration in an activity (Heutte et al., 2016b). The authors validate this model by regrouping the first three constructs (D1, D2 and D3) into a single latent CA construct (cf. Figure 2 right). The EduFlow model proposes that the autotelic state (D4) is the result of CA (D1+D2+D3). In their study on 4,420 MOOC participants, Heutte et al. (2016b) confirm that CA is significantly predictive of the autotelic state ($\beta = .410$).

In line with existing research, we propose that learning intentions are antecedents of flow state, as modeled by Heutte et al. (2016b), assuming the validity of the EduFlow model in our research context.

Additionally, previous research shows evidence that flow state can lead to positive learning outcomes, such as learning success and persistence, while the antecedents of flow relate to social constructs: telepresence and social presence (Guo et al., 2016; Zhao et al., 2020). Perceived socialness is also found to be an antecedent of flow (through arousal) towards learning with multimedia material (Lee, Hsiao and Ho, 2014). Hassell, Goyal, Limayem and Boughzala (2012) show that virtual presence and co-presence, along with flow, are predictors of learning in a 3D environment. As flow is often found to predict learning persistence and engagement, it is therefore regarded as a promising means of encouraging learners to commit to learning activities (Erhel and Jamet, 2019).

In the early 2000s, Konradt, Filip and Hoffmann (2003) found that flow leads to learning in computer-mediated contexts. Many studies later on also found that flow is predictive of learning in various contexts: in business education (Guo et al., 2007); on perceived learning during hospital internship (Wang and Chen, 2015); in an online information management course (Rossin, Ro, Klein and Guo, 2009); on perceived learning and satisfaction in a classroom setting (Buil, Catalán and Martínez, 2019); on comprehension and memorization with an educational computer game (Erhel and Jamet, 2019); on achievement in a serious game (Brom, Buchtová, Šisler, Děchtěrenko, Palme and Glenk, 2014); in a digital educational problem-solving-based adventure game (Hou and Li, 2014); in tablet-PC game-based learning (Hung, Sun and Yu, 2015); on performance in elementary students' game-based learning (Hsieh, Lin and Hou, 2016); on exam performance of undergraduate students (Schüler, 2007); on achievement in a corporate e-learning context (Joo, Lim and Kim, 2012) and on achievement of college students with a digital game-based tool (Chang, Warden, Liang and Lin, 2018).

A meta-analysis conducted on twenty-two studies in sporting and gaming tasks contexts (Harris, Allen, Vine and Wilson, 2021) found a medium-sized flow–performance direct relationship.

Overall, the main studied research context using the flow framework is education, with 28.8% of all empirical studies on flow published between 2000 and 2016 (Peifer, Wolters, Harmat, Heutte, Jasmine, Freire, Dionisia, Fonte Carla, Andersen, van den Hout, Šimleša, Pola, Ceja and Triberti, 2018).

Our literature review of flow in education shows that, on the one hand, learning intentions could act as antecedents of flow in an educational context, and on the other hand, flow can predict learning outcomes in various learning settings. Hence, these different results suggest that flow could act as a mediator between learning intentions and learning outcomes in a MOOC context. Studying this possibility could make us better understand how to enhance MOOC success and hindering dropout (people registering for a variety of reasons), by focusing on the links between enrollment intentions, flow and MOOC learning achievements.

Based on previous research and following the model of educational flow/autotelic experience proposed by Heutte et al. (2016b), we aim to answer our second research question: RQ2: does flow/autotelic experience act as a mediator between enrollment intentions in a MOOC and learning outcomes? To answer RQ2, we propose two last hypotheses: *H3: flow/autotelic experience mediates between online learning enrollment intentions and MOOC success*, and *H4: flow/autotelic experience mediates between online learning enrollment intentions and MOOC dropout*.

3. Method

3.1. Context and data collection

We used data from a French MOOC on Project Management (PM) ran on an OpenEdX platform. Held biyearly since 2013, it was the first French MOOC to offer a certificate and throughout 19 successive editions, over 250,000 persons have signed up for it (with about 45,000 participants who have obtained a certificate). In this study, we used data from the 16th edition of the PM MOOC held in Fall 2020 with 15,320 participants enrolled, among them 5,948 obtained the completion certificate.

During the PM MOOC, two self-administered questionnaires (SAQ) were used. SAQ1 was filled in before starting the MOOC and SAQ2 at the beginning of week 3 out of 6 (after 10 to 20 hours of study). SAQ1 included the 13-item OLEI questionnaire (Kizilcec and Schneider, 2015) as well as a question on participants' agreement with the fact they were here to obtain the MOOC certificate, with a 5-point Likert scale ranked from 1 (completely disagree) to 5 (completely agree). The SAQ2 included the 12-item questionnaire EduFlow-2 about Flow in education (Heutte et al., 2021). SAQ2 was administered halfway through the course as the flow questionnaire aims to collect information about the participants' feelings about the state of flow experienced during their online educational activities. Hence, they needed to have experienced enough PM MOOC activities to report their perceived flow states. Having the questionnaire halfway through the course let learners experience enough MOOC activities to report their perceived flow states. Beyond video courses and quizzes, MOOC activities are social (discussions threads pertaining to questions asked at the of each video, deliverable homework shared/discussed on Facebook) and live discussions (one hour every week on Thursday night).

3.2. Participants

Overall 1,338 participants answered to SAQ1 and 623 answered to SAQ2. SAQs and final MOOC completion were matched using tokens to re-identify participants. After data alignment, the dataset used for the indirect models verification was made of answers from $N_{MS} = 349$ participants (Main Sample). The sample consists of 45% of Females and a mean age of 36.32 ($SD = 10.16$). In regard to education level, three respondents (0.9%) indicated that they did not have a high school-level degree, 11 respondents (3.2%) had a high school degree, 32 respondents (9.1%) were preparing their bachelor degree, 72 respondents (20.6%) had a college-level degree, 204 respondents (58.5%) had a master's degree, and 27 respondents (7.7%) had a doctoral degree.

3.3. Measures

3.3.1. OLEI

Proposed by Kizilcec and Schneider (2015), the OLEI questionnaire is made of 13 items elaborated from open-ended answers and for which one can reply whether it applies or not to one of the reasons why one enrolled in that particular MOOC (e.g. “[I enrolled in this MOOC] to meet new people”). We emphasize that OLEI must be seen as an inventory of independent items and not as a “standard scale” aimed at measuring a single construct (the authors themselves did not attempt to validate OLEI as a standard scale with factorial analysis).

3.3.2. EduFlow-2

Proposed and validated in French in several educational contexts by Heutte et al. (2021), the EduFlow-2 questionnaire is made of 12 items, for which one can indicate one's level of agreement using a 7-point Likert scale (e.g. “[In this MOOC,] I am deeply focused on what I am doing”). It measures four different constructs of flow as seen in 2.2. Heutte, Caron, Fenouillet and Vallerand (2016a) suggest that dimensions D1 ($\omega = 0.74$), D2 ($\omega = 0.80$) and D3 ($\omega = 0.90$) predict a latent *cognitive absorption* construct that predicts D4 ($\omega = 0.89$) (cf. Figure 2).

3.3.3. Learning outcome: final grade

Final grade of the MOOC was calculated by taking into account four weekly partial exams (weighted 5% each) and the final exam (weighted 80%).

3.3.4. Learning outcome: dropout score

The dropout term in a MOOC context may have multiple definitions. Contrary to a traditional course, the variety of intentions when registering to a MOOC should be taken into account to differentiate a participant who quits after a few weeks because he was simply interested in an brief initiation on the topic covered by the first week of content, from another one who initially intended to obtain the certificate and eventually gave up (for intrinsic or extrinsic reasons). To calculate a dropout score, we used the method from Chaker and Bachelet (2020), which takes learning intentions into account to calculate a dropout score, thus respecting our

research paradigm. Hence, we define a *dropout score* calculated as the gap between (1) the initial intention to obtain the certificate measured on a 5-point scale in SAQ1, and (2) actual persistence in the MOOC, measured as taking the four weekly assessments as well as the final exam (e.g. taking no assessment gives a persistence score of 0, taking week 1 assessment a score of 1 and so on). Hence, it is worth pointing out that by doing so we focus on late attrition, rather than on early dropout, since we consider the participants who had at least answered to the SAQ1. What we name “dropout score” in our study is thus an integer variable between -5 and 5, where 0 corresponds to an alignment between initial intentions and observed behavior, and a positive (resp. negative) value corresponds to a participant who ended up being more (resp. less) active than suggested by their initial intention to obtain the certificate, i.e. with an overestimated (resp. underestimated) forecast of achievement.

3.4. Data analysis

To verify our hypotheses, we ran path analyses and structural equation modeling using the IBM SPSS Amos 23 package, to analyze direct and indirect effects respectively, between enrollment intentions and MOOC final grade and dropout, using the Maximum Likelihood Estimation method. Then, to verify if the indirect (flow mediated) effects models were significantly enhanced from the direct effects models, we used the model comparisons method by measuring the significance of the deltas between the χ^2 indices of the models.

4. Results

4.1. Descriptive statistics

4.1.1. OLEI

As OLEI is a dichotomous scale, we counted the numbers of “Apply” for each of the 13 items and calculated the percentage over the total number of $n = 1,338$. We also calculated the means' scores out of 1, as the OLEI items will be correlated with other constructs (cf. Table 1). Descriptive results show that the five most selected intentions are in order of importance: “General interest” (96.9%; $SD = 0.17$); “For personal growth” (96.3%; $SD = 0.19$); “Job relevant” (86.2%; $SD = 0.35$); “Degree relevant” (76.7%; $SD = 0.42$) and “To earn a certificate” (76.0%; $SD = 0.43$).

We verified for potential differences between samples from SAQ1 and SAQ2 regarding the OLEI descriptive results, to verify for a sampling bias in our conclusions about the effect of enrollment intentions on flow and learning outcomes. We ran independent *t*-tests between OLEI SAQ1 and SAQ2 results. The two compared samples are:

- n_1 , accounting for the participants who only answered SAQ1: $n_1 = 715$.

- N_{MS} , accounting for the participants who answered SAQ1 and also SAQ2: $N_{MS} = 349$.

Independent *t*-test yield no significant differences for OLEI means between n_1 and N_{MS} samples: $t \in [-1.27; 1.62]$; $p \in [0.129; 0.906]$. These results indicate that sampling bias is limited between SAQ1 and SAQ2, as the sample who only

Table 1
OLEI items descriptive statistics
($n = 1,338$)

OLEI item	# of "Apply"	M	SD
general interest	1297	0.97	0.17
job relevant	1153	0.86	0.35
degree relevant	1026	0.77	0.42
for academic research	547	0.41	0.49
for personal growth	1288	0.96	0.19
career change	765	0.57	0.50
for fun & challenge	681	0.51	0.50
to meet new people	380	0.28	0.45
to experience online course	478	0.36	0.48
to earn a certificate	1017	0.76	0.43
prestigious university	723	0.54	0.50
to take with friends/colleagues	332	0.25	0.43
to improve French	203	0.15	0.36

responded to the first questionnaire do not differ from the sample who also answered the second questionnaire on the MOOC's third week in terms of enrollment intentions.

4.1.2. EduFlow

Results show that Eduflow dimensions display satisfying to excellent internal consistencies ($\alpha \in [0.68; 0.92]$ – cf. Table 2). The mean values ($M \in [5.08; 5.30]$) indicate relatively high flow indices. We used several measures of fit to find out to what extent the EduFlow model explains the data: the chi-squared degrees of freedom ratio (χ^2/df), the Comparative Fit Index (CFI), the Non-Normal Fit Index (NNFI) and the root mean square error of approximation (RMSEA). Hu and Bentler (1999) consider that a value greater than 0.95 is preferable for the CFI and NNFI, and also suggest that the RMSEA should be equal or lower than 0.06. Confirmatory factorial analysis of our data indicates satisfying indices of fit with the model: $\chi^2/df = 4.58$; $NNFI = 0.97$; $CFI = 0.97$; $RMSEA = 0.063$.

We verified for potential differences with independent t -tests between the flow sample from SAQ2, and N_{MS} , since they will be integrated into the same model later in the article. The two compared samples are:

- n_2 , accounting for the total participants who only answered SAQ2: $n_2 = 623$.
- N_{MS} , accounting for the participants who answered SAQ1 and also SAQ2: $N_{MS} = 349$.

Independent t -test yield no significant differences for flow means between n_2 and N_{MS} samples: $t \in [-0.51; 1.85]$; $p \in [0.063; 0.604]$. These results indicate that sampling bias is limited between n_2 and N_{MS} for flow, in other words, the sample who only responded to the second questionnaire do not differ from the sample who also answered the first questionnaire in terms of flow.

4.1.3. Learning outcomes

We processed the two indicators considered for learning outcomes: Final grade mean is $M = 50.52$; $SD = 36.95$ and the Dropout score is $M = -1.84$; $SD = 2.50$ ($N_{MS} = 349$).

Table 2
EduFlow dimensions descriptive statistics ($n2 = 623$)

EduFlow dimensions	α	M	SD
D1 (Cognitive Control)	0.68	5.30	0.93
D2 (Time transformation)	0.75	5.12	1.15
D3 (Loss of self-consciousness)	0.92	5.14	1.64
D4 (Autotelic experience)	0.85	5.08	1.24

4.2. Correlations

Kolmogorov-Smirnov tests indicate for OLEI items and EduFlow dimensions non-normal distributions of residuals ($p < .01$), which leads us to use the non-parametric Spearman rho correlation test. Results show limited correlation links between OLEI items and EduFlow dimensions and between OLEI items and learning outcomes (cf. Table 3). “General interest” correlates with all EduFlow constructs (D1, D2, D3 and D4) ($\rho \in [0.129; 0.166]$; $p \in [0.01; .05]$), and “Prestigious university” correlates with “D2-time transformation” ($\rho = 0.107$; $p < 0.05$) and with “D4-Autotelic experience” ($\rho = 0.123$; $p < 0.05$). The rest of the results show significant correlations only between “D4-Autotelic experience” and four other OLEI items: “For academic research” ($\rho = 0.197$; $p < 0.01$), “To meet new people” ($\rho = 0.315$; $p < 0.01$), which is the highest index, “To earn a certificate” ($\rho = 0.228$; $p < 0.01$) and “To take with friends or colleagues” ($\rho = 0.246$; $p < 0.01$). Two main results can be highlighted at this point: (1) the EduFlow construct that interacts the most with enrollment intentions is - its “last stage” - “D4-Autotelic experience” (6 out of the 10 correlation links). (2) We notice that two intention items relate to the will to socialize (“Meet new people” and “Take with friends or colleagues”), corresponding to the only two OLEI items linked to social aspects, and they display the highest correlation indices. As for final grade and dropout, they both correlate with seven items from the OLEI inventory, among them social items, such as (respectively) “To meet new people” ($\rho = 0.143$; $p < 0.001$; $\rho = -0.169$; $p < 0.001$) and “Take with friends or colleagues” ($\rho = 0.131$; $p < 0.001$; $\rho = -0.129$; $p < 0.001$).

4.3. RQ1: Do learning intentions directly predict MOOC learning outcomes?

4.3.1. The direct effect of OLEI on final grade

We ran a path analysis as a first step to verify H1. The result yields a model where the OLEI items do not display significant paths towards MOOC final grade (cf. Figure 3). Our data indicates excellent indices of fit with the model (A): $\chi^2/df = 1.17$; $p = 0.248$; $NNFI = 0.98$; $CFI = 0.99$; $RMSEA = 0.004$. In model A, the explained variance of MOOC final grade is very low: $R^2 = 3\%$.

4.3.2. The direct effect of OLEI on MOOC dropout

The path analysis, as a first step to verify H2, yields a model where four OLEI items display a significant link with dropout (cf. Figure 4): general interest ($\beta = 0.09$; $p < 0.001$),

Table 3
Correlations between OLEI items, EduFlow dimensions and learning outcomes variables

	D1	D2	D3	D4	Final grade	Dropout
general interest	0.143**	0.113*	0.129*	0.166**	0.098**	-0.100**
job relevant	0.017	-0.007	0.007	-0.074	0.015	0.029
degree relevant	-0.007	0.012	-0.034	-0.031	0.005	-0.055*
academic research	0.059	-0.011	-0.081	0.197**	0.127**	-0.122**
personal growth	0.028	0.042	0.042	0.104	-0.014	-0.005
career change	-0.016	0.070	0.063	0.127*	0.081*	-0.007
fun and challenge	0.050	0.074	0.005	0.086	0.068	-0.026
meet new people	0.056	0.088	0.009	0.315**	0.143**	-0.169**
experience online course	0.023	0.011	-0.012	0.066	0.013	0.026
earn a certificate	0.018	0.105	-0.002	0.228**	0.103**	-0.176**
prestigious university	0.073	0.107*	0.012	0.123*	-0.031	-0.025
take with friends	0.029	0.044	0.027	0.246**	0.131**	-0.129**
improve French	-0.051	-0.031	-0.101	0.078	0.145**	-0.127**

* $p < 0.05$; ** $p < 0.01$

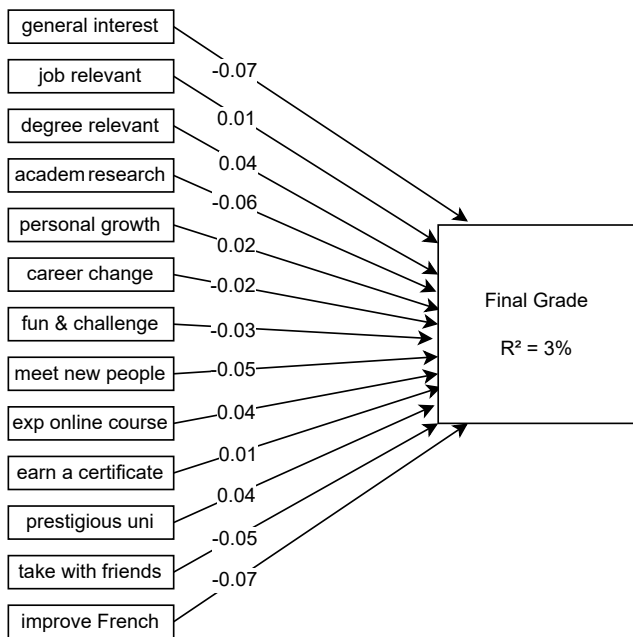


Figure 3: Model A: OLEI as predictors of MOOC achievement

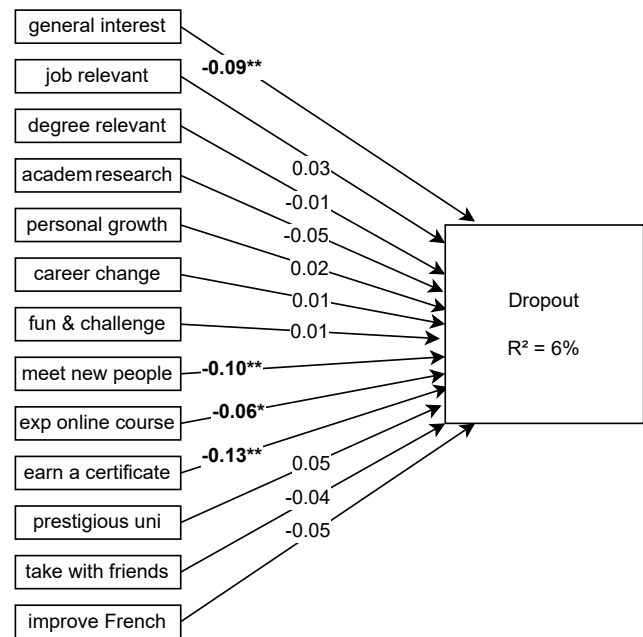


Figure 4: Model C: OLEI as predictors of MOOC dropout

meet new people ($\beta = 0.13$; $p = 0.002$), experience online course ($\beta = 0.06$; $p = 0.046$) and earn a certificate ($\beta = 0.132$; $p < 0.001$). Dropout explained variance is $R^2 = 6\%$. The data indicates excellent indices of fit with the model (C): $\chi^2/df = 1.17$; $p = 0.249$; $NNFI = 0.98$; $CFI = 0.99$; $RMSEA = 0.004$. These results indicate that direct paths between initial enrollment intentions and dropout are possible, despite a low explanatory power.

4.4. RQ2: Does Flow/autotelic experience act as a mediator between OLEI and learning outcomes?

4.4.1. Flow/autotelic experience as a mediator between OLEI and final grade

As we found that learning enrollment intentions do not directly and significantly predict final grade, we aim to study “what happens” between learning intentions and MOOC performance. In other words, if a psychological construct, such as the flow state characterized by an optimal learning experience through autotelism, plays a mediating role between initial intentions and learning results. We used the structural equation modeling (SEM) method to integrate OLEI,

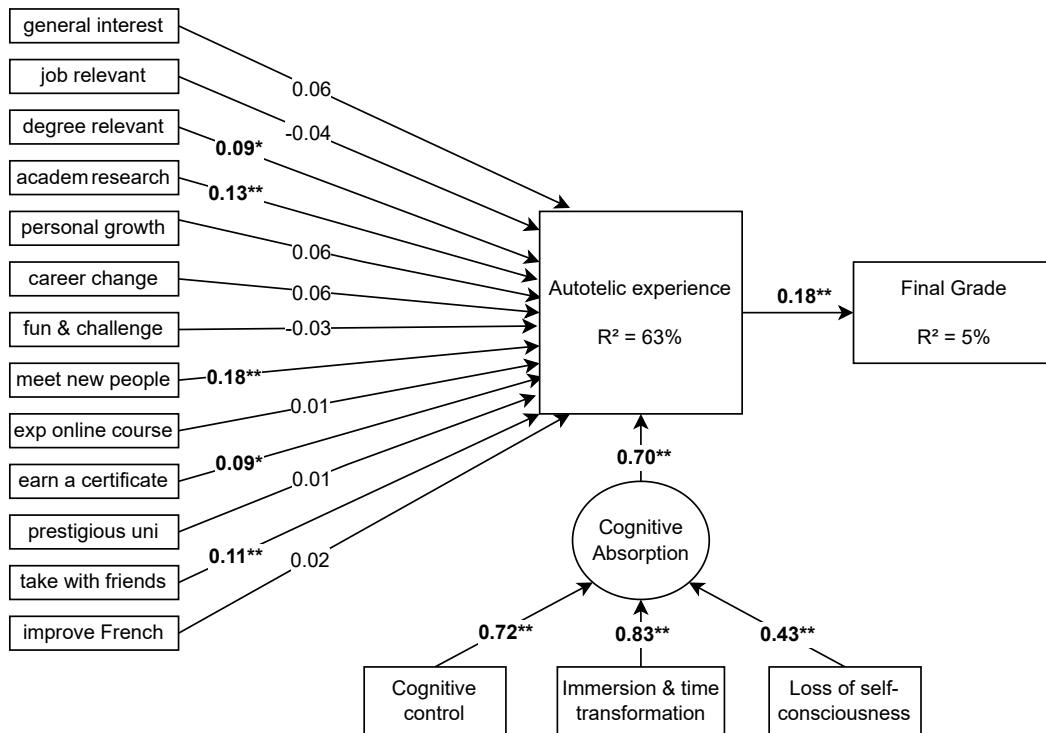


Figure 5: Model B: Flow mediating between intentions and final grade

EduFlow and final grade in a single model to verify H3 (cf. Figure 4). Results indicate that five OLEI items significantly predict autotelic experience, which in turn significantly predicts final grade ($\beta = 0.18; p < 0.001$) for an explained variance of $R^2 = 5\%$. The five OLEI items are: degree relevant ($\beta = 0.09; p = 0.021$), academic research ($\beta = 0.13; p = 0.002$), meet new people ($\beta = 0.18; p < 0.001$), earn a certificate ($\beta = 0.09; p = 0.028$) and take with friends ($\beta = 0.11; p = 0.002$). Our data indicates excellent indices of fit with the predicted model (B): $\chi^2/df = 1.34; p = 0.019$; $NNFI = 0.98$; $CFI = 0.98$; $RMSEA = 0.006$. In line with EduFlow’s model (Heutte et al., 2016b), cognitive absorption - as a latent component resulting from D1, D2 and D3 - significantly predicts autotelic experience ($\beta = 0.70; p < 0.001$; $R^2 = 63\%$). In model B, results show that the Flow construct plays a mediating role between OLEI and final grade. The second step for verifying H2 requires to compare model A (direct path between OLEI and final grade) and model B (path between OLEI and final grade mediated by flow). Comparison shows that model B is significantly better than model A: $\Delta\chi^2(\Delta df) = 83.35(57); p = 0.018$.

4.4.2. Flow/autotelic experience as a mediator between OLEI and dropout

As previously, we used SEM to integrate OLEI, EduFlow and dropout in a single model, as a first step towards H4 verification (cf. Figure 6). Results indicate that five OLEI items significantly predict autotelic experience, which in turn significantly predicts dropout ($\beta = -0.38; p < 0.001$) for an explained variance of $R^2 = 14\%$. The five OLEI items

are: general interest ($\beta = -0.08; p = 0.025$), academic research ($B = -0.12; p = 0.002$), meet new people ($\beta = -0.18; p < 0.001$), earn a certificate ($\beta = -0.14; p < 0.001$) and take with friends ($\beta = -0.10; p = 0.01$). Our data indicates excellent indices of fit with the predicted model (D): $\chi^2/df = 1.58; p = 0.001$; $NNFI = 0.94$; $CFI = 0.98$; $RMSEA = 0.007$. As expected, the latent factor cognitive absorption significantly predicts autotelic experience with the same measures as in model B. In model D, results show that Flow construct plays a mediating role between OLEI and dropout. The second step for verifying H4 requires to compare model C (direct path between OLEI and dropout) and model D (path between OLEI and dropout mediated by flow). Comparison shows that model D is significantly better than model C: $\Delta\chi^2(\Delta df) = 70.05(44); p < 0.001$.

4.5. Results synthesis and hypothesis testing

Preliminary results of model A testing shows that there are no direct significant paths between OLEI items and final grade. Hence, we reject H1: *Learning intentions do not directly predict MOOC performance*. Conversely, model B significantly enhances model A and displays significant relationships between five OLEI items and flow/autotelic experience, which, in turn, significantly predicts final grade. It also displays better explanatory power ($R^2 = 5\%$ against $R^2 = 3\%$). Hence, we accept H3: *low/autotelic experience mediates between online learning enrollment intentions and MOOC success*.

As for model C, testing displays four significant paths between OLEI items and dropout. Hence, we partially ac-

The mediating effect of autotelic experience in a MOOC

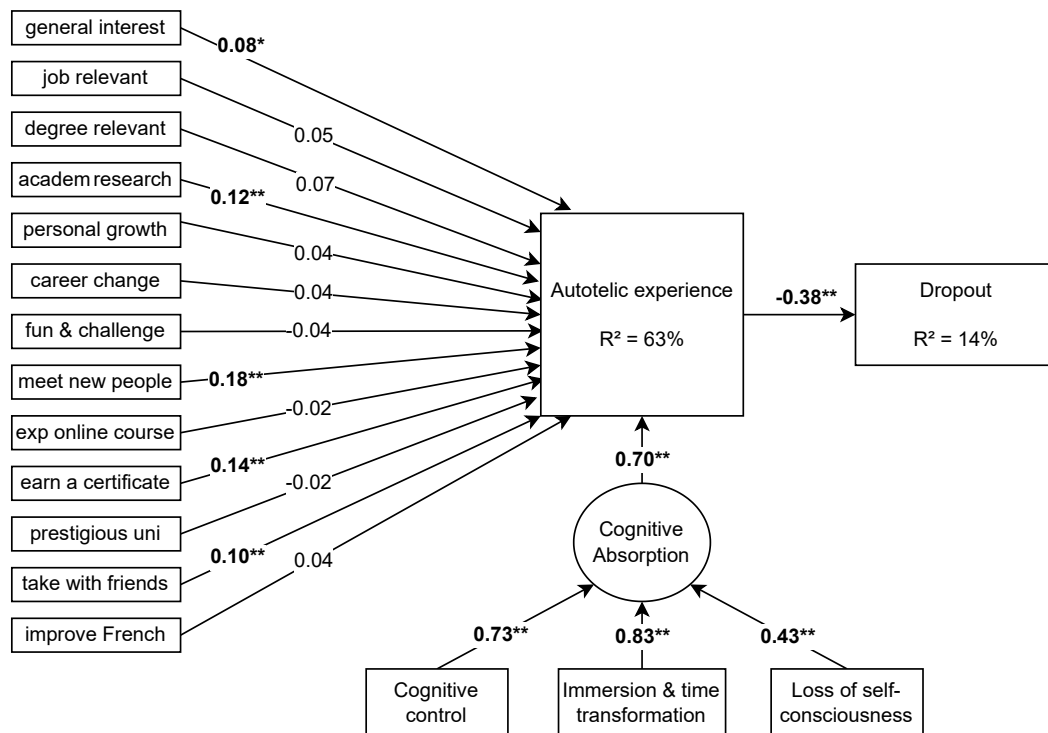


Figure 6: Model D: Flow mediating between intentions and dropout

Table 4
Model comparisons

Model	χ^2	df	χ^2/df	p	NNFI	CFI	RMSEA
A	30.47	26	1.17	0.248	0.98	0.99	0.004
B	111.82	83	1.34	0.019	0.99	0.99	0.006
$\Delta B - A$	69.97	44	n/a	0.018	n/a	n/a	n/a
C	30.46	26	1.17	0.249	0.98	0.99	0.004
D	131.49	83	1.58	0.001	0.98	0.98	0.007
$\Delta D - C$	101.03	57	n/a	0.001	n/a	n/a	n/a

cept H2: some learning intentions directly predict MOOC dropout. Furthermore, model D significantly enhances model C and displays significant relationships between five OLEI items and flow/autotelic experience, which, in turn, significantly predicts dropout. It also displays better explanatory power ($R^2 = 14\%$ against $R^2 = 6\%$). Hence, we accept H4: low/autotelic experience mediates between online learning enrollment intentions and MOOC dropout.

These results indicate that an integrated model explaining the process from learning intentions toward learning outcomes, measuring autotelic experience helps us better understand the learning process. In other words, when taking into consideration learning intentions, autotelic experience leads to moderately better learning achievements: higher retention (measured as continuing weekly assessments) as well as higher final grade.

5. Discussion and conclusion

Our study aimed to investigate the psychological states of online learners in a MOOC, as mediators between learning intentions and learning outcomes such as final grade and dropout. Our results show that, to better explain success in a MOOC is to not consider the enrollment intentions and psychological states during the learning process separately but together in the same predictive model. Our models comparisons demonstrate that the model with a greater explanatory power of learning outcomes is a model that takes into account enrollment intentions as antecedents of flow, which in turn predicts success and dropout, in a causal path where it acts as a mediating variable between intentions and learning outcomes. The antecedents with significance in our models, for both learning outcomes, are intentions linked to extrinsic motivation, such as earning a certificate, academic research and socialization goals (take with friends and meet new people). There is an additional extrinsic motivational antecedent item for final grade (degree relevant) and an additional intrinsic motivation (i.e. linked to the task) item for dropout (general interest). These results show that different enrollment intentions can lead to different learning outcomes, both with the autotelic dimension of flow as a mediating effect.

We chose to study the determinants and the effects of flow in a MOOC context, as it relates to the optimal learning experience, strongly linked with the most often studied psychological constructs in adult learning contexts, such as self-regulated learning, motivation, self-perceived efficacy, or achievement goals. In line with previous research that has

shown various antecedents of flow, such as telepresence, interactivity and social presence, we also demonstrated that social variables to be antecedents of flow. Furthermore, consistent with previous research which found that learning outcomes such as knowledge gain, performance, persistence and intended continuance are among the predicted outcomes of flow, we found dropout to be predicted by flow in a MOOC context.

5.1. Theoretical implications

5.1.1. Flow in a situated approach

We measured flow with two distinct dimensions: cognitive absorption (as a second-level factor measuring absorption, cognitive control and loss of self-consciousness) and autotelic experience, as the result of cognitive absorption, as modeled by Heutte et al. (2016b) after Csikszentmihályi's works on flow and optimal experience (Csikszentmihályi and Csikszentmihályi, 1992). Our results revealed two predicted models, where in total six learning intentions are antecedents of flow: General interest, academic research, degree relevant, to earn a certificate, and two socially related intentions (to take with friends or colleagues and to meet new people). Final grade is weakly affected by the predicted model (5%), whereas dropout score is predicted with a larger effect (14%). One of our main findings, is the fact that, when integrating enrollment intentions in online learning explanatory models, it helps better explain the positive learning experience, which in turns helps to better explain learning retention and learning success. The remaining question is: how to understand the explained variance differences between dropout and final score? We propose two possible explanations:

1. We measured dropout taking into account the initial intention to obtain the certificate, whereas we used the "raw" final score. Hence, we measured flow towards a contextualized dropout variable, the autotelic experience (which is predicted by high levels of immersion and absorption due to the learner's task motivation) in order to predict a situated behavior (our dropout score). Conversely, the final grade variable does not integrate the intention to obtain a high final grade, hence it encompasses a population whose intention to validate all the tests is not clearly identified. This difference could then explain the gap in all the models' explained variances between dropout score and final grade. In the situated approach, research data must be interpreted in relation to the situation and the context: in our case, the learners' initial intentions. As a theoretical implication, we found in our study that flow predicts contextualized phenomena in a more powerful manner than un-contextualized phenomena.
2. A second possible explanation could also be given by the works of Cowley, Palomäki, Tammi, Frantsi, Inkilä, Lehtonen, Pölönen, Vepsäläinen and Lappi (2019) and Palomäki, Tammi, Lehtonen, Seittenranta, Laakasuo, Abuhamdeh, Lappi and Cowley (2021) who found that flow is related to anticipated performance more so than

to absolute performance. In other words, flow is reported whenever participants performed better than would be expected from their learning curve. Our dropout score, by the way it is calculated, also measures an estimated forecast of achievement, as we explained in section 3.3.4.

5.1.2. Social intentions and flow

Among the OLEI items predicting the model, two relate to social intentions: "To take with friends or colleagues" and "To meet new people". These findings are in line with Kizilcec and Schneider (2015) study which found social intentions to be linked with subsequent behavior: the intention to meet new people predicted more posts on the discussion forum; and the intention to take the course with colleagues or friends predicted more engagement with the contents (and videos) and an improved performance. More interestingly, we notice that flow is a mediator of certain enrollment intentions but not others. For instance, the change from Model C to Model D added "Take with friends" as an antecedent of autotelic experience, predicting in turn MOOC dropout. In Model C, there is only "Meet new people" among the two socially-linked items that predicted learning outcomes. Additionally, "experience online course" stopped being a predictor towards MOOC achievement when flow constructs integrated the main model as mediators. These results underline the fact that socially-linked intentions are stronger antecedents of flow towards learning outcomes, than individually-driven intentions like "experience online course".

One can be surprised to find socially-driven intentions to be key elements in a predictive model explaining performance in an online course designed for the masses to learn individually. In their study Li, Kim and Xiong (2020) found indeed that MOOC activity is mostly made of individual learning whereas only a very small portion is associated to interactive learning. Moreover, Poquet, Dowell, Brooks and Dawson (2018) found that MOOC participants tend to not capitalize enough on the opportunities for social learning.

Conversely, building on the self-determination theory, it is not surprising to see social intentions to be integrated in a model where they are linked with optimal experience in an online adult learning context. For Deci and Ryan (2008, p. 183), satisfaction of the basic needs for relatedness predicts psychological well-being in all cultures: "[it is] essential for optimal functioning in a broad range of highly varied cultures". Educational activities, as many of the activities of life, involve others and are directed at experiencing the feeling of belongingness (Deci and Ryan, 2008). This is also in line with situated learning theory which stresses out the importance of social relations (Kakavelakis and Edwards, 2012) to understand the context in which the learning takes place. Therefore, we can posit that enrolled participants perceived the social affordance provided by the MOOC instructional environment. Indeed, since telepresence was first introduced by Hoffman and Novak (1996) as one of the flow pre-conditions in the Internet environment, by which Internet users' perceptions about computer-mediated environments

may be measured, it has been included in various studies to show that when technology users perceive a sense of telepresence in mediated environments, it can create a perceptual illusion of being present and highly engaged, thus allowing flow to occur (Guo et al., 2016; Zhao et al., 2020). Nevertheless, as pointed out by Kizilcec and Schneider (2015), some learners might complement interaction spaces with more conventional social media: “Learners with [the intention to take with friends or colleagues] were less likely to engage heavily on the discussion forum, possibly because they communicate via other channels with the people they took the course with” (p.15). Moreover, in their study among participants in MOOC for health professionals, Brooks, Stalburg, Dillahunt and Robert (2015), found that learners who signed up with friends/colleagues had higher completion rates than those who did not. They also found out that the mean number of forum postings per user was higher for those who signed up with friends or colleagues, and that they interacted outside of the course using other communication tools. Similarly, when using a peer recommender in a MOOC, Labarthe, Bouchet, Bachelet and Yacef (2016b) showed that merely increasing the perception of presence of other learners in a MOOC helped in increasing the overall retention of students. This result is consistent with the study from Bulger et al. (2015) about MOOC participants, who found performance to be connected with the sense of belonging to the group. More generally, we found that flow is mainly predicted by intention items that could be related to extrinsic motivations to the learning activity itself, in line with previous studies such as Heutte et al. (2016a).

5.1.3. From flow to performance

Research on flow and performance did not find closure as to the direction of the causal link between these two variables. The direction of the relationship was often questioned. For example, Schattke, Brandstätter, Taylor and Kehr (2014) found that climbers with a high achievement motive experienced more flow after repeating a skill exceeding route. Palomäki et al. (2021) also found “a prominent effect of learning (...) on self-reported Flow” (p.9). In our study, by its protocol, we measured the flow as it was perceived by learners at half of the educational activities in the MOOC, then we measured the performance at the end of the course. The time lapse between flow and performance measurements is approximately two weeks. We can therefore say that it is the self-reported flow in the middle of the course that gave way to the performance as measured. Without definitively concluding the causal link between the two, we propose in our research context a causal model where the direction of the relation goes from flow to performance.

5.2. Limitations of our study

Firstly, our results can only be applied on the studied sample of the 16th edition of the PM MOOC, and the method used would need to be replicated in different contexts. Another limitation of our work relates to the indicators chosen to qualify and quantify learning outcomes. As we saw, MOOC success can be reached beyond the traditional indicators of

academic success and should be linked with initial learning intentions. One of the achievement indicators we used in this study is the dropout score, which was calculated taking into account the initial intention of earning a certificate. This calculation method intentionally leads to excluding early dropouts, keeping only participants whom at least answered the first self-administered questionnaire. Hence, in our study, the dropout score characteristic reflects the initial intention to validate the course and its subsequent behavior.

Additionally, as we noted, the flow framework is strongly linked with the theory of self-determination in a motivational continuum (Deci and Ryan, 2002) integrating the different types of regulations. Almost all dimensions of regulated self-determination correlate with most components of flow (Heutte et al., 2016b): the correlations generally follow a progression matching the continuum of self-determination. A blind spot of our study is that we did not include the whole theoretical self-determination theory which could have been assessed more precisely beyond the simple question of enrollment intentions. In this regard, the assessment of registrants’ motivation is still to be done, as it is known that intrinsic motivation is deeply intertwined with flow (Csikszentmihalyi, Montijo and Mouton, 2018; Keller, Ringelhan and Blomann, 2011; Meyer, Klingenberg and Wilde, 2016; Schüler et al., 2013). Indeed, an intrinsic interest in the activity leads to immersion and loss of time perception. However, some results show that optimal experience at work is associated with both autonomous regulation and controlled regulation (Bassi and Fave, 2012). In a study among MOOC participants, Heutte et al. (2016a) found that the autotelic experience is more related to the integrated regulation of extrinsic motivation than to intrinsic motivation. It is the balance between the task demands, social expectations, personal competencies and achievement goals that leads toward an autotelic optimal learning experience. As an agentic variable in the self-determination theory, self-efficacy has also been found to be predictive of flow (Mahdi Hosseini and Fattahi, 2014; Rodríguez-Sánchez et al., 2011; Peifer, Schönfeld, Wolters, Aust and Margraf, 2020). For instance, Hong, Tsai, Hsiao, Chen, Chu, Gu and Sitthiworachart (2019) found that flow mediates between self-efficacy and learning continuance intention in a game-based learning context.

5.3. Future research

Future research should then integrate the measurement and identification of motivations underlying the “intentions-behaviour-outcomes” process in MOOC learning, to help better understand how optimal experience is reached towards learning. Moreover, future studies should also focus more on initial intentions, not only to assess the dropout (rate or score), but also to assess final grade, course content engagement, course completion and certification, for measurement methods to be more contextualized and specific to learners’ motivations.

Another interesting future track is taking into account prior knowledge of learners, when studying the role of flow in education, as for Hoekman, McCormick and Gross (1999,

p. 193): “Optimal learning is facilitated when educational opportunities are not only responsive to students’ interests, abilities, and individual differences, but actually extend their prior knowledge”. Prior knowledge activation being a skill associated to metacognition abilities, assessing those abilities could also help understanding the flow process. Similarly, learners’ skills could be worth taking into account as studies showed that high ability is related to the autotelic personality. For instance, empirical evidence shows that high flow is connected with high abilities (Garces-Bacsal, Cohen and Tan, 2011) and prior experience (Cowley et al., 2019; Palomäki et al., 2021). Flow has even been studied as an outcome in high potential (gifted) primary school learners (Eysink, Gersen and Gijlers, 2015). Moreover, Csikszentmihalyi et al. (2018) proposed that the reward of reaching the flow state leads to intrinsic motivation, among learners with high abilities. In a game-based learning context, Tsai, Huang, Hou, Hsu and Chiou (2016) also showed that higher achievers experienced higher flow of control and concentration.

Finally, we saw that participants expressed socially-linked initial learning intentions, identifying the sociability potential of a MOOC environment. Future research should focus on:

1. stronger indicators of socially-driven intentions during enrollments, such as the need for belonging and relatedness, the will to engage in collaborative work, to integrate a learning community and group work;
2. objective indicators of socialization among MOOC learners, by analyzing their participation in discussion forums, their use of informal means of communication, their organization in local cohorts, and how all these social activities may lead to fulfilling optimal experience and well-being towards learning achievement and engagement.

5.4. Implications for practice

Research has already shown that social capital in a MOOC is a moderating factor towards co-regulated learning (Chaker and Impedovo, 2021), suggesting that the social dimension in online learning can become a lever on which instructional design can rely on, to reach positive learning outcomes. It also showed that “the sense of belonging in online learning platforms through formal and informal interaction” (p. 914) can act as means to enhance learning outcomes. As the perceived potential of sociability is an essential factor to foster enrollment in a MOOC and improve the learning experience, instructional designers as well as MOOC providers should further develop and communicate about social features in the learning environment. This includes providing and promoting learning and communication spaces such as forums, geolocation maps, team projects, social networks, or live videos sessions. Of course sociability is also “in person” and therefore “bolstering engagement through local cohorts taking courses together” (Kizilcec and Schneider, 2015) is paramount. In their study, Bulger et al. (2015) found that face-to-face MOOC meetings constitute an added extra to the learning experience, with students looking to create new

personal and professional connections. Instructional designers should also facilitate the use of complementary informal social media, especially for learners taking the course with friends/colleagues or from the same environment/context, so that they could use familiar tools for socializing and collaborating. Finally, as learners’ well-being is an important factor of success in MOOCs, underlying its importance for instructional designers could be a key element toward better online learning achievement and retention.

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