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To enrol or not to enrol: What are the risks in choosing a massive open online course (MOOC)?

Gábor Pörzse[1] · Zsófia Kenesei[2]

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Abstract

Massive open online courses (MOOCs) offer a unique opportunity for lifelong learning by providing a learning platform for a large and diverse audience. Although their popularity is still growing, industry experts had anticipated a higher level of acceptance than has actually occurred. One possible reason for the slower-than-expected growth is the perceived risk to learners. This study examines the factors influencing MOOC adoption based on perceived risk theory. Using survey-based quantitative analysis (with responses from 300 university students), the authors define four main dimensions of perceived risk: value, non-financial investment, social risk and security. Their findings show that uncertainty about the value offered by MOOCs is one of the most important dimensions in assessing risk. The second most important risk factor is learners' non-financial investment. The main sources of this investment, time and effort, are finite for learners and thus represent a critical dimension in the educational context of risk research. Social factors also have an impact on perceived risk, albeit to a lesser extent, while security factors do not. The results suggest that MOOC developers and providers play an important role in reducing risks associated with delivery uncertainty and in optimising learners' time and energy.

Keywords MOOC · perceived risk · value · non-financial investments · lifelong learning

Résumé

S'inscrire ou ne pas s'inscrire : quels sont les risques liés au choix d'un cours en ligne ouvert à tous (MOOC) ? – Les cours en ligne ouverts à tous (MOOC) offrent une opportunité unique d'apprentissage tout au long de la vie en fournissant une plate-

✉ Zsófia Kenesei
zsofia.kenesei@uni-corvinus.hu

Gábor Pörzse
porzse.gabor@semmelweis.hu

[1] Department of Social Sciences, Semmelweis University, Budapest, Hungary

[2] Institute of Marketing and Communication Sciences, Centre for International Higher Education Studies, Corvinus University of Budapest, Budapest, Hungary

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forme d'apprentissage à un public large et diversifié. Bien que la popularité de ces cours continue de croître, les experts du secteur attendaient un niveau d'acceptation plus élevé que celui constaté dans la réalité. L'une des raisons possibles de cette croissance plus lente que prévu réside dans le risque perçu par les apprenants. Cette étude examine les facteurs influençant l'adoption des MOOC sur la base de la théorie du risque perçu. À l'aide d'une analyse quantitative étayée par une enquête (réalisée auprès de 300 étudiants universitaires), les auteurs définissent quatre dimensions principales du risque perçu : la valeur, l'investissement non financier, le risque social et la sécurité. Leurs conclusions montrent que l'incertitude quant à la valeur apportée par les MOOC est l'un des aspects les plus importants dans l'évaluation des risques. Le deuxième facteur de risque le plus important est l'investissement non financier des apprenants. Les principales sources de cet investissement, à savoir le temps et les efforts, sont limitées pour les apprenants et représentent donc un aspect essentiel dans le contexte éducatif de la recherche sur les risques. Les facteurs sociaux ont également un impact sur la perception du risque, bien que dans une moindre mesure, contrairement aux facteurs de sécurité. Les résultats suggèrent que les concepteurs et les prestataires de MOOC jouent un rôle important dans la réduction des risques liés à l'incertitude de la prestation et dans l'optimisation du temps et de l'énergie des apprenants.

Introduction

Over the past decade, the development of digital technology has revolutionised education, creating new opportunities for learners worldwide. The phenomenon of massive open online courses (MOOCs) has brought about a paradigm shift in education that allows for broad, global access in different fields of knowledge. MOOCs are a form of online learning that allows participants to take courses regardless of their age, occupation or geographical location, and in some cases, their prior education level. The first MOOC was launched in 2008.[1] Since then, many universities, educational institutions and enterprises have embraced the initiative, offering free or paid courses to participants.

MOOCs play an important role in lifelong learning, which is increasingly becoming a vital component of modern education. They provide a flexible, accessible platform for individuals seeking to develop their knowledge and skills throughout life (Ossiannilsson et al. 2016). This educational model emphasises continuous personal and professional development, allowing learners to pursue their interests at their own pace and convenience. A key advantage of MOOCs is their openness, allowing anyone with internet access to participate in a wide range of courses. This

[1] In 2008, online learning specialist Stephen Downes and connectivism theorist George Siemens developed and taught a course on "Connectivism & Connective Knowledge". According to the McGill Association of University Teachers, "[t]heir intention was to exploit the possibility for interactions between a wide variety of participants made possible by online tools so as to provide a richer learning environment than traditional tools would allow. 25 students attended the course on the campus of the University of Manitoba, and a further 2,300 from around the world participated online" (MAUT n.d., online).

democratisation of education promotes an inclusive learning environment where individuals from diverse backgrounds can participate in lifelong learning (Kundu and Bej 2020). The flexibility of MOOCs allows learners to balance their educational aspirations with personal and professional commitments. This is an attractive option for those who may not have the time or resources to participate in traditional education or who wish to complement their university studies.

Moreover, MOOCs are designed to cater to different learning styles and preferences, offering a range of subjects and formats. This diversity encourages learners to explore new areas of interest, thereby promoting lifelong learning opportunities (Bordoloi et al. 2020). The possibility of accessing high-quality educational content from world-renowned institutions and experts further enhances the attractiveness of MOOCs as a source of lifelong learning (Bettiol et al. 2022).

One of the most recognised classifications divides MOOCs into two main types: xMOOCs and cMOOCs. Often associated with traditional teaching methods, xMOOCs (the x stands for extended) focus on delivering content through video presentations and assessments, concentrating on the acquisition and mastery of knowledge. In contrast, cMOOCs are rooted in connectivist pedagogy and support knowledge creation through collaborative learning and participant interaction (Keshavarz and Ghoneim 2021; Smith and Eng 2013). This distinction highlights the different teaching philosophies underlying these courses, with xMOOCs being more instructor-led and cMOOCs promoting a learner-centred environment.

MOOCs can also be classified according to their content and target audience. For example, some MOOCs focus on specific topics such as health, technology or sustainability, while others target specific demographic groups such as professionals seeking further education or students preparing for university (Hueske et al. 2021). This specialisation allows institutions to tailor their offerings to the needs of different learner groups, thereby increasing the relevance and applicability of courses.

One of the key advantages of MOOCs is that they can be delivered from anywhere, as long as the learner has an internet connection. However, the global reach of education in this way raises cultural, social and educational issues that may affect its acceptance (Loizzo and Ertmer 2016). In addition, the technological environment in which MOOCs operate varies significantly across regions. Factors such as internet accessibility, technological infrastructure and digital literacy levels can have a major impact on MOOC adoption (Ma and Lee 2019). The expectation of effort, such as the perceived ease of using technology, also plays a crucial role in determining behavioural intentions towards MOOCs (Wu and Chen 2017). This suggests that improving technological infrastructure and providing adequate training can facilitate greater adoption of MOOCs worldwide.

The main feature of MOOCs is their ability to accommodate large numbers of learners, creating extensive and diverse learning communities (Buhl and Andreasen 2018). However, the development of these courses has not unfolded as expected by industry experts (Shah 2023). Despite an initial surge in popularity and enthusiasm, MOOCs have faced significant challenges in terms of completion rates and monetisation.

Research on MOOCs has mainly focused on the benefits that facilitate adoption (Shah et al. 2021). While it is important to identify the factors contributing to the adoption of MOOCs, Vincent-Wayne Mitchell (1999) suggests that potential consumers (learners) tend to make decisions to reduce perceived risks rather than increase existing benefits. Hence, exploring risks is essential in understanding the background of learners' decisions. In the field of education, research studies (Doan 2021; Sarosa 2022) have already shown that perceived risk is an influential factor in the choice of online education. However, most studies do not identify the sources of this perceived risk or the underlying factors that make the decision risky and potentially discourage learners.

The main objective of our study was to identify the risk elements that learners enrolling in a MOOC face when making their decision. We pursued this objective through two research questions. The first sought to identify the elements of perceived risk in learning through MOOCs. The second was to consider how these risk factors affect learners' attitudes towards MOOCs and, ultimately, their decision to enrol. To address these questions, we conducted a survey targeting potential and current MOOC learners to gather insights on their perceptions of risk.

Our research took place in Hungary, a country with well-developed infrastructure similar to that of most European nations. However, the prevalence of MOOCs in Hungary does not match that of Western European countries (Statista 2025). While Western Europe leads in MOOC adoption, Eastern European nations, including Hungary, are increasingly recognising the value of MOOCs for enhancing educational access and promoting lifelong learning. The development of local platforms and courses tailored to regional needs became especially important during the COVID-19 pandemic. According to Statista (2025), 23% of Hungarians have participated in online courses or used online learning materials during their studies, which represents a 14 percentage-point increase compared to 2019. Notably, the use of online learning materials was particularly high among individuals aged 16 to 25.

Following a review of the literature, we present the study methodology and outline the two phases of the project. We then discuss the results and make theoretical and practical recommendations for MOOC design and implementation.

Literature review

Acceptance of MOOCs

Research based on the technology acceptance model, an extension of the theory of planned behaviour (Ajzen 1991), posits that perceived usefulness (PU) and perceived ease of use (PEOU) are critical determinants of students' intentions to adopt MOOCs. This approach aligns with the constructs of the theory of planned behaviour (Wu and Chen 2017; Tao et al 2022; Ucha 2023). The research also indicates that learners' computer self-efficacy significantly impacts their perceptions of both PU and PEOU, thereby influencing their acceptance of MOOCs (Al-Adwan 2020). Design of the MOOC platform, and academic and emotional support, also play vital roles in shaping learners' experiences and perceptions (Li and Luo 2024). Moreover, the motivation of learners, including their academic self-efficacy and engagement, significantly influences their acceptance of MOOCs (Alamri 2022).

Course design and content quality also emerge as pivotal elements that can either enhance or hinder user engagement, thereby affecting overall acceptance rates (Ucha 2023). High-quality courses that align with learners' needs and expectations tend to foster greater satisfaction and retention. Conversely, poorly designed courses can lead to frustration and disengagement, contributing to the high dropout rates often associated with MOOCs (Alemayehu and Chen 2023). Understanding these dynamics is essential for MOOC providers to tailor their offerings to better meet user expectations and improve adoption rates.

Cultural factors further complicate the acceptance of MOOCs. Different cultural contexts can shape learners' attitudes towards online education, influencing their willingness to adopt MOOCs. Fernanda Malaquias and Romes Da Silva (2020) highlight the importance of cultural dimensions such as uncertainty avoidance and masculinity in influencing the adoption of MOOCs. Their results suggest that MOOCs must be adapted to different learner groups' cultural contexts to increase their effectiveness. The role of language proficiency is a critical barrier to MOOC adoption, especially for non-native speakers of English. Long Ma and Chei Sian Lee (2019) emphasise that the majority of MOOCs are delivered in English, which poses a challenge for learners without native language skills. Learners in developing countries face several challenges when studying in MOOCs. Based on a qualitative study, Ma and Lee (2019) identified 14 factors that create resistance to accepting MOOCs, with self-control and internet access being the main concerns of learners.

Although various aspects of technology acceptance have been studied in MOOC research over the past few years, the issue of perceived risk associated with enrolling in a MOOC has not been emphasised.

Perceived risk theory

Risk research has a long history with regard to the purchase of services. Raymond Bauer (2001) is associated with defining perceived risk in purchase decision-making. In Bauer's interpretation, perceived risk is a psychological construct related to the uncertainty that a purchase situation represents (ibid.). Perceived risk can be linked to both the negative consequences of the outcome and the uncertainty associated with it. Overall, the greater the perceived risk associated with a product or service, the less likely consumers are to purchase it (Mitchell 1999). In the decades since, research on perceived risk has become a diverse and cross-disciplinary topic. Its most significant focus relates to the dimensions of risk. Jacob Jacoby and Leon B. Kaplan (1972) originally distinguished five dimensions of risk: physical, psychological, social, financial and performance-related risks.

Education and perceived risk

Perceived risk is a relatively under-researched topic in educational research, and it features even less in the studies investigating the phenomenon of MOOCs. This is somewhat surprising, as learners face a variety of uncertainties when purchasing an educational service. The main reason for the uncertainty is that educational services can be described as having mainly search and credence qualities (Shostack 1977). In education, search qualities are aspects you can judge before enrolling (e.g., tuition, curriculum outline, accreditation, facilities), while credence qualities are aspects that are hard to verify even after completing the course (e.g., the true quality of teaching, whether feedback genuinely improved the learner's skills). Thus, the outcome of the purchase is uncertain, with many unknowns. Moreover, learners often do not know at course completion to what extent they will use the knowledge, since this depends on future needs.

The consumption of educational services (i.e. enrolment in a course) is often not (only) a financial investment for learners, but also one of time and effort. As both time and effort spent on learning are finite, they represent a significant cost and increase the perceived risk for learners. Since the quality of education is difficult to estimate in advance, there is also a significant risk factor in whether learners will get exactly what they expect (Laroche et al. 2004). Traditional risks may be accompanied by additional elements for online services, such as data protection (Featherman and Pavlou 2003) and payment security (Mamman et al. 2015).

The issue of perceived risk in educational research has been investigated in two main areas: technology acceptance and COVID-19. Long Kim et al. (2022) found that perceived risk negatively affects perceived usefulness, while Samiaji Sarosa (2022) demonstrated that perceived risk has a direct negative effect on attitude and a partial mediating effect on intention to use online learning. From a different perspective, Thuy Thanh Thi Doan (2021) and Sheng-Ju Chan et al. (2023) found that the perceived risk of COVID-19 – a physical (health) risk dimension – had a direct positive effect on intention to use online learning, while V. G. Girish et al. (2022) found a direct positive effect on attitudes towards online learning. Nasser Sabah and Ali Altalbe (2022) examined the moderating role of perceived risk on the relationship between educational use of social media and satisfaction and academic performance. What these studies have in common is that they all treated risk as a unidimensional variable. For example, Kim et al. (2022) included financial and performance risk elements, while Sabah and Altalbe (2022) measured privacy and psychological risks on a common scale. Thus, the impact of each type of risk cannot be isolated nor the factors examined separately.

Dimensions of perceived risk in education

The only area where the dimensions of perceived risk have been investigated in an educational context is in international education. Norazlyn Kamal Basha et al. (2015) examined the factors that contribute to the perceived risks of studying abroad. In their study, they grouped the dimensions of risk into three categories: performance-related, financial and social risks. Jason Lam et al. (2017) differentiated seven risk factors when studying perceived risk and the risk reduction strategies of international students: security, physical and tension-related, time and opportunity-related, social, financial, performance-related and psychological risks.

Based on this extant risk research, we identified six factors that cover the risks related to MOOC education:

(1) *Financial risk* – potential expenditure in relation to purchase price (Grewal et al. 1994). Two types of costs are associated with MOOCs: the cost of the course itself and the cost of internet connection, with the associated risk that the financial investment will not be recouped (Ma and Lee 2019).
(2) *Social risk* – potential loss of status in one's social group due to purchase of the product or service – in this case, the course (Mitchell 1992).
(3) *Security risk* – uncertainty associated with how personal and financial transaction data are handled (Kamalul Ariffin et al. 2018).
(4) *Performance risk* – uncertainty about whether the product or service will perform as expected; it might fail to deliver the desired benefits (Grewal et al. 1994).
(5) *Psychological risk* – consumer self-perception when purchasing a product or service (Mitchell 1992). In a MOOC context, the main psychological threat learners face is lack of self-motivation and self-regulation to finish the course (Danka 2020).
(6) *Time risk* – possible waste of time invested by consumers in researching and making a purchase (Mitchell 1992). In MOOCs – besides effort and money – time is the biggest investment learners make (Li et al. 2022). In addition, René Kizilcec and Sherif Halawa (2015) reported that the main reason for attrition is deadlines and time constraints perceived by learners.

Research questions and method

Although qualitative studies indicate that learning in MOOCs requires significant time, energy and often financial investment (Ma and Lee 2019), the risks associated with enrolling in and learning from MOOCs are not well researched. Consequently, the main purpose of our study was to explore these risks and to highlight the impact of each factor on MOOC adoption. Based on our objective, our two main research questions (RQs) were:

RQ1: *What are the various risks associated with learning through MOOCs?*
RQ2: *How might these risks impact learners' future adoption of MOOCs?*

To answer these questions, we designed a survey to define risk dimensions and to assess the impact of the determined dimensions. We divided our analysis into two phases. In the first phase, we tested the perceived risk dimensions with the help of exploratory factor analysis and confirmatory factor analysis. Based on the results, we then used structural equation modelling (SEM) to test the relationship between the dimensions of risk and future behavioural intentions.

Phase 1

Scale development

As there is limited research on the risks of using educational services, we developed our survey questionnaire and scale items based on: traditional risk research (Grewal et al. 1994; Mitchell 1992); scales already existing in education but also used in other contexts (Kamal Basha et al. 2015; Lam et al. 2017); and online risk scales (Featherman and Pavlou 2003; Kamalul Ariffin et al. 2018). To better understand the risk factors that influence MOOC adoption, we also drew on previous research that examined barriers to enrolling in MOOCs (Ma and Lee 2019), reckoning that its inclusion might provide a good approximation of the risk factors learners face.

In addition, in a qualitative component of the study, we interviewed learners who had already participated in a MOOC, as well as those who had never registered for a course (but had knowledge of them), about their risk perception, and asked them to rate the scale items we had developed based on the literature. In this phase, one-on-one face-to-face in-depth interviews were conducted with 13 respondents (7 female, 6 male) who gave qualitative feedback on their experiences and evaluated the scale items presented. Out of the 13 respondents, seven had already participated in a MOOC, while six had never taken such a course, although they were familiar with the concept. Both groups of respondents were necessary to help identify the risk factors that are most likely to impede enrolment.

Based on our interpretation of the literature on MOOCs and feedback from the qualitative interviews, we finalised the scale dimensions and corresponding scale items of risks of learning in a MOOC. Table 1 presents the scale dimensions and corresponding scale items, along with sources and means with standard deviations.

Sample

Following development of the questionnaire and scale items, we recruited potential respondents with any knowledge of MOOCs, even if they had not yet enrolled in one. We initially piloted the questionnaire with 20 university students and refined it based on their feedback. We then published the questionnaire on the Qualtrics online platform and used a convenience sampling method by sharing it on Hungarian university forums. To accelerate completion, we offered festival tickets to respondents as an incentive. The first question was a screening one to filter out those who were not familiar with the educational form of a MOOC. In total, 300 respondents submitted a response, of which 58% were female, with an average age of 24 years, and 72% were students at various universities. The demographic details of the sample can be found in Table 2.

Among our respondents, 30% had already registered for a MOOC. Of those who registered, 49% had completed their course. Most participants (67%) reported enrolling in between two and four MOOCs, while 23% had registered for only one course and 33% had enrolled in more than four. Additionally, most courses on offer (69%) were free of charge. Around half of the courses (53%) were conducted in Hungarian, while nearly half (44.5%) were in a foreign language, primarily English.

Table 1 Scale dimensions and items with means, standard deviations and sources

Scale dimensions and items	min.	max.	*M*	*SD*	Source
Financial risk (FR)					Featherman and Pavlou (2003); Ma and Lee (2019)
The course may not be worth the money I spent.	1	5	2.62	1.211	
It can be expensive to get an internet connection.	1	5	1.67	1.016	
Social risk (SoR)					Kamalul Ariffin et al. (2018)
Enrolling in a MOOC may not be recognised by relatives or friends.	1	5	1.73	1.110	
Enrolling in a MOOC may result in disapproval from my friends and relatives.	1	5	1.71	1.082	
Security risk (SeR)					Kamalul Ariffin et al. (2018)
My credit or debit card details are not secured.	1	5	1.88	1.161	
The website can be insecure.	1	5	1.95	1.177	
Performance risk (PeR)					Masoud (2013)
I may not get professional knowledge.	1	5	2.61	1.173	
I may not receive what I expect to get.	1	5	2.80	1.182	
I might not receive the exact quality of a course that I expect.	1	5	2.82	1.159	
It is difficult for me to assess the quality of the course.	1	5	3.29	1.245	
Psychological risk (PsR)					Kamalul Ariffin et al. (2018)
It takes too much effort to complete the course.	1	5	2.72	1.212	
I will not be motivated enough to finish the course.	1	5	2.74	1.313	
Time risk (TR)					Featherman and Pavlou (2003)
Enrolling in a MOOC may be a waste of time.	1	5	2.80	1.263	
I will not have sufficient time to finish the course.	1	5	2.80	1.333	

Note: M = mean; *SD* = standard deviation

Table 2 Demographic distribution of the study sample

Demographic	Number of respondents	Percentage of total respondents
Gender		
Male	126	42
Female	174	58
Status		
Student	218	72
Employed	70	23
Self-employed	10	3
Inactive (e.g. retired)	2	1
Residence		
Capital city	147	49
City	124	41
Village	29	10
Age		
20 or under	67	22
21–30	204	68
31–50	23	8
51 or older	6	2
Education		
Elementary school	2	1
Secondary school	188	62
Bachelor of Arts degree	77	26
Master's or higher degree	33	11

Scale development results

First, we employed exploratory factor analysis (EFA) to check the dimensionality of the constructs, using SPSS v27. We tested the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (0.87) and Bartlett's test of sphericity ($p < 0.001$). Both values indicated that our data were highly acceptable to perform factor analysis. We then included all 14 items and conducted a principal component analysis (PCA) using varimax rotation with Kaiser normalisation. The cumulative variance contribution rate was 78%. The factor loadings can be found in Table 3.

The results indicate that the two financial risk items did not form one factor. The lowest average risk was given by respondents to the financial risk of the internet (Table 1). However, while internet cost may not cause a problem for learners, course prices were of greater concern. Based on this result, we deleted the statement "It can be expensive to get an internet connection" from the item pool and used the remaining 13 items in our further analysis.

An additional result of our factor analysis was that financial risk and performance risk items were combined into one factor, suggesting that respondents tended to view courses from a value-oriented perspective. Thus, we used a common value

Table 3 Exploratory factor analysis*

Scale item	Value risk factor	Non-financial investment risk factor	Security risk factor	Social risk factor	Factor 5
I may not receive what I expect to get.	**0.807**	0.231	0.134	0.086	–0.133
I might not receive the exact quality of a course that I expect.	**0.803**	0.209	0.118	0.063	0.218
I may not get professional knowledge.	**0.792**	0.182	0.190	0.242	0.032
It is difficult for me to assess the quality of the course.	**0.726**	0.320	0.114	–0.047	0.232
The course may not be worth the money I spent.	**0.598**	0.296	0.277	0.291	–0.185
I will not be motivated enough to finish the course.	0.180	**0.855**	0.058	0.069	–0.067
I will not have sufficient time to finish the course.	0.271	**0.825**	–0.035	0.087	0.062
It takes too much effort to complete the course.	0.233	**0.787**	0.231	0.074	0.058
Enrolling in a MOOC may be a waste of time.	0.299	**0.695**	0.075	0.235	0.257
My credit or debit card details are not secured.	0.233	0.100	**0.894**	0.169	0.105
The website can be insecure.	0.201	0.090	**0.893**	0.172	0.125
Enrolling in a MOOC may not be recognised by relatives or friends.	0.121	0.099	0.139	**0.901**	0.105
Enrolling in a MOOC may result in disapproval from my friends and relatives.	0.147	0.170	0.193	**0.822**	0.209
It can be expensive to get an internet connection.	0.075	0.110	0.204	0.301	**0.841**

Note: *Bold figures indicate the corresponding factor risk factor in our further analysis. Similarly, psychological risk and time risk items resulted in a common factor, suggesting that both represented some form of personal non-financial investment for respondents in the case of MOOCs. Finally, social risk and security risk items formed separate factors as expected. Factor 5 was excluded from further analysis. In the remainder of our analysis, we examine the impact of the four emerging risk factors: value, non-financial investment, social factors and security.

Confirmatory factor analysis

In the next stage, we assessed the internal consistency and reliability of the newly formed composite measures, with the help of confirmatory factor analysis (CFA) and Cronbach's alpha. Cronbach's alpha for the six constructs ranged from 0.77 to 0.91, suggesting that the latent measures were acceptably reliable (Table 4). For the factor weights, we set the minimum values generally at 0.5 with *p*-values below 0.001. All item-to-construct loadings reached the threshold level of 0.50, and all the loadings were significant, supporting convergent validity.

Table 4 Factor loadings and Cronbach's alpha

Construct	Factor loading	Cronbach's alpha
Non-financial investment risk		0.86
NFR1	0.766	
NFR2	0.785	
NFR3	0.815	
NFR4	0.783	
Social risk		0.83
SoR1	0.907	
SoR2	0.787	
Security risk		0.89
SeR1	0.892	
SeR2	0.914	
Value risk		0.87
VR1	0.789	
VR2	0.775	
VR3	0.703	
VR4	0.827	
VR5	0.726	
Attitude		0.77
ATT1	0.658	
ATT2	0.745	
ATT3	0.789	
Behavioural intention		0.88
BI1	0.866	
BI2	0.904	

Table 5 Discriminant validity*

	CR	AVE	Attitude	NFI risk	Social risk	Security risk	Value risk	BI
Attitude	0,804	0,508	0,712					
NFI risk	0,867	0,620	–0,382	0,787				
Social risk	0,837	0,721	–0,358	0,396	0,849			
Security risk	0,898	0,816	–0,303	0,320	0,473	0,903		
Value risk	0,876	0,586	–0,432	0,663	0,421	0,514	0,765	
BI	0,879	0,784	0,526	–0,224	–0,158	–0,109	–0,210	0,885

Note: *Correlation matrix, where values along the diagonal are the square root of average variance extracted (AVE); CR = composite reliability; NFI = non-financial investment; BI = behavioural intention

Table 6 Goodness-of-fit indices

Index	Recommended criteria value	Measurement model	Structural model
χ^2/df	< 3	1.79	2.14
CFI	> 0.90	0.96	0.94
NFI	> 0.90	0.92	0.91
RMSEA	< 0.08	0.051	0.068

Note: χ^2/df = Chi-square divided by degrees of freedom; CFI = comparative fit index; NFI = Normed fit index; RMSEA = root mean square error of approximation

We found the composite reliability (CR) to be above the cut-off value 0.7, so the scales were reliable (Hair et al. 2014). Average variance extracted (AVE) values exceeded the threshold level of 0.5 (Table 4). We checked and accepted discriminant validity using Claes Fornell and David Larcker's (1981) criterion, as the AVE square root values were just above the correlation values, so the discriminant validity of the model was also adequate (Table 5).

Table 6 summarises the results of the goodness-of-fit indices. The values indicate a good fit for the measurement model.

Phase 2

To answer our second research question, on the impact of risks on learners' future adoption of MOOCs, we first developed five hypotheses (*H*) that we could test. Based on the theory of planned behaviour (Ajzen 1991), we proposed that the risk dimensions would first create a general positive or negative attitude towards MOOCs which would then affect the intention to use them. In a study of perceived risks on the use of online learning by high school students, Sarosa (2022) proved that perceived risk affects intention to use, with the mediation of attitude. Our hypotheses were:

H1 Perceived value risk has a negative impact on attitudes towards MOOCs.

H2 Perceived non-financial investment risk has a negative impact on attitudes towards MOOCs.
H3 Perceived social risk has a negative impact on attitudes towards MOOCs.
H4 Perceived security risk has a negative impact on attitudes towards MOOCs.
H5 A positive attitude towards MOOCs increases the intention to use them.

In this second phase, we tested the hypotheses using structural equation modelling (SEM). SEM is an adequate method to simultaneously analyse all relationships between observed and unobserved (latent) variables (Hair et al. 2014). We used IBM SPSS Statistics v27 for data cleaning, descriptive statistics and EFA, and IBM SPSS Amos Graphics v27 for modelling and hypothesis testing.

Results

Assessment of the structural model

To test our hypotheses, we employed SEM to analyse complex relationships among the multiple variables. It has the advantage of assessing measurement error and estimating latent variables based on the observed variables (Byrne 2016). Based on the model assessment (Table 7), we found that the value risk significantly negatively influenced attitudes towards MOOCs (β = –0.25), as did non-financial investment risk (β = –0.17) and social risk (β = –0.20). Based on these results, we accepted *H1*, *H2* and *H3*. The effect of security risk was not significant (β = 0.06); thus, we rejected *H4*. Attitude was found to positively influence future behaviour towards accepting MOOCs (β = 0.50), so we accepted *H5*.

Mediation analysis

Based on our theoretical model, we speculated that attitude might mediate the relationship between the risk dimensions and intention to enrol in a MOOC. To test whether mediation existed, and to determine the type of mediation, we used a

Table 7 Results of hypothesis testing

Structural relationship	Standardised regression weight	*t*-value	Result
Value risk => Attitude	–0.252***	–3.68	*H1* is accepted
Non-financial investment risk => Attitude	–0.174*	–2.58	*H2* is accepted
Social risk => Attitude	–0.198*	–2.45	*H3* is accepted
Security risk => Attitude	–0.056 (ns)	–0.74	*H4* is not accepted
Attitude => Behavioural intent	0.50***	6.44	*H5* is accepted

*p < 0,05; ***p < 0,001; ns = not significant

bootstrap method to analyse the indirect and direct effects (Hayes 2013). Table 8 presents the results of the mediation analysis.

Our mediation analysis provided evidence that value risk, non-financial investment risk and social risk indirectly affected behavioural intention to enrol in a MOOC, through attitude towards MOOCs. The insignificant direct effects in these cases suggest that there is a full mediation between the variables.

Discussion and theoretical implications

In the study presented here, we examined the risks of MOOCs from the perspective of learners. It is important to consider risk because the quality of educational services, especially those offered online, is difficult to determine in advance but requires a significant investment – both financially and in terms of time and effort. While in other areas, such as e-commerce and banking, several studies have explored the role of perceived risk in purchasing decisions (Lee et al. 2019; Masoud 2013), research on the impact of risk in the field of education is scarce (Kim et al. 2022; Sarosa 2022). Even less researched is the distinction between the dimensions of perceived risk and their impacts on learners' decisions (Kamal Basha et al. 2015; Lam et al. 2017).

We first developed scale items to measure the dimensions of perceived risk of enrolling in a MOOC, and then examined the extent to which the dimensions affected our respondents' future usage intentions. In our analysis, we tested the variables for six dimensions of risk found in education or other contexts: financial, social, security-related, performance-related, psychological and time-related

Table 8 Mediation analysis

Indirect effect	Standardised indirect effect	Percentile 95% confidence intervals	
		Lower	Upper
Value risk => Attitude => BI	–0.131*	–0.244	–0.04
Non-financial investment risk => Attitude => BI	–0.086*	–0.174	–0.014
Social risk => Attitude => BI	–0.103*	–0.200	–0.004
Security risk => Attitude => BI	–0.033 ns	–0.158	0.042
Direct effect	**Standardised direct effect**	**Percentile 95% confidence intervals**	
		Lower	Upper
Value risk => BI	0.018 ns	–0.166	0.204
Non-financial investment risk => BI	–0.048 ns	–0.214	0.107
Social risk => BI	0.016 ns	–0.152	0.196
Security risk => BI	0.056 ns	–0.126	0.212

* $p < 0{,}05$; *** $p < 0{,}001$; ns = not significant; BI = behavioural intention

risks. This disaggregation of perceived risk into dimensions, and exploration of its impacts, is an important contribution of our study to understanding the slower-than-expected growth in MOOC adoption. While past research into online education has only measured the impact of perceived risk in general terms (Sarosa 2022), our study not only confirms that perceived risk has an important impact on future enrolment but also shows which of the different types of risk are most important and have the greatest impact on learners' decision to enrol.

Below, we examine each of the four risk factors that emerged from our analysis – value, non-financial investment, social risk and security – in more detail.

Value risk

Based on the results of the EFA, we aggregated the performance and financial risk dimensions into one common dimension: value risk. The survey respondents frequently perceived a significant risk in not being certain they were receiving what they paid for (i.e. value for money) with regard to MOOCs. In other cases, respondents suggested that a major risk was the difficulty in assessing course quality in advance; thus, they were reluctant to pay a large amount for a course upfront. These responses point to a kind of value-based risk perception. With this mindset, performance uncertainty is closely related to perceived risk regarding the return on financial investment and "worth the price"-type thinking. The results of our hypothesis testing suggest that value risk has the strongest effect on attitudes, indicating that it is particularly important to provide information that helps learners assess the quality of a MOOC in advance. In contrast to countries where internet access can lead to issues (Ma and Lee 2019), our findings suggest that in regions where the internet is widely accessible and integrated into daily life, financial risks associated with internet connectivity do not deter learners from the use of MOOCs. As a result, these financial implications do not pose a significant risk factor in such contexts.

Non-financial investment risk

In many cases – especially if a MOOC is free or low-priced – the main investment for learners is the time and intellectual effort spent on training. Research on MOOCs has confirmed that one of the biggest difficulties in completing a course is investing sufficient time and effort (Li et al. 2022; Reparaz et al. 2020). From this point of view, and supported by our analysis of the study responses, time and effort function similarly as psychological risk factors; therefore, we grouped them into a single factor. Respondents perceived the risk of non-financial investment as relatively high, and we found its effect on attitudes to be significant. Although the dimensions of perceived risk have not been distinguished in previous research on online education, it is important to highlight the role of non-financial investment, as we found it to be the second most important risk factor in our study, after uncertainty about the value a MOOC can offer. Contrary to commonly accepted risk dimensions of other online services (Featherman and Pavlou 2003), in the case of online education, the time and effort learners must invest seem to be critical in evaluating the possible risks they face.

Social risk

The effect of social risk on attitudes towards MOOCs was moderately strong in our results. This indicates that, although social risk was not considered significant based on average responses, for individuals who perceived it as a major risk, it may strongly influence their intention to enrol. This suggests that there is a group of learners for whom peer pressure and acceptance are important considerations for future MOOC use.

Security risk

Despite the growing importance of privacy today, our study shows that it is neither a particularly strong nor influential factor in MOOC adoption. This result somewhat contradicts previous research findings in other industries (Featherman and Pavlou 2003; Lee et al. 2019), insofar as two interpretations of our results are possible. Either this finding indicates that learners perceive MOOC platforms as secure and use them just like any other university learning management system (e.g. Moodle), or it suggests they are not particularly concerned about the security of their data in educational services.

Beyond identifying the dimensions of perceived risk, an important finding from our study is that each risk dimension does not directly affect intention to use; rather, its effect occurs through attitude, with full mediation. Thus, attitude plays a significant role in MOOC adoption. Consequently, attitudes towards MOOCs must first be positively shaped before potential learners opt into enrolment. Our results suggest that reducing certain risk factors holds the potential to influence learner attitudes in a positive direction.

Recommendations for MOOC design and implementation

Besides the theoretical contributions, this study has important practical implications for educators, institutions and policymakers. The first conclusion we can draw from our findings is that learners face multiple risk factors when making decisions about MOOCs. These risk factors can vary greatly between individuals, so MOOC developers need to know their target audience well enough to be able to identify the factors that are most crucial to them. Accordingly, when designing a MOOC, the focus should be on the risk factors that are most relevant to potential learners. Our main recommendation in this respect is that, in addition to identifying the needs of the target audience during preliminary market research, it is important to also assess the risks they face before the enrolment decision.

Value risk

An important finding of our research is that users assess performance on a value basis – that is, they do not separate performance from the price paid for it. This attitude is best illustrated by learners' responses that, unless they are sure about quality, they are reluctant to pay for such a course. Thus, the issue is not whether a MOOC is cheap or expensive, but whether it is worth the price. As it has traditionally been difficult to assess the quality of educational services in advance (which is why value was found to be the most important risk factor), it is important for institutions offering a MOOC to use all the tools they can to help learners assess quality before they enrol.

One aspect that can increase value perception is quality assurance of MOOCs. Quality assurance can take two forms: external and internal. External quality assurance mainly refers to certificates and accreditations. In this case, an external quality assurance system assures learners that they are paying for a reliable course. A similar function is involved when a MOOC provider develops courses in partnership with a university. Internal quality assurance requires developing processes to ensure all courses meet quality standards. An important part of this process is developing quality standards for MOOCs and helping instructors produce courses that meet them. These standards are a key factor in consistent and reliable course quality.

To reduce value risk, quality must not only be developed but also communicated to potential learners. There are several aspects to this. On the one hand, appropriate communication shapes expectations, making it clear to learners what to expect during a course. On the other hand, it provides assurances of quality. Such assurances can include, for example, a money-back guarantee, which is a powerful risk mitigation tool. Another important tool for communicating quality is conducting a review of learners who have already completed a course. The importance of reviews cannot be underestimated, as an important way to reduce risk is to explore the experiences of learners who have already completed the course.

In the communication and promotion of MOOCs, it is worth focusing on the value a course can bring to learners' lives. Accordingly, it is worth highlighting the opportunities that can arise by completing the course, and the knowledge that learners will gain. If the course is vocational, the types of jobs that can be obtained on completion of the course, and the types of roles that can be filled, can be communicated. It is also possible to contact former students who have successfully applied for a job as a result of the course and ask them to endorse it.

Non-financial investment risk

The second most important attitude-forming risk element is the risk of wasted time and effort. If learners feel it is risky to invest sufficient time and effort in a course in order to complete it, they are unlikely to enrol. In light of this finding, courses should be designed both to estimate the time and effort required in advance and to give learners as much opportunity as possible to complete the course. A consistent and clearly articulated framework and learning activities that are feasible with regard to student workload should also be established.

Self-management tools commonly offered by MOOCs may also serve to reduce non-financial investment risk. This type of risk reduction tool can help students with goal-setting strategies, such as giving them a detailed description of the time needed to complete each learning task. The inclusion of a calendar function can also help with planning.

Finally, interaction with either the teacher or with fellow students can help learners navigate the more difficult parts of a course. Participants in the qualitative interviews we conducted during Phase 1 of our study mentioned that the possibility of interaction with fellow students can be very helpful in coping with more difficult periods and parts of the curriculum. Thus, creating discussion forums or any other communication method can benefit learners.

Social risk

Social risk has a significant impact on learners' attitudes and, hence, future use of MOOCs. Therefore, a learner's social environment is relevant to participation in a MOOC. The social environment of learners comprises both controllable and uncontrollable elements. Interaction with former or current students can help reinforce a potential learner's intentions and reduce social risk. Again, this can be improved through the use of communication tools such as student forums and common chat areas. Encouraging positive word-of-mouth (WOM) feedback is significant in this context. Thus, institutions offering MOOCs should find ways to promote their courses through WOM or e-WOM. When designing testimonials, presenting the experiences of former learners similar to the target cohort of the course can also help to reduce social risk.

Limitations and future research

This study has some limitations, which provide an opportunity for further research. It is possible that there are regional specificities in our results and that different risk factors would be more pronounced in other sociocultural contexts. In this respect, it is worth extending risk research to other regions. Additionally, part of our sample (28%) included non-student respondents. It may be worthwhile conducting a survey specifically with this target group, as their perception of risk may be different to that of other age groups. In this study, we also did not address the factors that learners use to reduce their risks, although this is an important next step in exploring perceived risks. It may be worthwhile to conduct a study to investigate risk reduction strategies for each type of risk. Finally, an important issue for MOOCs is trust. Perceived risk and trust are closely related, so exploring this relationship could lead to interesting results.

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References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Adwan, A. S. (2020). Investigating the drivers and barriers to MOOCs adoption: The perspective of TAM. *Education and information technologies, 25*(6), 5771–5795. https://doi.org/10.1007/s10639-020-10250-z

Alamri, M. M. (2022). Investigating students' adoption of MOOCs during COVID-19 pandemic: Students' academic self-efficacy, learning engagement, and learning persistence. *Sustainability*, *14*(2), Article no. 714. https://doi.org/10.3390/su14020714

Alemayehu, L., & Chen, H. L. (2023). Learner and instructor-related challenges for learners' engagement in MOOCs: A review of 2014–2020 publications in selected SSCI indexed journals. *Interactive Learning Environments, 31*(5), 3172–3194. https://doi.org/10.1080/10494820.2021.1920430

Bauer, R. A. (2001). Consumer behavior as risk taking. In M. J. Baker (Ed.), *Marketing: Critical perspectives on business and management* (Vol. 3, pp. 13–21). Routledge.

Bettiol, S., Psereckis, R., & Macintyre, K. (2022). A perspective of massive open online courses (MOOCs) and public health. *Frontiers in Public Health, 10,* Article no. 1058383. https://doi.org/10.3389/fpubh.2022.1058383

Bordoloi, R., Das, P., & Das, K. (2020). Lifelong learning opportunities through MOOCs in India. *Asian Association of Open Universities Journal, 15*(1), 83–95. https://doi.org/10.1108/AAOUJ-09-2019-0042

Buhl, M., & Andreasen, L. B. (2018). Learning potentials and educational challenges of massive open online courses (MOOCs) in lifelong learning. *International Review of Education, 64*(2), 151–160. https://doi.org/10.1007/s11159-018-9716-z

Byrne, B. M. (2016). *Structural equations with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge.

Chan, S. J., Nong, T. X., & Nguyen, T. T. T. (2023). Students' online learning adoption during an emergency situation: Integrating the self-determination and perceived risk theories. *Human Behavior and Emerging Technologies*, *2023*(1), Article no. 128584. https://doi.org/10.1155/2023/6128584

Danka, I. (2020). Motivation by gamification: Adapting motivational tools of massively multiplayer online role-playing games (MMORPGs) for peer-to-peer assessment in connectivist massive open online courses (cMOOCs). *International Review of Education, 66*(1), 75–92. https://link.springer.com/article/10.1007/s11159-020-09821-6

Doan, T. T. T. (2021). The effect of perceived risk and technology self-efficacy on online learning intention: An empirical study in Vietnam. *The Journal of Asian Finance, Economics and Business*, *8*(10), 385–393. https://doi.org/10.13106/jafeb.2021.vol8.no10.0385

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Fornell, C., & Larcker, D. F. (1981). Evaluation structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Girish, V. G., Kim, M. Y., Sharma, I., & Lee, C. K. (2022). Examining the structural relationships among e-learning interactivity, uncertainty avoidance, and perceived risks of COVID-19: Applying extended technology acceptance model. *International Journal of Human-Computer Interaction, 38*(8), 742–752. https://doi.org/10.1080/10447318.2021.1970430

Grewal, D., Gotlieb, J., & Marmorstein, H. (1994). The moderating effects of message framing and source credibility on the price-perceived risk relationship. *Journal of Consumer Research, 21*(1), 145–153. https://doi.org/10.1086/209388

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. M. (2014). *A premier on partial least squares structural equation modeling (PLS-SEM)*. SAGE.

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis. A regression-based approach*. Guilford Press.

Hueske, A., Pontoppidan, C., & Iosif-Lazăr, L. (2021). Sustainable development in higher education in Nordic countries: exploring e-learning mechanisms and SDG coverage in MOOCs. *International Journal of Sustainability in Higher Education, 23*(1), 196–211. https://doi.org/10.1108/ijshe-07-2020-0276

Jacoby, J., & Kaplan, L. B. (1972). The components of perceived risk. In *Proceedings of the Annual Conference of the Association for Consumer Research, 10,* (pp. 382–393). West Lafayette, IN: Department of Psychological Sciences, Purdue University Advertising Research Department. Manuscript retrieved 17 November 2025 from https://www.researchgate.net/publication/247814928_The_Components_Of_Perceived_Risk

Kamal Basha, N., Sweeney, J. C., & Soutar, G. (2015). Effects of country and delivery mode on perceived risk in international higher education. *Journal of Marketing for Higher Education, 25*(2), 171–203. https://doi.org/10.1080/08841241.2015.1031313

Kamalul Ariffin, S., Mohan, T., & Goh, Y. N. (2018). Influence of consumers' perceived risk on consumers' online purchase intention. *Journal of Research in Interactive Marketing, 12*(3), 309–327. https://doi.org/10.1108/JRIM-11-2017-0100

Keshavarz, M., & Ghoneim, A. (2021). Preparing educators to teach in a digital age. *The International Review of Research in Open and Distributed Learning, 22*(1), 221–242. https://doi.org/10.19173/irrodl.v22i1.4910

Kim, L., Pongsakornrungsilp, P., Pongsakornrungsilp, S., Cattapan, T., & Nantavisit, N. (2022). Determinants of perceived e-learning usefulness in higher education: A case of Thailand. *Innovative Marketing, 18*(4), 86–96. https://doi.org/10.21511/im.18(4).2022.08

Kizilcec, R. F., & Halawa, S. (2015). Attrition and achievement gaps in online learning. In *Proceedings of L@S 2015, the second ACM conference on learning@ scale* (pp. 57–66). New York: Association for Computing Machinery (ACM). https://doi.org/10.1145/2724660.2724680

Kundu, A., & Bej, T. (2020). Perceptions of MOOCs among Indian state university students and teachers. *Journal of Applied Research in Higher Education, 12*(5), 1095–1115. https://doi.org/10.1108/JARHE-08-2019-0224

Lam, J. M., Tong, D. Y. K., & Ariffin, A. A. M. (2017). Exploring perceived risk and risk reduction strategies in the pursuit of higher education abroad: A case of international students in Malaysia. *Journal of Studies in International Education, 21*(2), 83–104. https://doi.org/10.1177/1028315316662980

Laroche, M., McDougall, G. H., Bergeron, J., & Yang, Z. (2004). Exploring how intangibility affects perceived risk. *Journal of Service Research, 6*(4), 373–389. https://doi.org/10.1177/1094670503262955

Lee, J. M., Lee, B., & Rha, J. Y. (2019). Determinants of mobile payment usage and the moderating effect of gender: Extending the UTAUT model with privacy risk. *International Journal of Electronic Commerce Studies, 10*(1), 43–64. https://doi.org/10.7903/ijecs.1644

Li, H., & Luo, Z. (2024). University students' acceptance intention to MOOC learning: The involvement of academic and emotional support. In *Proceedings of the 2024 9th International Conference on Distance Education and Learning (ICDEL '24)* (pp. 382–387). New York: Association for Computing Machinery (ACM). https://doi.org/10.1145/3675812.3675830

Li, S., Wang, S., Du, J., Pei, Y., & Shen, X. (2022). MOOC learners' time-investment patterns and temporal-learning characteristics. *Journal of Computer Assisted Learning, 38*(1), 152–166. https://doi.org/10.1111/jcal.12597

Loizzo, J., & Ertmer, P. A. (2016). MOOCocracy: The learning culture of massive open online courses. *Educational Technology Research and Development, 64*(6), 1013–1032.

Ma, L., & Lee, C. S. (2019). Understanding the barriers to the use of MOOCs in a developing country: An innovation resistance perspective. *Journal of Educational Computing Research, 57*(3), 571–590. https://doi.org/10.1177/0735633118757732

Malaquias, F. F. D. O., & Da Silva, R. J. (2020). Understanding cultural determinants of MOOCs offering: A cross-country study. *Turkish Online Journal of Distance Education, 21*(4), 195–205. Retrieved 17 November 2025 from https://dergipark.org.tr/tr/download/article-file/1321343

Mamman, H., Maidawa, M., & Saleh, M. (2015). Effects of perceived risk on online shopping. In *Proceedings of the 1st Management, Technology, and Development Conference* (pp. 318–323). Bauchi, Nigeria: ATB University Bauchi. Retrieved 17 November 2025 from https://www.researchgate.net/publication/376812428_Effects_of_Perceived_Risk_on_Online_Shopping

Masoud, E. Y. (2013). The effect of perceived risk on online shopping in Jordan. *European Journal of Business and Management, 5*(6), 76–87.

MAUT (McGill Association of University Teachers) (n.d.). A brief history of MOOCs [McGill University web content]. Retrieved 15 December 2025 from https://www.mcgill.ca/maut/news-current-affairs/moocs/history

Mitchell, V. W. (1992). Understanding consumers' behaviour: can perceived risk theory help? *Management decision*, *30*(3), online. https://doi.org/10.1108/00251749210013050

Mitchell, V. W. (1999). Consumer perceived risk: conceptualisations and models. *European Journal of marketing, 33*(1/2), 163–195. https://doi.org/10.1108/03090569910249229

Ossiannilsson, E., Altinay, F., & Altinay, Z. (2016). MOOCs as change agents to boost innovation in higher education learning arenas. *Education Sciences*, *6*(3), Article no. 25. https://doi.org/10.3390/educsci6030025

Reparaz, C., Aznárez-Sanado, M., & Mendoza, G. (2020). Self-regulation of learning and MOOC retention. *Computers in Human Behavior*, *111*, Article no. 106423. https://doi.org/10.1016/j.chb.2020.106423

Sabah, N. M., & Altalbe, A. A. (2022). Learning outcomes of educational usage of social media: The moderating roles of task–technology fit and perceived risk. *Sustainability*, *14*(14), Article no. 8895. https://doi.org/10.3390/su14148895

Sarosa, S. (2022). The effect of perceived risks and perceived cost on using online learning by high school students. *Procedia Computer Science, 197*, 477–483. https://doi.org/10.1016/j.procs.2021.12.164

Shah, D. (2023). 2022 year in review: The "new normal" that wasn't. *Class Central,* 9 January [online article]. Retrieved 17 November 2025 from https://www.classcentral.com/report/2022-year-in-review/

Shah, J., Khanna, M., & Patel, H. (2021). Technology adoption and continuance of MOOCs: A systematic literature review, synthesis and future research agenda. *Journal of Content, Community and Communication, 14*(7), 106–132. https://doi.org/10.31620/JCCC.12.21/10

Shostack, G. L. (1977). Breaking free from product marketing. *Journal of Marketing, 41*(2), 73–80. https://doi.org/10.1177/002224297704100219

Smith, B., & Eng, M. (2013). MOOCs: A learning journey: Two continuing education practitioners investigate and compare cMOOC and xMOOC learning models and experiences. In S. K. S. Cheung, J. Fong, W. Fong, F. L. Wang, & L. F. Kwok (Eds), *Hybrid Learning and Continuing Education: 6th International Conference, ICHL 2013. Proceedings 6* (pp. 244–255). Berlin/Heidelberg: Springer. https://doi.org/10.1007/978-3-642-39750-9_23

Statista (2025). Share of Hungarians attending online courses or using online learning materials from 2019 to 2021 [online resource]. New York: Statista. Retrieved 17 November 2025 from https://www.statista.com/statistics/1318205/hungary-attending-online-courses-and-using-online-learning-materials/

Tao, D., Fu, P., Wang, Y., Zhang, T., & Qu, X. (2022). Key characteristics in designing massive open online courses (MOOCs) for user acceptance: An application of the extended technology acceptance model. *Interactive Learning Environments, 30*(5), 882–895. https://doi.org/10.1080/10494820.2019.1695214

Ucha, C. R. (2023). Role of course relevance and course content quality in MOOCs acceptance and use. *Computers and Education Open*, *5*, Article no. 100147. https://doi.org/10.1016/j.caeo.2023.100147

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in human behavior, 67*, 221–232. https://doi.org/10.1016/j.chb.2016.10.028

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Gábor Pörzse is an associate professor at Semmelweis University in Budapest with a research focus on Innovation. He studied Health Management, Science, and Innovation Policy at Imperial College Management School London, and J. F. Kennedy School, Harvard University. He founded and directed Hungary's first center of grants and innovation at Semmelweis University. He is co-founder and former member of the board of the Hungarian E-health and Telemedicine Association, and also a former member of the presidium of the Hungarian Association for Innovation.

Zsófia Kenesei is a full professor of Marketing at the Institute of Marketing and Communication Sciences at Corvinus University of Budapest, Hungary. She is also a member of the Center for International Higher Education Studies (CIHE). Her primary research areas include services marketing and educational technologies. She is involved in various research projects, focusing on the acceptance of educational technologies, the forced usage of self-service technologies, and service recovery. She has published her findings in several international journals and presented at various conferences. Additionally, Zsofia is the founding president of the Association for Marketing Education and Research.