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Learners don't know best: Shedding light on the phenomenon of the K-12 MOOC in the context of information literacy

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A B S T R A C T

Massive Open Online Courses (MOOCs) have received much attention in higher education; however, evidence about MOOCs at the K-12 level is scarce. To shed light on the phenomenon, we use the i-MOOC that aims at fostering upper secondary level students' information literacy. The i-MOOC is a blended MOOC developed and refined in a design research process; it meets established criteria for high-quality MOOCs. In 2020, 1032 upper secondary level students in German-speaking Switzerland took the i-MOOC; the sample comprises N = 167 students who voluntarily filled in a questionnaire. The students are mainly from high schools and vocational schools. Learning effects are captured with a performance test. Information literacy gains are significant and medium in size: d = 0.75. The technology acceptance of students is evaluated using the extended unified theory of acceptance and use of technology (UTAUT2). Student technology acceptance of K-12 MOOCs is primarily driven by hedonic motivation, i.e., perceived fun and entertainment. However, this type of motivation negatively predicts learning gains. Implications for teachers and educational decision makers are discussed.

1. Introduction

Massive Open Online Courses (MOOCs) are a much debated phenomenon in tertiary education (L. Li, Johnson, Aarhus, & Shah, 2022; Reich & Ruipérez-Valiente, 2019). They are built to be attended by a large number of students (massive) with unrestricted access (open), and to be performed on the web (online) within a self-sufficient learning environment (course). Research activity on MOOCs have experienced a sharp increase (Joksimović et al., 2018; Zhu, Sari, & Lee, 2020), during the course of which several challenges have been identified. One of the most prominent is the notoriously high dropout rate (Hone & El Said, 2016; Paton, Scanlan, & Fluck, 2018).

In light of such challenges, the integration of MOOCs into formal learning settings has gained attention, i.e., MOOCs are integrated into in-class courses (Meet & Kala, 2021; Yousef & Sumner, 2021; Zhu, Sari, & Lee, 2020). Such *blended MOOCs* aim to combine the advantages of in-class and online learning (Chen, Zou, Xie, & Zou, 2020; Israel, 2015; Wang, Hall, & Wang, 2019; Zhu, Sari, & Lee, 2020). Blended MOOCs comprise in-class learning enriched with available traditional MOOCs, as well as MOOCs specifically designed for blended learning purposes. Both settings might be valuable if appropriately implemented (Bralić & Divjak, 2018). In traditional MOOCs, students usually lack sufficient guidance and support (Kasch, Van Rosmalen, & Kalz, 2021), and struggle with self-regulation

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(Jansen, van Leeuwen, Janssen, Conijn, & Kester, 2020; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). In blended MOOCs, lecturers could provide elaborate feedback to students, for instance, using the functionalities of learning analytics (Lu et al., 2018). Available evidence points to positive engagement and learning effects of blended MOOCs (K. Wang & Zhu, 2019). Moreover, high dropout rates may not be a problem in blended MOOCs (Cohen & Magen-Nagar, 2016; Muñoz-Merino et al., 2013). Against this backdrop, it is not surprising that blended MOOCs are increasingly being implemented (de Moura et al., 2021); however, there may also be downsides to blended MOOCs. They are more resource intensive to scale for a massive number of students than traditional MOOCs as lecturers are necessary. Furthermore, designing a high-quality blended MOOC is challenging and learning outcomes might be poor if the blended MOOC were inappropriately used by lecturers (Bralić & Divjak, 2018; de Moura et al., 2021).

Despite the widespread attention given to (blended) MOOCs in higher education, there is little evidence about K-12[1] MOOCs. The literature review of Koutsakas, Chorozidis, Karamatsouki, and Karagiannidis (2020), covering the years 2013–2020, identified only twenty-one studies on K-12 MOOCs. Most of these address STEM-related topics. For instance, the Department of Computer Science at the University of Helsinki offers a computer science MOOC that can be taken by any student in any Finnish school (Kurhila & Vihavainen, 2015).

Evidence from higher education may not be directly helpful to gain an understanding of the phenomenon K-12 MOOCs: K-12 learning processes are different from those at the tertiary level (Briggs & Crompton, 2016; Koutsakas, Chorozidis, et al., 2020). Moreover, it may be suboptimal to use MOOC content tailored to tertiary education at the K-12 level: high quality instruction should consider learners' prior knowledge and background (Bransford, Brown, & Cocking, 2000).

The aim of the paper at hand is to shed light on the phenomenon of K-12 MOOCs by providing quantitative evidence from an information literacy blended MOOC offered in German-speaking Switzerland to upper secondary level students. The project was funded by the Swiss National Science Foundation. We make three contributions to the literature. First, based on a review of the literature, we present a conceptual framework showing how K-12 MOOCs can be evaluated. Second, to our knowledge, we are the first study to provide quantitative empirical evidence about K-12 MOOCs that goes beyond univariate analyses. Third, we discuss the criteria that should be taken into account when deciding whether to integrate a MOOC into K-12 education.

2. Review of the literature

2.1. Search strategy

The recent literature review of Koutsakas, Chorozidis, et al. (2020) on K-12 MOOCs covers the period from January 2013 to March 2020. We utilized the search strategy of these authors to identify further studies published between March 2020 and December 2021, including ones in German. From the twenty-one studies reviewed by Koutsakas, Chorozidis, et al. (2020), we excluded two. They do not provide empirical evidence (Dziabenko & Tsourlidaki, 2018) or do not follow our conception of a MOOC (Canessa & Pisani, 2013). The latter investigated the delivery of recorded lectures, which is not a self-sufficient learning environment, i.e., does not meet our definition of a course. On the other hand, we included two studies published in 2020 and 2021, and three studies published in German. Overall, we identified twenty-four studies that:

- address MOOC(s) in a K-12 setting,
- are published in peer-reviewed journals or in peer-reviewed conference proceedings,
- report empirical evidence based on primary research,
- are published between January 2013 and December 2021,
- are in English or German.

The supplementary material S1 shows our identification strategy, the reviewed studies, and summarizes the evaluation approaches and main findings of the studies.

2.2. Characteristics of K-12 MOOCs

As Table 1 illustrates, the MOOCs in the reviewed studies can be classified according to three criteria: 1) blended MOOC (yes/no), 2) designed for K-12 (yes/no), and 3) the topic of the MOOC.

Blended MOOCs are integrated in a formal school setting and combine (= blend) both online and in-class learning activities (Bralić & Divjak, 2018; Israel, 2015). In general, face-to-face learning in a classroom is combined with online learning outside the classroom; participation is typically compulsory for the students. In this setting, teachers support their students on a regular basis and, therefore, dropout rates are low (de Kereki, & Paulos, 2014; de Waard & Demeulenaere, 2017; Filvà, Guerrero, & Forment, 2014; Grella, Staubitz, & Meinel, 2016). Two studies examine specific cases of blended K-12 MOOCs. Grover, Pea, and Cooper (2016) investigate a blended MOOC that is exclusively used inside the classroom. Khalil and Ebner (2015) investigate a MOOC that is embedded in a classroom setting but not compulsory for the students. From the reviewed twenty-four studies, thirteen address blended MOOCs.

On the other hand, there are *non-blended MOOCs* that students can attend in their free time (de Kereki & Manataki, 2016; Hermans

[1] K-12 refers to pre-tertiary education, ranging from kindergarten to the 12th grade.

Table 1
Studies presenting empirical evidence for K-12 MOOCs.

Authors	Blended	Designed for K-12	Topic
Blazquez-Merino et al. (2018)	Yes*	Yes	Physics
de Kereki and Manataki (2016)	No	Yes	CS
de Kereki and Paulos (2014)	Yes	Yes	CS
de Waard and Demeulenaere (2017)+	Yes	No	Foreign languages
Filvà et al. (2014)	Yes	Yes	CS
Grella, Staubitz, Teusner, & Meinel (2016)	No	Yes	CS
Grella, Staubitz, Teusner, & Meinel (2016)	Yes	Yes	CS
Grover et al. (2016)	No**	Yes	CS
Hermans and Aivaloglou (2017)	No	Yes	CS
Janisch et al. (2017)+	Yes	Yes	CS
Khalil and Ebner (2015)	Yes***	Yes	Physics
Koutsakas, Karagiannidis, et al. (2020)	No	Yes	CS
Kurhila and Vihavainen (2015)	No	No	CS
Magen-Nagar and Cohen (2017)	Yes	No	Various sciences
Najafi et al. (2014)	Yes	Yes	Economics
Nigh et al. (2015)	No	No	Pedagogy
Panyajamorn, Kohda, Chongphaisal, & Supnithi (2016)	Yes	No	Chemistry
Perach and Alexandron (2021)+	Yes	No	CS
Politis, Koutsakas, & Karagiannidis (2017)	No	Yes	CS
Sands and Yadav (2020)+	No	No	CS
Staubitz et al. (2019)	Yes	Yes	CS
Tomkins and Getoor (2019)+	No	Yes	CS
Tomkins et al. (2016)	No	Yes	CS
Yin, Adams, Goble, & Vargas-Madriz (2015)	No	Yes	Biology

Note. * blended setting but focus of the study not on the MOOC; ** MOOC used exclusively in the classroom; *** blended setting but participation not compulsory; + Study not included in Koutsakas, Chorozidis, Karamatsouki, and Karagiannidis (2020); CS = Computer Science (e.g., programming, computational thinking, introduction to ICT).

& Aivaloglou, 2017; Politis et al., 2017). Distinguishing between blended and non-blended MOOCs might be important: the learning processes, motivation, and retention of blended and non-blended K-12 MOOCs may be substantially different (de Kereki, & Paulos, 2014; Magen-Nagar & Cohen, 2017). In line with the evidence from the tertiary level, blended K-12 MOOCs could be especially promising.

Seventeen studies investigate MOOCs specifically developed for K-12 education. In general, they aim at secondary level students. The two exceptions are Hermans and Aivaloglou (2017), who compared students younger than twelve with students older than twelve, and Yin, Adams, Goble, & Vargas-Madriz (2015), who relied on a diverse sample of children working on MOOCs together with their parents. The other seven studies investigate MOOCs that do not have a specific target group (de Waard & Demeulenaere, 2017; Panyajamorn et al., 2016; Sands & Yadav, 2020), or that are aimed at university students (Kurhila & Vihavainen, 2015; Magen-Nagar & Cohen, 2017; Perach & Alexandron, 2021) and teachers (Nigh, Pytash, Ferdig, & Merchant, 2015). Since K-12 students are different from adult learners, it may be beneficial to develop specific K-12 MOOCs (Briggs & Crompton, 2016; Filvà et al., 2014; Yin, Adams, Goble, & Vargas-Madriz, 2015).

In terms of topic, sixteen out of the twenty-four studies investigate MOOCs in the realm of computer science, e.g., programming (de Kereki & Manataki, 2016; Grella et al., 2016) or an introduction to the basics (Perach & Alexandron, 2021). Five studies address other STEM topics, such as biology (Yin, Adams, Goble, & Vargas-Madriz, 2015), physics (Blazquez-Merino et al., 2018; Khalil & Ebner, 2015), and chemistry (Panyajamorn et al., 2016). Only three out of the twenty-four studies provide evidence on MOOC learning in the social sciences (de Waard & Demeulenaere, 2017; Najafi, Evans, & Federico, 2014; Nigh et al., 2015).

2.3. Evaluation methods and findings

Concerning qualitative evidence, based on twelve interviews Yin, Adams, Goble, & Vargas-Madriz (2015) report that children use MOOCs differently to adult learners. Children seem to engage less with video lecturers and need more support. Interviews with teachers and students (de Kereki, & Paulos, 2014), and focus groups with students (de Waard & Demeulenaere, 2017), report high perceived and observed learning effects. Grella et al. (2016) conducted a workshop with teachers on K-12 MOOCs, which reveals a high workload for preparing blended MOOC settings. A qualitative analysis of transfer tasks indicates that K-12 MOOC acceptance is higher among more active and motivated students (Nigh et al., 2015).

Concerning quantitative evidence, twelve studies use questionnaires to capture student assessment of K-12 MOOCs. The response rates differ substantially between voluntary (2.7%–9.0%) (de Kereki & Manataki, 2016; Koutsakas, Karagiannidis, et al., 2020) and compulsory questionnaires (100%) (Blazquez-Merino et al., 2018). Overall, students may be willing to learn with MOOCs (de Kereki, & Paulos, 2014; Nigh et al., 2015; Politis et al., 2017); however, evidence for the factors predicting the acceptance of K-12 MOOCs is scarce. An exception is the study by Magen-Nagar and Cohen (2017), who report positive correlations among the students' learning strategies, motivation, and perceived learning effects. However, the authors call for more evidence explaining the learning effects and student motivation in K-12 MOOCs. Moreover, the used MOOC is not deliberately designed for the K-12 level.

A further quantitative evaluation approach is to utilize data from the MOOC platform. Such data is used to investigate retention (de Kereki & Manataki, 2016; Hermans & Aivaloglou, 2017; Khalil & Ebner, 2015; Kurhila & Vihavainen, 2015) and learner activity (Grella et al., 2016; Kurhila & Vihavainen, 2015; Tomkins, Ramesh, & Getoor, 2016; Tomkins & Getoor, 2019). Students who receive support participate more actively and perform better in a posttest (Tomkins et al., 2016; Tomkins & Getoor, 2019). Khalil and Ebner (2015) report that even if a K-12 MOOC is integrated into formal learning (blended), the retention rate is low if participation in the MOOC is voluntary. Students seem to struggle with unsupported MOOC learning (Blazquez-Merino et al., 2018).

Ten studies address learning outcomes in a blended setting and one in a non-blended setting. Five of these eleven studies rely on perceived learning outcomes, i.e., self-assessments (de Kereki, & Paulos, 2014; de Waard & Demeulenaere, 2017; Magen-Nagar & Cohen, 2017; Politis et al., 2017; Staubitz, Teusner, & Meinel, 2019). The results seem promising—students, in general, report substantial perceived learning outcomes. The results from the six studies using objective measurement also report positive outcomes. However, the most extensive study (N = 182) covers a highly specific situation in rural Thailand (Panyajamorn et al., 2016). Blazquez-Merino et al. (2018) compare the performance of (N = 77) students who studied in an online physics lab with (N = 77) students who studied in an offline lab. Students in both groups achieved similar results. However, the MOOC only served to standardize the instruction in order to compare the learning effects of offline and online physics labs. The other four studies are based on rather small samples of K-12 students using a blended MOOC; N = 55 (Perach & Alexandron, 2021), N = 28 (Grover et al., 2016), N = 15 (Najafi et al., 2014), and N = 14 (Janisch, Ebner, & Slany, 2017); the authors call for more research on learning effects. Overall, student support and deliberate integration into the curriculum may be conducive to learning (Najafi et al., 2014; Staubitz et al., 2019).

In summary, the available evidence points to MOOCs as a promising means for K-12 learning, especially in the form of blended MOOCs. However, most studies were carried out in the disciplines of STEM. Studies about student perception of K-12 MOOCs mostly do not rely on established technology acceptance models. Studies that utilize performance tests to assess learning effects often do not even provide enough information to calculate effect sizes, or are based on quite small samples.

2.4. *The present study*

2.4.1. *The i-MOOC*

To shed further light on the phenomenon of K-12 MOOCs, the study at hand utilizes the i-MOOC (https://i-mooc.ch/). The i-MOOC aims at fostering Swiss upper secondary level students' information literacy (IL). IL is a learning goal for these students specified in the relevant curricula (BBT, 2006; EDK, 1994; SBFI, 2013). To create awareness for the i-MOOC, we contacted all pertinent schools in German-speaking Switzerland. Interested teachers contacted the project team and got access to the i-MOOC free of charge. Moreover, teachers received technical support and pedagogical advice upon request.

The i-MOOC is a blended MOOC. The students were enrolled and supported by their teachers during in-class instruction. The theoretical background of the i-MOOC is the 7i framework (Seufert, Guggemos, Moser, & Sonderegger, 2019). It specifies what constitutes IL and the learning goals that should be pursued. The i-MOOC covers these learning goals by means of six modules. The intended time to fully complete the i-MOOC is 6 h. However, depending on the level of support, some teachers used up to 7.5 h.

Information literacy may be a suitable content for a K-12 MOOC: IL is regarded as a key 21st-century skill and an important educational goal (Fraillon, Ainley, Schulz, Duckworth, & Friedman, 2019; Oberländer, Beinicke, & Bipp, 2020; Yang et al., 2021). Indeed, it may be important to foster students' information literacy; the idea of digital natives who competently use technology without instruction is a myth (Kirschner & Bruyckere, 2017).

The i-MOOC was implemented using the OpenEdX platform and hosted by Swissuniversities. From a technical and conceptual point of view, the i-MOOC could be taken by a virtually unlimited number of students. It comprises explanatory videos, information material, cheat sheets, quizzes, and peer feedback tasks. For MOOCs, in particular, it is important to ensure a high-quality course design (Kim et al., 2021). In light of this, we developed the i-MOOC using a design research approach. Based on criteria for high-quality MOOCs (Egloffstein, Koegler, & Ifenthaler, 2019; Margaryan, Bianco, & Littlejohn, 2015), we developed, evaluated, and refined the initial version. For a detailed description of the design research process of developing and improving the i-MOOC, see Seufert, Guggemos, Moser, & Sonderegger (2019) and Moser, Guggemos, & Seufert (2021). Supplementary material S2 outlines how the design criteria for high-quality MOOCs are considered in the i-MOOC.

2.5. *Theoretical framework for evaluation*

According to Whetten (1989), the crucial point in theory development is a good trade-off between comprehensiveness and parsimony. This trade-off guided our evaluation strategy. Overall, we aim at answering three related research questions:

RQ1: What is the learning effect of a K-12 MOOC?

RQ2: What are the predictors of student acceptance of a K-12 MOOC?

RQ3: What are the predictors of the learning effect of a K-12 MOOC?

Concerning MOOC research, Reich (2015) calls for studies that put learning outcomes into focus. A generally applied approach to evaluate educational technology interventions is to determine the achieved effect size of this intervention (Scheiter, 2021). An effect size can be based on the comparison of student posttest scores with their pretest scores, or comparing the scores of a treatment group with those of a control group after the intervention (Hattie, 2009, p. 8). To claim effectiveness, it may not be sufficient to demonstrate a statistically significant positive effect. Rather, an effect size of greater than 0.4 could be in the desirable zone (Hattie, 2009; Reeves & Lin, 2020). Since the i-MOOC was thoroughly developed based on established design principles, we hypothesize an effect size (Cohen's d) in the zone of desirable effects, i.e., statistically significantly greater than 0.4.

To evaluate educational technology, investigating student technology acceptance is an established approach (Al-Emran, Mezhuyev, & Kamaludin, 2018; McGill, Klobas, & Renzi, 2014; Raffaghelli, Rodríguez, Guerrero-Roldán, & Bañeres, 2022). However, for blended K-12 MOOCs the nature of technology acceptance may be different from general technology. In this case, teachers decide to use, or not to use, a MOOC in their instruction. The actual use is not within the control of the students. Hence, the acceptance of K-12 MOOCs could address whether students have the intention to use, or want their teachers to use, MOOCs. Although students do not decide on the use, a lack of student technology acceptance could hinder the adoption of K-12 MOOCs. Teachers, whose students are reluctant to study with MOOCs, may not use them (in the future). To evaluate student technology acceptance, we rely on the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). The UTAUT is a well-founded theory suitable for educational technology research (Novak, 2021; Valtonen et al., 2022); it integrates other theories such as the technology acceptance model. The UTAUT implies that student behavioral intention, e.g., to use a MOOC (technology acceptance), can be explained by performance expectancy, effort expectancy, and social influence. The UTAUT has been extended to the UTAUT2 (Venkatesh, Thong, Xu, Venkatesh, & Xu, 2012). UTAUT2 constructs, definitions, and items are reported in Table 2. From the additional predictors implied by the UTAUT2, beyond the UTAUT, only hedonic motivation may be relevant in our context. We do not consider facilitating conditions because all necessary resources for using the i-MOOC, such as digital devices, are available to the students. In Switzerland, 99% of upper secondary level students own a smartphone (Bernath et al., 2020) and this allows them to use the i-MOOC anywhere. In our case, habits do not play a role as blended K-12 MOOCs are a new phenomenon for the students. Price value is irrelevant because students do not have to pay to use the i-MOOC. Overall, the hypothesized positive predictors for student acceptance of K-12 MOOCs are performance expectancy, effort expectancy, social influence, and hedonic motivation.

The UTAUT is, as the name implies, a unified theory that integrates several theories (Novak, 2021). It is informed by motivation theories (Venkatesh et al., 2003, 2012). The expectancy-value theory is among the most established motivation theories (Wigfield, Muenks, & Eccles, 2021). It implies that performance can be predicted by expectancies for success and the task values. Ranellucci, Rosenberg, and Poitras (2020) argue that although technology acceptance and expectancy-value literature both use different terminology, they may be compatible in nature. The predictors of technology acceptance implied by the UTAUT2 could be regarded as manifestations of either expectancies of success or task values. In sum, we hypothesize performance expectancy, effort expectancy, social influence, and hedonic motivation to positively predict IL gain. Relying on these technology acceptance predictors may allow for a good trade-off between comprehensiveness and parsimony of the overall evaluation strategy.

The UTAUT2 proposes three moderators of the relationships between the constructs: age, gender, and experience. In the specific circumstances of our study, technology experience can be excluded because the phenomenon blended MOOC is new to the students in the sample. However, we add school type as a potential moderator; school type is regularly considered in meta-analyses (e.g., concerning the association between motivation and performance, see Kriegbaum, Becker, & Spinath, 2018).

3. Method

3.1. Sample

In 2020, 1032 students, nested in fifty-six classes, attended the i-MOOC; 880 students completed the IL pretest and posttest integrated into the i-MOOC. All 880 students were subsequently asked to fill in a questionnaire; participation was entirely voluntarily and follows the ethical standards of the University of St.Gallen. Overall, 170 students filled in the questionnaire. The response rate equals 19.3%, which is higher than in all the reviewed K-12 MOOCs where filling in the questionnaire was also voluntary (max = 9.0%). By means of Mahalanobis distances, we checked for outliers (Leys, Delacre, Mora, Lakens, & Ley, 2019). We identified three statistically significant ($\alpha = 0.01$) outliers that we inspected. These three students, for instance, did not show any variance in their answers. We concluded there was a lack of sufficient test motivation for these students and, consequentially, we excluded all three of them. The final sample comprises N = 167 upper secondary level students nested in thirty-one classes. This implies a substantial reduction in our sample (from 1032 to 167); we will come back to this point in section 5. From these 167 students, 1.3% of the data is missing. Based on Little's test of missing completely at random (χ^2 (80) = 75.3, p = .628), as well as an inspection of the data, we might conclude this data is missing completely at random. The average age of the students was 17.80 years (SD = 2.19), median = 17 years, mode = 16 years, min = 16 years, max = 25 years; 51% of the students were female; 49% attended a vocational school, 44% a high school, and 7% other school types.

3.2. Data analysis

The IL pretest and posttest scores are the basis for answering RQ1 and RQ3. Considering these as latent variables in subsequent analyses is not possible due to our rather small sample size. However, we relied on factor scores as they are superior to sum scores (McNeish & Wolf, 2020). Furthermore, using factor scores based on confirmatory factor analysis allows us to assess the overall fit of the measurement model. We can also demonstrate measurement invariance over time, which is necessary to allow for a valid comparison of pre- and posttest scores (van de Schoot, Lugtig, & Hox, 2012). To check for measurement invariance over time, we use the approach of van de Schoot et al. (2012). We compare an unrestricted model, where all parameters for the pre- and posttest are individually

Table 2
Constructs and items for evaluating technology acceptance based on the UTAUT(2) (Venkatesh et al., 2003, 2012).

Construct	Definition	no.	Item	M	SD	Min	Max
Performance expectancy	Degree to which MOOCs are perceived as valuable for learning	1	The i-MOOC helps me to learn more.	3.3	1.6	1	7
		2	The i-MOOC helps me to learn faster.	3.3	1.6	1	7
		3	The i-MOOC is useful for learning.	3.7	1.8	1	7
Effort expectancy	Degree of ease associated with the use of MOOCs	4	I can use the i-MOOC without help from others.	5.4	1.8	1	7
		5	It is easy for me to use the i-MOOC.	3.5	1.7	1	7
Social influence	Degree to which students believe significant others want them to use MOOCs	6	People I care about think I should study with online courses, like the i-MOOC.	2.5	1.7	1	7
		7	My parents think I should study with online courses, like the i-MOOC.	2.4	1.7	1	7
		8	My friends think I should study with online courses, like the i-MOOC.	2.3	1.6	1	7
Hedonic motivation	Degree of fun or pleasure derived from studying with MOOCs	9	Studying with the i-MOOC is fun.	2.9	1.8	1	7
		10	Studying with online courses, like the i-MOOC, would make school more entertaining.	3.1	1.9	1	7
Technology acceptance	Degree of intended use of MOOCs or appreciation of their use by teachers	11	If possible, I would study more with online courses, like the i-MOOC.	2.9	1.9	1	7
		12	I would like my teachers to use more online courses, like the i-MOOC.	2.9	1.9	1	7

Note. The items were presented in random order to the students and measured on a seven-point scale of rating, ranging from entire disagreement to entire agreement.

estimated, with a model where intercepts and loadings are restricted to be equal across both tests. A significant χ^2-test would indicate a violation of scalar measurement invariance. In this case, we free parameters across groups to achieve partial measurement invariance; this could allow for a valid comparison across the two timepoints (van de Schoot et al., 2012). We use a robust maximum likelihood (MLR) estimator in the confirmatory factor analysis because the data are (by nature) not normally distributed.[2] Moreover, this allows us to handle missing data (test items not answered) by means of full information maximum likelihood (Jia & Wu, 2019). This approach is superior to simply handling missing data as incorrect answers (Köhler, Pohl, & Carstensen, 2017). We perform all these analyses using the R package lavaan 0.6–9 (Rosseel, 2012).

To answer RQ1, we rely on paired t-tests to assess the statistical significance, and Cohen's d to quantify the effect size of the increase in IL. Since the IL test scores are not normally distributed (Shapiro-Wilk test: $p < .001$) and clustered (students nested in classes), we use bootstrapping to calculate standard errors using the R package MKinfer 0.6 (Kohl, 2020). We opt for using Bartlett factor scores as they yield unbiased estimators for the true scores (DiStefano, Zhu, & Mîndrilã, 2009).

Concerning RQ2 and RQ3, we use covariance-based structural equation modeling to predict acceptance of K-12 MOOCs, and the IL posttest score (R package lavaan 0.6–9). Missing data are handled with full information maximum likelihood. To assess the quality of the measurement models, we rely on the cut-off values proposed by Hair, Risher, Sarstedt, and Ringle (2019), and for the overall model-fit, on the cut-off values of Hu and Bentler (1999). Since our data is clustered, we use cluster-robust standard errors (McNeish, Stapleton, & Silverman, 2017). Moreover, teachers can use the i-MOOC in various ways. In particular, they can offer their classes different degrees of guidance and support. Since this between-class heterogeneity is likely to influence the perception of the i-MOOC, we use group-mean centered variables in our structural equation models (McNeish & Kelley, 2019), i.e., for answering RQ2 and RQ3. This means every student is compared with their classmates. Between-class heterogeneity is removed and we can analyze pure individual-level effects. This approach may be suitable, in particular, for small samples (McNeish & Kelley, 2019). Class-mean centering, indeed, seems to be necessary as the between-class variance (ICC1) is substantial for the posttest score of IL: 19.3%. For the pretest score, the ICC1 equals 7.3%. For the UTAUT2 variables, it ranges between 0.0% (item 10, see Table 2) and 12.1% (item 5, see Table 2) with a mean of 4.8% ($SD = 4.0$). To control for moderators implied by the UTAUT2, we carry out multigroup analysis. The groups are: gender, male vs. female; age, ≥18 years vs. <18 years; and school type, high schools vs. vocational schools.

Concerning RQ3, we use a regressor-variable model (Aichele, Hartig, & Michaelis, 2021), where the IL posttest score is used as the dependent variable, and the pretest score, as well as the UTAUT2 predictors, as independent variables. Following Skrondal and Laake (2001), we use regression factor scores for the independent variable (IL pretest score) and the Bartlett factor score for the dependent variable (IL posttest score). All other variables are latent.

3.3. Measurement instruments

To measure student IL, both before and after the i-MOOC, we utilize a short version of a validated performance test (Seufert, Stanoevska-Slabeva, & Guggemos, 2020) that covers the 7i framework of IL. The items can be found in the supplementary material S3. It comprises twenty-two binary items. Using a performance test instead of self-assessment may be important because students' ability to correctly evaluate their IL seems to be low (Mahmood, 2016). Since both the i-MOOC and the IL test are based on the 7i framework, we may have achieved instructional sensitivity (Deutscher & Winther, 2018; Naumann, Rieser, Musow, Hochweber, & Hartig, 2019):

[2] A 'weighted least square mean and variance adjusted' (WLSMV) estimator (C.-H. Li, 2016) yields identical ($r = 0.997$) results.

Sample item of the information literacy performance test.

In the afternoon, your best friend calls and asks you: "Can you please help me with my research on the Swiss President? I have to give a 15-minute lecture on him tomorrow in class."
What is the most important thing you need to find out to help your friend with his problem?

- ○ Where I can find information about the Swiss President
- ○ What my friend has already found out
- ○ Whether the Swiss President has a profile on a social media platform (e.g., Instagram, Twitter)
- ○ What exactely the assignment is

Corresponding item from the formative quiz in the i-MOOC.

It is important to identify my information needs because ...

- ○ I can search for information goal-oriented.
- ○ I like it.
- ○ it allows to evaluate the usefulness of found information.
- ○ it helps to identify fake-news.

Corresponding instruction material in the i-MOOC.

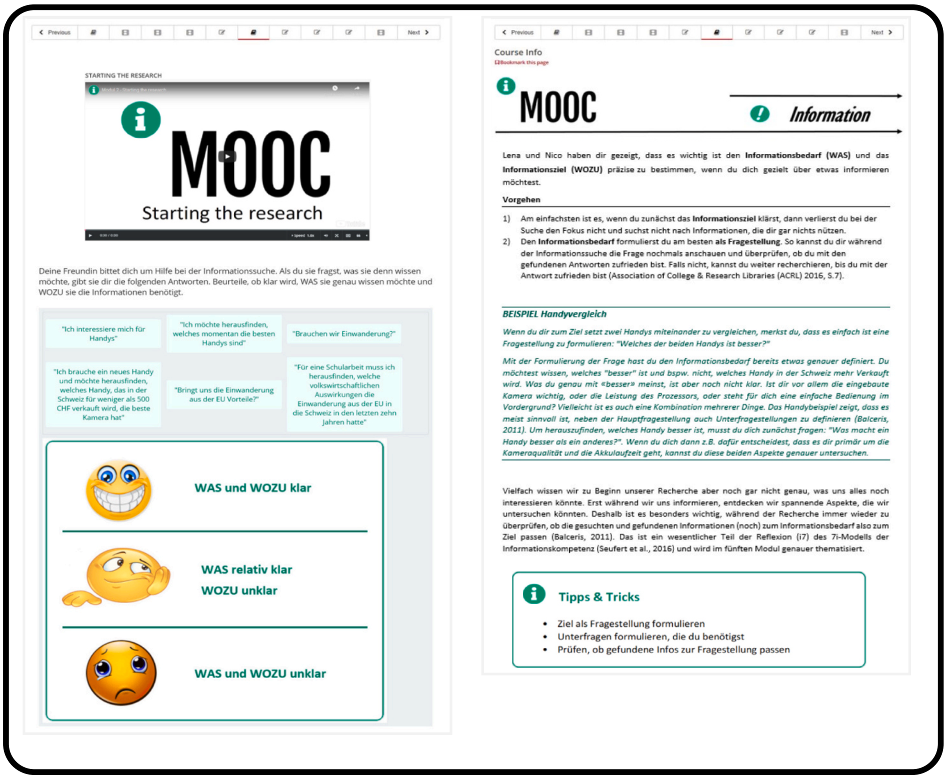

Fig. 1. Sample item of the information literacy performance test, corresponding quiz item, and instruction material in the i-MOOC.

the 7i framework acts as the curriculum, i.e., it specifies what kind of task students should be able to carry out in order to demonstrate IL. The i-MOOC is designed to enable students to master these tasks, which can be assessed with the used IL test. On the other hand, however, teaching to the test has to be avoided (Popham, 2001). In our context, teaching to the test would imply that course material and quizzes are similar to the test items. To prevent this, the IL performance test and the quizzes in the i-MOOC are based on different content. An example of an item from the IL test, as well as the corresponding instruction and quiz item from the i-MOOC, can be found in Fig. 1. In addition, students did not receive feedback whether answers to specific items in the pretest were correct in order to avoid learning effects due to test taking. However, they did receive an overall percentage score to gauge their level of IL before starting the i-MOOC.

We adapted the UTAUT and UTAUT2 questionnaires (Venkatesh et al., 2003, 2012) to our context. The questions are depicted in Table 2. They are measured on seven-point scales of rating, ranging from entire disagreement to entire agreement.

4. Results

4.1. Assessment of measurement instruments

The joint confirmatory factor analysis of the IL pretest and posttest yielded a decent fit: YB-χ^2 (392) = 398.955, p = .393, CFI = 0.987, TLI = 0.985, RMSEA = 0.010, SRMR = 0.057. However, scalar measurement invariance (equal intercepts and loadings) across time is not achieved: χ^2 (42) = 62.163, p = .023. After allowing three intercepts of items to be different across the pre- and posttest, the difference in fit between the unrestricted model and the restricted model, ensuring partial measurement invariance, is no longer significant: χ^2 (39) = 30.978, p = .820.

Apart from two exceptions, the measurement models are sound (see Table 3). Internal consistency reliability is decent with α and ω greater than 0.7. Convergent validity is achieved as the average variance extracted is greater than 0.5. Discriminant validity might also be ensured; the highest heterotrait–monotrait ratio equals 0.74 (between performance expectancy and technology acceptance). This is well below the cut-off value of 0.9 for conceptually similar constructs. The two exceptions are: first, the internal consistency reliability of the pretest IL score (0.67) is slightly below the cut-off value of 0.7; second, there is a lack of discriminant validity between hedonic motivation and the acceptance of K-12 MOOCs. This can be seen from a heterotrait–monotrait ratio of 0.97, 95% CI [0.94, 1.01], i.e., not significantly smaller than 1. This means these two constructs, albeit different from a conceptual point of view (UTAUT2), are hard to empirically separate. We will come back to this point in the discussion section.

4.2. Learning effect of information literacy K-12 MOOC (RQ1)

On a descriptive level, in the pretest the students scored on average 10.38 out of 22 points (SD = 3.51), median = 11 points, min = 1 point, max = 18 points. In the posttest, they scored on average 12.89 (SD = 3.99) points, median = 14 points, min = 1 point, max = 22 points. This equals a medium effect: d = 0.66, 95% CI [0.43, 0.89], p < .001. Based on Bartlett factor scores and established partial measurement invariance, the posttest score is significantly higher than the pretest score with a medium effect size: d = 0.75, 95% CI [0.53, 0.97], p < .001. As the confidence interval does not include 0.4, the effect is significantly higher than 0.4 and, hence, in the zone of desirable effects.

There are no differences concerning age, gender, and school type in terms of the increase in IL (p > .352). Fig. 2 shows the normalized learning gain in IL grouped by gender and type of school based on Bartlett factor scores. The normalized learning gain (g) is defined as: g = (post – pre)/(100 – pre), where post- and pretest scores are given as a percentage (Marx & Cummings, 2007). The median normalized learning gain across all groups equals 24.9%, depicted as a horizontal line in Fig. 2.

Table 3
Assessment of the measurement models (N = 167).

	Construct	Sum/Mean	SD	α	ω	AVE	Below diagonal correlations; above diagonal HTMT						
							1	2	3	4	5	6	7
1	Pretest score IL	10.4	3.5	.64	.67	–	1	–	–	–	–	–	–
2	Posttest score IL	12.9	4.0	.75	.78	–	**.50**	1	–	–	–	–	–
3	Performance expectany	3.4	1.5	.90	.90	.75	-.06	**.21**	1	.45	.56	.74	.64
4	Effort expectancy	4.9	1.6	.74	.76	.62	.01	**.29**	**.44**	1	.24	.35	.28
5	Social influence	2.4	1.5	.91	.91	.77	.04	**.20**	**.56**	**.26**	1	.64	.57
6	Hedonic motivation	3.0	1.7	.87	.87	.92	-.04	.08	**.75**	**.37**	**.65**	1	.97
7	Technology acceptance	2.9	1.8	.95	.95	.77	-.06	.07	**.63**	**.29**	**.56**	**.97**	1

Note. Sum/Mean = sum of correctly answered binary test items out of 22/mean of UTAUT2 variables (see Table 2), SD = standard deviation, α = Cronbach's alpha, ω = McDonald's omega total, AVE = average variance extracted, HTMT = heterotrait-monotrait ratio. The correlations are based on group-mean centered variables (group = class). All correlation in bold are significant at the 5% level (two-sided) considering the cluster structure of the data (students nested in classes). Pretest scores are regression factor scores, posttest scores are Bartlett factor scores; the UTAUT2 constructs 3–7 are latent variables measured on a seven-point scale of rating.

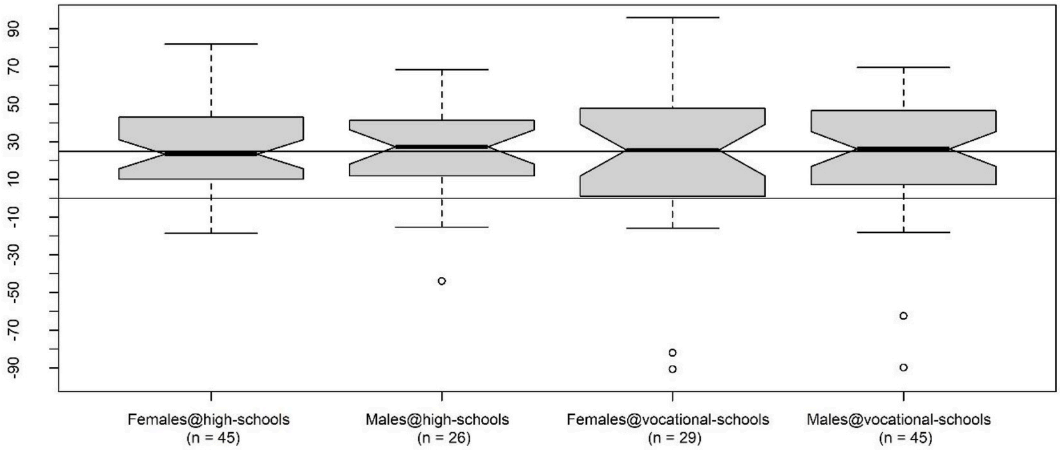

Fig. 2. Information literacy normalized learning gain grouped by gender and school type.

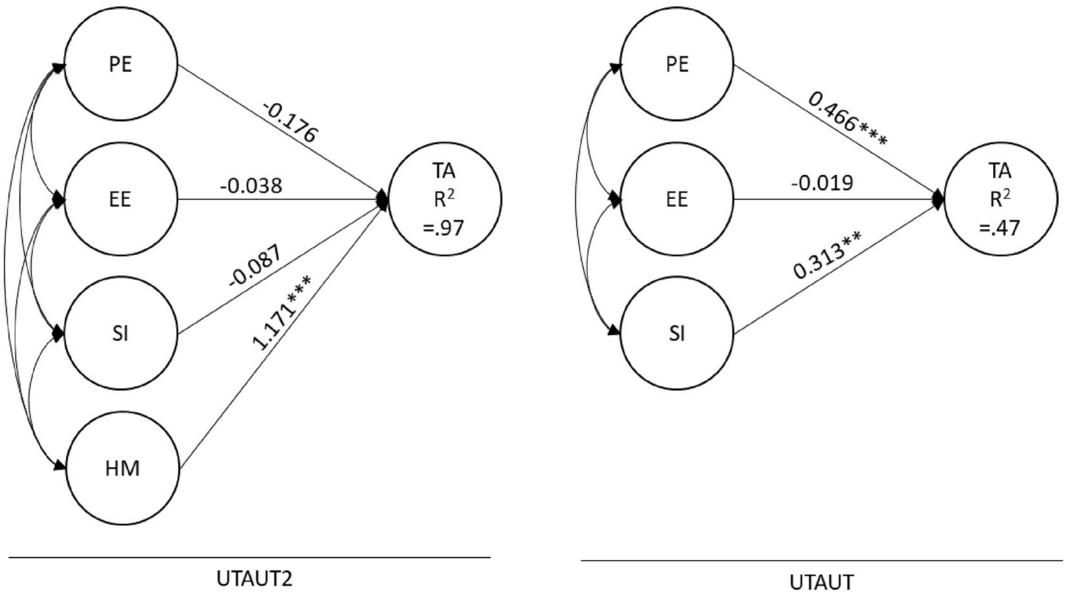

Fig. 3. Structural equation models to predict student acceptance of K-12 MOOCs (N = 167). PE = Performance Expectancy, SI = Social Influence, EE = Effort Expectancy, HE = Hedonic Motivation, TA = Technology Acceptance. Note. Standardized path coefficients based on group-mean centered-variables. Assessment of significance based on cluster robust standard errors (cluster = classes). * $p < .05$, ** $p < .01$, *** $p < .001$. Fit values of UTAUT2 model: YB-χ^2 (44) = 52.38 (p = .181), CFI = 0.995, TLI = 0.992, RMSEA = 0.034 (90% CI [0.000, 0.065]), SRMR = 0.026. Fit values of UTAUT model: YB-χ^2 (29) = 30.08 (p = .410), CFI = 0.999, TLI = 0.999, RMSEA = 0.015 (90% CI [0.000, 0.064]), SRMR = 0.023. All factor loadings are significant ($p < .001$).

4.3. Predicting acceptance of K-12 MOOC (RQ2)

Student acceptance of our K-12 MOOC is rather low. Based on a seven-point scale of rating, it equals 2.89 (SD = 1.82), median = 2.50, min = 1, max = 7. The fit values of the UTAUT2 model are excellent: CFI = 0.995, TLI = 0.992, RMSEA = 0.034, SRMR = 0.026. Fig. 3 depicts this model. As can be seen, the only significant predictor for student acceptance of K-12 MOOCs is hedonic motivation ($\beta = 1.171$, $p < .001$); the explained variance equals 97%. Due to the identified lack of discriminant validity, we also estimated the UTAUT model, which does not consider hedonic motivation (see Fig. 3). In this model, performance expectancy ($\beta = 0.466$, $p < .001$) and social influence ($\beta = 0.313$, $p = .002$) significantly predict student acceptance of K-12 MOOCs. However, effort expectancy is not a significant predictor ($\beta = -0.019$, $p = .847$).

The multigroup analyses, considering measurement invariance, did not yield overall significant differences: gender ($\Delta\chi^2$ (58) = 71.638, p = .108), age ($\Delta\chi^2$ (58) = 60.049, p = .401), and school type ($\Delta\chi^2$ (58) = 61.419, p = .355).

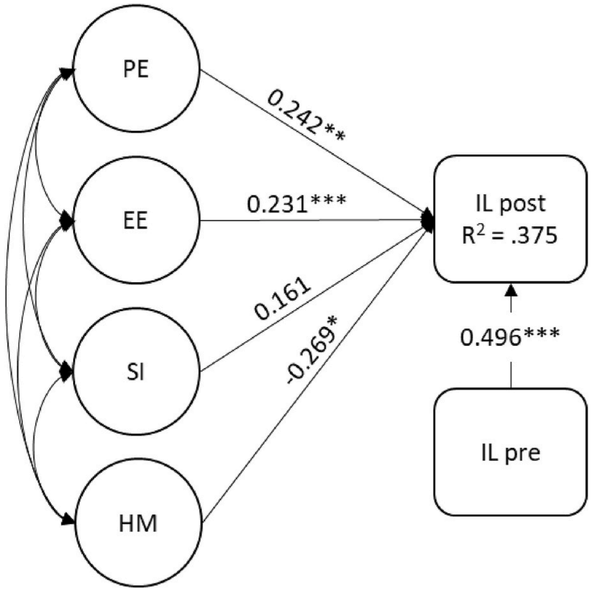

Fig. 4. Structural equation model to predict Information Literacy (IL) after attending the i-MOOC (N = 167). IL post = IL posttest score (Bartlett factor score), IL pre = IL pretest score (regression factor score), PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, HM = Hedonic Motivation. Note. Standardized path coefficients. Assessment of significance based on cluster robust standard errors (cluster = classes). * p < .05, ** p < .01, *** p < .001. Fit values: YB-χ^2 (41) = 53.52 (p = .091), CFI = 0.991, TLI = 0.985, RMSEA = 0.043 (90% CI [0.000, 0.067]), SRMR = 0.028. All factor loadings are significant (p < .001).

4.4. *Predicting information literacy after K-12 MOOC attendance (RQ3)*

Fig. 4 shows the model used to predict student performance in the IL posttest when controlling for performance in the pretest. The fit is excellent: CFI = 0.991, TLI = 0.985, RMSEA = 0.043, SRMR = 0.028. Performance expectancy (β = 0.242, p = .009) and effort expectancy (β = 0.231, p < .001) positively predict the IL posttest score when controlling for the pretest score. However, hedonic motivation is a negative predictor: β = −0.269, p = .034.

The multigroup analyses, considering measurement invariance, did not yield overall significant differences: gender ($\Delta\chi^2$ (53) = 62.485, p = .175), age ($\Delta\chi^2$ (53) = 61.530, p = .197), and school type ($\Delta\chi^2$ (53) = 52.250, p = .503).

5. Post hoc power analysis and robustness checks

Our sample may be regarded as small (N < 200). However, the required sample size depends on the specific situation (Wolf, Harrington, Clark, & Miller, 2013). Hence, we carried out a post hoc power analysis. Concerning RQ1, we can detect a small effect (d = 0.21) with a probability of 80%. To determine the achieved power for answering RQ2 and RQ3, we used the powerSEM 1.1.0 (Moshagen & Erdfelder, 2016) and pwrSEM 0.1.2 (Y. A. Wang & Rhemtulla, 2021) packages in R. We can identify a misspecified model (RMSEA > 0.08) with a probability of 97% and 93%, respectively. Assuming factor loadings of 0.7 for all the UTAUT2 constructs, which implies a sufficient convergent validity of the measurement model (Hair et al., 2019), we can detect standardized path coefficients of 0.300 with a probability of at least 86% and 73%, respectively. Standardized path coefficients of greater than 0.300 may be reasonable (Scherer, Siddiq, & Tondeur, 2019). Overall, our sample may yield sufficient power to answer our research questions.

Concerning RQ3, we used a regressor-variable model, i.e., the pretest score is used as an independent variable to predict the posttest score (see Fig. 4). The alternative specification in a pre-posttest design would be a change-score model, where the difference between posttest and pretest scores acts as the dependent variable. Both models have specific assumptions; it might be beneficial to estimate both models and check if they agree (van Breukelen, 2013). In our case, the results are identical in terms of sign and statistical significance. The estimated associations with the change score are: performance expectancy (β = 0.285, p = .009), effort expectancy (β = 0.265, p < .001), social influence (β = 0.173, p = .179), and hedonic motivation (β = −0.301, p = .035). As the change score is the dependent variable in the change score model, we used Bartlett factor scores to form the change score (Skrondal & Laake, 2001). Since the two models yield identical results, two claims may be valid: 1) performance expectancy predicts the IL posttest score while controlling for the pretest score, and 2) performance expectancy predicts the IL gain or learning effect. Due to its more vivid interpretation, we will stick to the latter claim in the discussion section.

Although superior to sum scores, factor scores are not free of measurement errors (McNeish & Wolf, 2020). Hence, we used the approach suggested by Savalei (2019) to check whether considering measurement error has an impact on our findings. We restricted the residual variances of the pretest and posttest scores to values corresponding with an internal consistency reliability of 0.8 (reasonable maximum). The findings are identical in terms of sign and statistical significance, e.g., technology acceptance on hedonic motivation: $\beta = -0.294$, $p = .033$.

Our sample may suffer from a self-selection bias. Hence, we checked to see if the 167 students in our sample are different from those students who did not fill in the questionnaire. There are no significant differences in terms of gender (χ^2 (1) = 3.646, p = .056), age group (χ^2 (1) = 1.441, p = .230), and school type (χ^2 (1) = 0.032, p = .856) between the two groups. Although not statistically significant at the 5% level, there is a tendency for females to volunteer more often to fill in the questionnaire. The finding of non-significant differences may be important because these variables could moderate the reported relationships when answering RQ2 and RQ3 (Kriegbaum et al., 2018; Venkatesh et al., 2012). Besides this, we compared the pretest and posttest scores of the students who filled in the questionnaire with those who refused to do so. T-tests with bootstrap standard errors show no differences concerning pretest score (d = 0.00, p = .995) and posttest score (d = −0.09, p = .464). Hence, the answer to RQ1 may not be influenced by student self-selection.

6. Discussion

6.1. Findings

Concerning RQ1, the learning effect is d = 0.75, which is in the zone of desirable effects (Hattie, 2009; Reeves & Lin, 2020). However, other K-12 MOOCs yield even higher effect sizes based on a pretest-posttest comparison (d = 2.4; Grover et al., 2016). On a descriptive level, the learning gain may be regarded as modest: on average, the students scored 10.38 points in the pretest and 12.89 points in the posttest, out of 22 points. However, comparisons based on descriptive statistics may be misleading because they do not consider measurement invariance and are based on sum scores. Nevertheless, there may be reasons on the content level for our findings. The quality of educational technology use and the expected learning gains depend on teachers' technology-related knowledge, skills, and attitudes (Scheiter, 2021; Seufert, Guggemos, & Sailer, 2021). K-12 MOOCs are quite a new phenomenon for teachers. Education and training on how to use blended MOOCs in an effective way may be necessary to achieve high levels of student learning. In general, students' IL seems to be hard to improve. Although there may be consent about the importance of fostering IL among students, and despite the fact IL is part of national curricula, it does not seem to increase markedly over time (Fraillon et al., 2019).

The learning effect does not significantly differ among gender, school type, and age groups. By nature (being massive), MOOCs are designed for a broad target group. In the case of the i-MOOC, the target group consists of upper secondary level students in German-speaking countries. Although students in our sample are from school types that are quite different in nature (vocational schools and high schools), the i-MOOC yielded similar learning gains. Hence, it may be possible to develop a MOOC that suits a broad variety of upper secondary level students.

The effect size of d = 0.75 is based on a pretest-posttest comparison, i.e., there is no control group. Students' IL may also increase without attending the i-MOOC. However, Seufert, Stanoevska-Slabeva, & Guggemos (2020) reported that one school year yields an IL increase of d = 0.1 ($p < .01$). Against this backdrop, the i-MOOC may yield learning effects that are greater than the effects of general IL instruction during the course of one school year. Nevertheless, we cannot answer how the i-MOOC compares to other instructional means. For instance, teachers could use the 6 h of time that is required for the i-MOOC for unplugged IL instruction activities. Blazquez-Merino et al. (2018), however, reported similar learning effects of a K-12 MOOC in comparison to unplugged learning activities. Besides this, when evaluating an effect size, it is important to consider cost (Hattie, 2009). A K-12 MOOC may yield smaller learning effects than the well-developed instructional design of a teacher for a specific class; however, the MOOC can, with little effort, be used by a massive number of teachers and, hence, students.

Concerning RQ2, when predicting technology acceptance, there is an issue with discriminant validity in the UTAUT2 model. Adjustments to hypothesized models should be made in line with theory (Henseler, Ringle, & Sarstedt, 2015). Hence, we also estimated the UTAUT model by removing hedonic motivation from the UTAUT2 model. However, the finding of a very high correlation between hedonic motivation and technology acceptance may also be revealing. Since the constructs are conceptually different, as can be concluded from the items listed in Table 2, student acceptance of K-12 MOOCs may be purely driven by hedonic motivation. When this type of motivation is removed (UTAUT), the three remaining predictors—performance expectancy, effort expectancy, and social influence —can explain 47% of the technology acceptance variance. This is in line with technology acceptance studies in the context of education (Scherer et al., 2019). The best predictor in the UTAUT model is performance expectancy, i.e., the perception of MOOCs as a valuable learning resource. However, performance expectancy is on a rather low level (M = 3.40); the neutral scale mean equals 4. The perception of significant others (social influence) is also a notable predictor and on a low level (M = 2.41). Effort expectancy is the only construct with an overall positive evaluation (M = 4.90). However, other than hypothesized, effort expectancy is not a significant predictor for technology acceptance. Overall, student technology acceptance is below the neutral scale mean (M = 2.89). In contrast to this, all our reviewed studies report a favorable acceptance of K-12 MOOCs. However, these studies rely on a non-blended (voluntary) MOOC (Nigh et al., 2015), a blended MOOC with students from an elective course (Janisch et al., 2017), and a specific setting in rural Thailand (Panyajamorn et al., 2016). Our sample with students from thirty-one classes may provide a more realistic picture of student acceptance of K-12 MOOCs.

Concerning RQ3, as hypothesized, performance expectancy is a positive predictor for IL gain. Moreover, effort expectancy is a positive predictor for IL gain. This may also be in line with the cognitive load theory (Sweller, 2020): if a MOOC were difficult to use, this could imply extraneous cognitive load that hinders learning. Hedonic motivation, however, is not a positive predictor for IL gain, but negatively predicts it. This may be, at first glance, contradictory to findings in the context of academic performance where hedonic motivation predicts learning gain (Retelsdorf, Köller, & Möller, 2011). However, hedonic motivation in these cases addresses the learning content, e.g., reading. In our case, hedonic motivation addresses the means of instruction, namely, the i-MOOC. Our finding may be in line with Kirschner who argues that it is a myth that learning has to be fun to be efficient; rather, learning has to be rewarding (Kirschner, Verschaffel, Star, & van Dooren, 2017). Hedonic motivation does not predict IL gain when considered as the sole predictor. However, when considering performance expectancy, it negatively predicts it. Performance expectancy and hedonic motivation overlap ($\rho = 0.75$, $p < .001$). Pure hedonic motivation may be detrimental to learning whereas if a K-12 MOOC is perceived as rewarding (performance expectancy), this is conducive to learning. Indeed, studying with the i-MOOC may be hard work. Students have to carry out several (peer-feedback) tasks and answer quizzes. Students who overly assess the i-MOOC as fun and entertaining may be likely to only use it on a superficial level.

6.2. Limitations and recommendations for further research

Our study is not without limitations. We discuss them following Cachero, Barra, Melia, and Lopez (2020), by addressing internal, external, construct, and conclusion validity.

Compared to randomized field experiments as the gold standard, internal validity is suboptimal. We cannot claim that attendance of the i-MOOC caused the increase in IL as we do not have a control group (RQ1). Concerning technology acceptance (RQ2), data are cross-sectional, which does not allow for causal inference. Concerning the predictors for the posttest score (RQ3), there are further ones that may be considered. Such a predictor could be intrinsic value, which goes beyond hedonic motivation (Khechine, Raymond, & Augier, 2020). Again, the reported associations are correlational.

We collected data in a low stakes test environment. In particular, decreasing test motivation could downwardly bias effects (Finney, Sundre, Swain, & Williams, 2016). Fig. 2 may indicate that there are students with a substantial decrease in test motivation. Although we were able to demonstrate that students in our final sample are not different from those who refrained to fill in the questionnaire, in terms of observable characteristics, we cannot rule out differences in terms of unobservable characteristics.

A threat to external validity could be our sample. It is narrow in scope as it comprises only students from German-speaking Switzerland and only one K-12 MOOC. This sample is not representative of upper secondary level students in general. To make general claims about these students and K-12 MOOCs, replication studies would be necessary. Moreover, if MOOCs became a common phenomenon in K-12 education, it would be necessary to consider the level of habit as a predictor for technology acceptance; facilitating conditions should be considered if access to digital devices is limited (Venkatesh et al., 2012).

Concerning construct validity, a limitation is our reliance on relatively short IL tests and technology-acceptance scales. A reason for this is that in the first design research circle, teachers strongly requested a reduction in the quantity of research-related questions. Moreover, we only considered direct learning effects. However, there are likely to be positive side effects of using a MOOC, e.g., fostering students' digital skills. Further research could aim at a comprehensive picture of the learning outcomes of a K-12 MOOC.

Conclusion validity may be impaired as we only investigated individual-level associations, i.e., the student level. It is likely that class-level variables moderate the associations at the individual level. A likely moderator is the level of guidance and support offered by the teacher in a specific class. We were not able to model this multilevel structure due to our small class-level sample size ($N = 31$) (McNeish & Stapleton, 2016). Nevertheless, our (statistical) inferences are valid because we relied on class-mean centered variables and cluster-robust standard errors (McNeish et al., 2017; McNeish & Kelley, 2019). This approach may be the most suitable one for our data structure. However, for a comprehensive understanding of technology integration, it would be important to also consider teacher variables in the quantitative design. The effectiveness of educational technology use is likely to be moderated by the technology-related knowledge, skills, and attitudes of teachers (Scheiter, 2021; Seufert, Guggemos, & Sailer, 2021).

6.3. Implications

Kirschner and van Merriënboer (2013) raised concerns about whether students know best about what is conducive to their learning. Indeed, our findings show that teachers may be misguided if they give their students a choice whether to use (further) K-12 MOOCs in their instruction, when seeking IL gain. Student assessment may be purely based on whether they regard the MOOC as fun and entertaining (hedonic motivation); the acceptance of our MOOC can be almost perfectly predicted with hedonic motivation. However, hedonic motivation is a negative predictor for IL gain. If the student perspective is to be considered, it may be more revealing to ask them about their performance expectancy and effort expectancy as these are positive predictors for IL gain. In light of this, our research may help teachers and educational decision makers to ask students appropriate questions when deciding about integrating a MOOC at the K-12 level.

MOOCs are an important phenomenon in higher education; however, our study shows that upper secondary level students may have detrimental perceptions about them. It may be important to help students form realistic perceptions about MOOCs. According to Kirschner and Bruyckere (2017), it may be a myth that students can use technology, in our case a MOOC, without thorough instruction. A key variable in the instructional design is the level of guidance and support (Kirschner, Sweller, & Clark, 2006). When MOOCs are introduced at the K-12 level, teachers may provide their students with much guidance and support to help them acquire the skills conducive to successfully performing in the course. These skills could be (Castaño-Muñoz & Rodrigues, 2021): organization skills, self-regulation skills, and digital skills, e.g., digital collaboration and communication. The guidance and support may fade as students become more familiar with the use of MOOCs. Teachers may also point out that using a K-12 MOOC is not all about fun and entertainment (hedonic motivation). Rather, the successful completion of a MOOC could be rewarding (performance expectancy). Overall, a deliberate introduction of MOOCs at the K-12 level could foster the skills and attitudes that are necessary for successfully completing MOOCs. This may also yield benefits beyond higher education. MOOCs could play a vital role in workplace learning (Egloffstein & Ifenthaler, 2017). However, the current situation, where mostly highly qualified professionals use MOOCs, might be suboptimal

(Castaño-Muñoz & Rodrigues, 2021). A good example of the integration of MOOCs into a lifelong learning process is the initiative Digital Israel (https://campus.gov.il/en/about/): teachers in secondary education are required to use at least one MOOC during a semester in order to prepare students for this lifelong process (Seufert, Guggemos, & Moser, 2019).

As noted in the limitation section, our outcome variables, technology acceptance, and IL learning are narrow in scope. Positive side effects concerning the increase of digital skills as conceptualized by the DigComp 2.2 framework (Vuorikari, Kluzer, & Punie, 2022) are likely. As can be seen from the supplementary material S2, students communicate and collaborate to carry out the tasks, create digital content, e.g., videos, manage safety, e.g., use strong passwords, and solve digital problems, e.g., handling troubles when using the MOOC platform. Teachers could use K-12 MOOCs as a valuable learning resource to address important digital skills beyond the content matter (in the case of the i-MOOC, information literacy). While doing so, they may also improve their own technology-related knowledge and skills, e.g., in the realm of learning analytics (Ifenthaler, Gibson, Prasse, Shimada, & Yamada, 2021).

Credit author statement

Josef Guggemos: Conceptualization, Methodology, Validation, Formal analysis (statistical analysis), Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition, Project administration, Funding acquisition, **Luca Moser**: Investigation, Validation, Formal analysis (literature review), Data curation, Writing – original draft, Writing – review & editing, Project administration, **Sabine Seufert**: Conceptualization, Writing – review & editing, Resources, Supervision, Funding acquisition.

Declaration of competing interest

None.

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Appendix A. Supplementary data

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