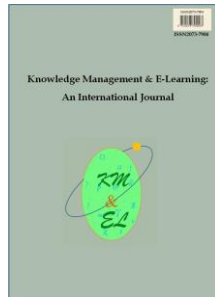

**The differential impact of interaction, environment and learner cognitive factors on online learning outcomes:
Insights from a European transition country**

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The differential impact of interaction, environment and learner cognitive factors on online learning outcomes: Insights from a European transition country

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Abstract: This article explores the multifaceted role played by interaction, cognitive, and environmental factors on various online learning outcomes in the context of Albania, a European transition country. More specifically, it scrutinises the differentiated impact of interaction (with content, peers and instructor), ease of use, attitudes, technical, and time constraints on three online learning outcomes, namely satisfaction, perceived learning, and quality of courses delivered online, aiming to achieve a nuanced understanding that can inform practitioners' decision-making. Drawing from a sample of 1698 graduate and undergraduate University students, hierarchical regression was employed to test the proposed models. Our findings for the pooled sample corroborate previous research results on the pivotal role of interaction in determining learning outcomes, albeit with some differences. While student-instructor and student-content interaction positively affect satisfaction, perceived learning and quality across models, the hypothesised effect of student-student interaction on satisfaction is not supported. Further, one of the cognitive factors analysed - ease of use - has no significant impact on learning outcomes. In contrast, attitude toward online learning is a major determinant affecting all outcomes. Environmental factors, such as technical constraints, negatively affect all three outcomes, while time constraints lower students' satisfaction. Finally, our results show differences among bachelor and master students. Interaction with the instructor is a critical determinant for all learning outcomes in the case of bachelor students, while interaction with peers is key to perceived learning for master students. This study contributes to the research stream focused on the differentiated impact on learning outcomes by introducing two environmental factors in the existing models. The implications for higher education

administrators and policymakers are further discussed.

Keywords: Perceived learning; Interaction; Satisfaction; Quality; Online learning; Attitudes; Environmental factors

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1. Introduction

Online learning popularity has recently increased with more institutions, especially universities, enriching and diversifying their offer, more learners attending open online courses and micro-credentials, and a rapidly growing EdTech sector (Salama & Hinton, 2023). Despite the significant shift to online learning, particularly following the COVID-19 pandemic, digital technology has changed but has yet to transform education (UNESCO, 2023). There is much untapped potential for online learning. Murphy (2020) noted that integrating technology into higher education is anticipated to reshape its future landscape by 2030, revolutionising pedagogies and enhancing learning outcomes.

Exploiting online learning opportunities at a learner and institution level requires setting clear priorities and conducting extensive planning. Moreover, comprehensive and in-depth research should guide such critical decisions. As stated by Demuyakor (2020), one of the most cited authors on this topic, university administrators are the primary users of research on online learning effects since it helps them to define long-term objectives and propose a forward-looking vision. However, research on online learning academic efficacy is limited and predominantly focused on developed countries' contexts (Ng et al., 2023). Besides, research is often supported by big tech providers; thus, independent and impartial research is needed to evaluate technology use in education and support an impartial, evidence-based decision-making process (UNESCO, 2023). This study aims to address this need by focusing on different learning outcomes in the context of Albania, a European transition country.

Historically, online and distance learning research has primarily focused on design, learner characteristics, and strategies to enhance interactivity (Berge & Mrozowski, 2001).

Later, researchers paid more attention to dimensions crucial to online learning outcomes, such as student individual characteristics, instructor teaching style, course type, technology used, course design, and the learning environment (Sun et al., 2008). Throughout the 2000s, online learning research focused on communication patterns in computer-mediated environments, instructional design, and learner attributes while the interest in educational technologies expanded (Catalano, 2018). The COVID-19 pandemic prompted a sudden switch to online learning. Understandably, such a worldwide transition drew the attention of many scholars, resulting in the proliferation of empirical studies on the phenomenon.

Nevertheless, amidst the development of new research streams, there is a research gap regarding the technology-assisted environment adaptation for optimal learning outcomes, the determinants of learning outcomes and their interplay, with few exceptions (e.g., Baber, 2020). As Klobas and McGill (2010) argued, research has focused more on the antecedents of adopting e-learning systems rather than understanding the outcomes. This dearth of attention towards assessing the success of e-learning systems impedes their strategic development and subsequent improvement of learning outcomes (Islam, 2013). Martin et al. (2020) systematic review showed that learning outcomes are among the least studied topics. However, the more recent meta-analyses and bibliographic reviews show a growing interest in various online learning outcomes and their determinants (Ng et al., 2023; Yu, 2022a), indicating a comeback of the topic in the research agenda. Therefore, in addressing the knowledge gap and in line with current scholarly work, our research focuses on three essential learning outcomes: satisfaction, perceived learning, and quality.

In this study, we test the differentiated impact of various factors on cognitive (i.e., perceived learning) and non-cognitive online learning outcomes (i.e., satisfaction and quality). The determinants include an array of factors suggested by recent literature (Santoso et al., 2024), such as three types of interactions, learner cognitive factors, and environmental factors – the latter identified by the authors of this study during the first phase of this exploratory study (see research design in data, methods and procedures section, for more). To test our hypotheses, we used a sample of master's and bachelor's students and employed regression analyses. In addition to the analysis of the pooled sample, we conducted two analyses of the two subsamples – bachelor and master students – to provide further evidence on differentiated strategies to achieve the aspired outcomes, answering Bernard et al. (2009) call for a more balanced focus on populations of bachelor and master students. From a theoretical standpoint, this research aims to contribute to the expanding body of knowledge concerning online learning outcomes and their determinants. From a practitioner's perspective, by exploring how different factors influence various online learning outcomes, the study seeks to provide valuable insights that can guide strategic decisions in higher education, especially in transition countries undergoing significant structural changes.

The rest of the paper is organised as follows: The second section presents the study's rationale and develops our research model and hypothesis. The third section comprises the research design, data, methods, and procedures used. The fourth section includes analysis and results, followed by discussions and implications.

2. Rationale, research model and hypotheses

The success of online learning must be judged by its effectiveness (Richardson & Swan, 2003). Indeed, given the acknowledged advantages of flexibility and cost savings, online

learning has been the subject of many examinations, focusing on its effects on learning outcomes. Even though it is expected that technology-mediated learning optimises the learning environment and processes and, as a result, enhances learning outcomes (Alavi & Leidner, 2001), the empirical evidence on the effectiveness of online learning compared to the traditional face-to-face format is still inconclusive (Nguyen, 2015).

The influential review of Tallent-Runnels et al. (2006) grouped learning outcomes into two categories: cognitive, usually measured by grades or pre and post-tests on knowledge, and affective, including students' attitudes, satisfaction, and perceptions of the online environment. In cases of students new to the experience of online learning, researchers suggest using perceptions of different learning outcomes as measures of effectivity (Marks et al., 2005). Thus, we focus on three outcomes: satisfaction, perceived quality and learning. Student satisfaction – among the most used outcomes in online learning research (Eom & Ashill, 2016) – is defined as “*the feeling or attitude of learners toward learning activities, which directly reflects the degree to which learners' expectations are fulfilled during the learning processes*” (Yu, 2022b). Course quality is another outcome that describes the student's educational experience based on their fulfilled needs, available information for decision-making, and improvement in learning outcomes (Vlachopoulos, 2016). Perceived high quality indicates that online courses are designed and delivered to provide opportunities for personalised profound learning experiences (Kauffman, 2015). Lastly, referring to perceived learning effectiveness, students' feelings regarding the acquired knowledge and skills in a certain field are a good measurement of actual learning (Marks et al., 2005).

Most studies focus on one specific outcome. However, some authors have analysed various outcomes of online learning, comparing online courses to face-to-face classes. For example, Eom and Ashill (2016) showed that learner, instructor and course design strategy determinants have a different effect on satisfaction compared to the effect on another outcome conceptualised as an aggregation of perceived learning and quality. Earlier, Ocker and Yaverbaum (1999) investigated whether asynchronous video conferencing was a good substitute of face-to-face collaboration and concluded that the results differ depending on the perceived learning outcome analysed (e.g., learning, quality, absorbed content, satisfaction with the learning process, discussion quality, assignment solution). Sebastianelli et al. (2015), focusing on online learning, found that course content, structure and rigour, as well as interaction and mentoring, have a differential impact on various online learning satisfaction, quality and learning. In a study by Arbaugh (2002), a comparable approach was used to examine how students, courses, learning environments, and instructor-related factors influence perceived learning and satisfaction, emphasizing the importance of interaction in achieving positive effects on both learning outcomes.

As these studies show, focusing on various outcomes and employing a comparative analysis to identify the differentiated effect of various factors on several outcome has important implications for practitioners. For example, student satisfaction is a very good proxy of students' future decisions to take a course online (Marks et al, 2005), while certain cognitive strategies, like interaction and social learning, are followed by new solutions (e.g. interaction with digital content, peers or instructors in a digital or hybrid learning environment) to existing problems like quality and actual level of learning (Alavi & Leidner, 2001). Considering these substantial implications, especially for faculty's decision-making, our study takes a similar approach.

2.1. Interaction-related factors and learning outcomes

Higher engagement and interaction in online courses are a vital feature of course design (Swan & Shih, 2005). Online learning makes interaction more challenging due to the learner's and instructors' distance and time separation, but supporting technologies provide opportunities for asynchronous interaction and knowledge sharing in a variety of formats, such as writing, video, and document sharing, facilitating higher academic performance (Strang, 2011). Learners' engagement through these mediums facilitates understanding of the course content and achievement of learning outcomes (Thurmond & Wombach, 2004). However, Bernard et al.'s (2009) meta-analysis of 74 studies indicated that while not all interaction types have a similar effect on outcomes, increasing the strength of different types of interactions affects students' achievement. Consequently, various interactions, whether with instructors or content, are frequently used as a predictor of learning outcomes due to their crucial role in the development of cognitive (Vygotsky, 1978) and physical skills (Barker, 1994).

Many studies have empirically validated the role of interaction in improving various online learning outcomes but also recognised the relationship between different types of interactions and learning outcomes as rather complex (Joksimović et al., 2015). Participant interaction is among the primary drivers of successful online course experiences (Arbaugh, 2002) since it impacts online learning climate, performance and perceived learning (Bernard et al., 2009; Picciano, 2002; Wu et al., 2010). Similarly, Richardson and Swan (2003) concluded that students' sense of belonging to a learning community developed through interaction positively impacts perceived learning and satisfaction with the instructor. However, despite the abundant empirical evidence on the positive effect of interaction on learning outcomes, some studies have questioned its effect due to the irreplaceable role of face-to-face interaction (Picciano, 2002), indicating that technologies supporting learning have not yet introduced adequate innovations that enhance communication through online tools.

Following Moore's (1989) categorisation of interactions in online learning settings, namely, student-student interaction, student-instructor interaction, and student-content interaction, we develop our research hypothesis for the three types of interaction.

2.1.1. Student-to-student interaction

Student-to-student interaction as an “*inter-learner interaction between one learner and other learners, alone or in group settings, with or without the real-time presence of an instructor*” (Moore, 1989), increases satisfaction (Nagy, 2018). Besides, some authors have found support for the positive impact of student-to-student interaction on learning, measured either by the perception of learning (Marks et al., 2005) or grades (Joksimović et al., 2015). Finally, student-to-student interaction's positive relationship with perceptions of quality was also supported by some scholars (Marks et al., 2005; Sebastianelli et al., 2015). Therefore, based on empirical research, we posit the following hypotheses:

H1a: Student – Student interaction positively affects satisfaction.

H1b: Student – Student interaction positively affects perceived learning.

H1c: Student – Student interaction positively affects quality.

2.1.2. Student-to-instructor interaction

The interaction between the learner and the expert who prepared the subject material is expected to be one of the most important types of interaction, although, in an online learning environment, time spent interacting with the instructor is reduced. Instructors plan and deliver various activities such as presentations, demonstrations, simulations, guided or self-directed assignments, or assessments to simulate students' motivation and learning (Moore, 1989). Optimal-size classes allow enough time for quality feedback and exchange, leading to students' higher satisfaction because they can consult course assignments and get continuous support in synchronous and asynchronous modalities (Alqurashi, 2018).

Research combining different factors impacting perceived learning or satisfaction in the web-based learning environment (Bolliger & Martindale, 2004; Marks et al., 2005) found that student-instructor interaction is the most critical form of interaction. Further, a positive relationship between interaction with the instructor and perceived learning or academic achievement was also supported by empirical studies (Alqurashi, 2018; Bernard et al., 2009; Fredericksen et al., 2000), especially if the instructor and the students feel affectively connected (Swan & Shih, 2005). Finally, Hunter and Ross (2019) found support for a positive relationship between student-instructor interaction and learning quality. Based on the theoretical arguments and empirical evidence, we advance the following hypotheses:

H2a: Student – Instructor interaction positively affects satisfaction.

H2b: Student – Instructor interaction positively affects perceived learning.

H2c: Student – Instructor interaction positively affects quality.

2.1.3. Student-to-content interaction

Interaction between the student and the subject content is a defining characteristic of education. “*This process of intellectually interacting with content results in changes in the learner's understanding, the learner's perspective, or the cognitive structures of the learner's mind*” (Moore, 1989). Aware of its importance, companies developing online learning platforms constantly improve their products. Digital tools facilitating online learning are continuously innovating, allowing for different forms of synchronous and asynchronous user interaction with various typologies of content that facilitate learning, be it text, multimedia, assignment, or even games, ultimately positively affecting the learner's performance (Mayer, 2003). From the instructor's perspective, various systems and applications allow access and students' activity tracing regardless of time and location, providing more opportunities to develop effective pedagogical approaches to online-only or blended learning.

Due to its importance, student–content interaction has drawn the interest of many researchers. Academics have empirically validated its positive effect on learning outcomes such as learning experience and satisfaction (Alqurashi, 2018; Joksimović et al., 2015) and quality (Sebastianelli et al., 2015). However, despite the extensive empirical findings, some authors (e.g., Sun et al., 2008) contest the effectiveness of student-content interaction. They argue that the media produced and accessible in open education resource repositories is sometimes time-consuming, not always quality-checked, and is not necessarily associated with higher performance and online learning satisfaction. While such arguments are compelling and supported by some anecdotic evidence collected during the exploratory phase of this study, following the extensive evidence presented above, we hypothesise:

H3a: Student – Content interaction positively affects satisfaction.

H3b: Student – Content interaction positively affects perceived learning.

H3c: Student – Content interaction positively affects quality.

2.2. *Learner's cognitive factors and learning outcomes*

According to Bandura's Social Cognitive Theory, performance expectations encompass an individual's perception of the potential outcomes of a particular behaviour, acting as a powerful influence on their actions. These expectations stem from personal assessments of the desirable consequences of specific behaviours. Bandura (1977) highlights that individuals are inclined to engage in behaviours they believe will yield favourable outcomes, emphasising the significance of perceived benefits in driving behaviour. In an online learning setup, cognitive factors refer to the learners' cognitive beliefs that influence their behaviours in participating in this (new) learning modality (Wu et al., 2010).

Yu's (2022a) meta-analysis suggests that behavioural intention is among the top ten research topics in the online learning research domain, while the Technology Acceptance Model (TAM) model (Venkatesh and Davis, 2000) is among the most used frameworks to study it. Core variables that affect users' behavioural intentions, such as ease of use, usefulness, and attitudes, are confirmed in traditional TAM models as determinants of future (expected) behaviour. TAM has been extended by adding online learning outcomes in the model, such as perceived learning and academic performance, as the ultimate effect of online learning behaviour (Islam, 2013). Following this approach, we aim to investigate the differentiated impact of core TAM variables in various learning outcomes.

2.2.1. *Ease of use*

According to Davis et al. (1989), ease of use refers to the degree to which a person believes that using technology will be free from effort. In the case of online learning, it means that the participants will easily use devices and systems. Research shows that ease of use impacts students' self-perception of their capacity to achieve learning outcomes (Chen et al, 2020; Wu et al., 2010). The positive effect of ease of use on online learners' satisfaction has been corroborated in different contexts (Nagy, 2018; Sun et al., 2008). Further, Hilmi et al. (2012) showed that ease of use positively relates to the quality of education. More recent research in the post-COVID-19 period indicates that ease of use positively impacts the perceived usefulness measured by the degree of learning outcomes enhancement (Nikou & Maslov, 2021). Moreover, Kesavaraj and Felisiya (2024) showed that ease of use increases satisfaction with the learning management system, while the latter has a strong positive effect on academic performance. Based on this evidence, we posit the following hypotheses:

H4a: Student's ease of use positively affects satisfaction.

H4b: Student's ease of use positively affects perceived learning.

H4c: Student's ease of use positively affects quality.

2.2.2. *Attitudes*

Individual attitudes, reflecting feelings of favourableness or non-favourableness toward using an IT-based system, are a function of beliefs, including behavioural beliefs directly

linked to a person's intention to perform a defined behaviour (Ajzen & Fishbein, 1980). Attitudes in an online learning setting are individual assessments, favourable or not favourable in this learning setting and expected to influence the future behavioural intention to follow or participate in online courses. Research on the link between attitudes and various learning outcomes is scarce, especially regarding its relationship with quality (Brooks, 2003). Some studies have shown that a positive learner's attitude towards online learning determines satisfaction (Sun et al., 2008) and the effectiveness of online learning (Piccoli et al., 2001). Further, some indirect evidence suggests that attitudes significantly influence online learning by enhancing various factors contributing to quality, including students' intellectual competence, academic performance, and online engagement (Ferrer et al., 2022). We expect attitudes to be an essential determinant of the three learning outcomes; thus, we advance to the following hypotheses.

H5a: Student attitude towards online learning positively affects satisfaction.

H5b: Student attitude towards online learning positively affects perceived learning.

H5c: Student attitude towards online learning positively affects quality.

2.3. Environment factors and learning outcomes

Studies have extensively analysed the environmental enablers and barriers students face in an online learning setting. According to the O'Doherty et al. (2018) review, time constraints, poor technical skills, inadequate infrastructure, and absence of institutional strategies are among the key barriers affecting the development and implementation of online learning. In their meta-analysis, Muilenburg and Berge (2005) suggest that administrative issues, time and support for studies, cost and access to the internet, and technical problems affect online learning effectiveness. Further, access to proper devices at home and institution (Bolliger & Martindale 2004), the internet, and especially the software supporting access to digital learning materials, significantly affect satisfaction with online learning (Piccoli et al., 2001) and perceived learning (Fredericksen et al., 2000).

The massive shift to online learning following the COVID-19 pandemic lockdown significantly impacted the learning environment and affected learners' access and success in online learning. As stated in the Global Education Monitoring Report, due to a lack of proper infrastructure, distance learning during the last pandemic failed to reach 31% of students worldwide – and 72% of the poorest (UNESCO, 2023). As a result, technology was featured as a top research theme when analysing learning outcomes (Ng et al., 2023). Poor internet network performance was the main factor leading to negative online experiences (Santoso et al., 2024). Filius et al. (2019), focusing on technology features, argued that having the means to access digital learning materials and employing technologies that enhance interactivity and peer feedback are prerequisites for students' learning. While important, environmental factors, especially those related to access to technology, differ across contexts, with developing and transition countries lagging behind developed ones. Given the lack of information about learning environment conditions, we conducted an exploratory survey with open questions as the first phase of this research to better investigate context-specific idiosyncrasies.

The exploratory phase of our study revealed that the main challenges students face are indeed related to the inappropriate learning environment, such as lack of connectivity and high internet costs, lack of proper devices to attend online classes (almost 70% of students used smartphones during online classes), lack of proper environment conditions to attend online classes, e.g., home environment is not always quiet enough to concentrate.

Especially during the pandemic lockdown, most students had to return to their home cities, use the living areas as study environments, and often share the space with family members. At home, often in rural areas, students suffer from bad internet connection, which bandwidth is limited once several users are accessing it. Time management was another challenge that emerged after the immediate shift from face-to-face to online learning. Students report that changing class schedules were frequent, especially at the beginning of the lockdown, where learners faced many changes in class schedules due to constraints faced by instructors in finding a work-family balance and resource sharing between family members (e.g., computers). This constraint is backed up by recent research suggesting that time can be both an opportunity for flexibility and personalisation (Panigrahi et al., 2018) and a hindering factor to effectiveness due to time management issues and procrastination (Davis et al., 2019). Based on the above arguments, the findings of our first phase and the exploratory factor analysis, we identified technical and time constraints as factors negatively affecting learning outcomes. Thus, we posit that:

H6a: Technical constraints negatively affect satisfaction.

H6b: Technical constraints negatively affect perceived learning.

H6c: Technical constraints negatively affect quality.

H7a: Time constraints negatively affect satisfaction.

H7b: Time constraints negatively affect perceived learning.

H7c: Time constraints negatively affect quality.

Fig. 1 below depicts the conceptual model describing the relationship between different dimensions and learning outcomes.

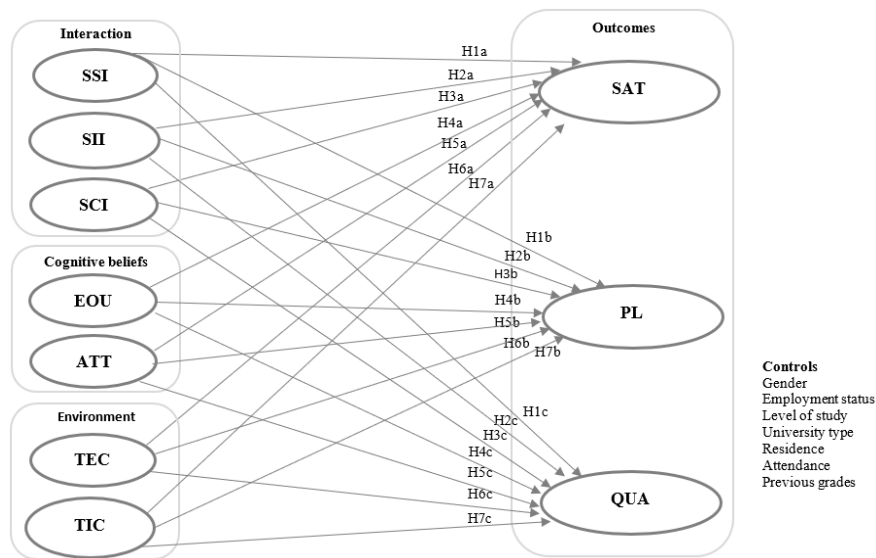


Fig. 1. Conceptual model. SAT: Satisfaction; PL: Perceived learning; QUA: Quality of online learning course; SSI: Student-student-interaction; SII: Student-instructor-interaction; SCI: Student-content-interaction; EOU: Ease of use; ATT: Attitudes; TEC: Technical constraints; TIC: Time constraints

3. Data, methods and procedures

3.1. Research design

We used an exploratory sequential mixed methods research design composed of three stages (see also Creswell, 2009). This research design denotes the following sequence of steps: the qualitative data obtained in the first stage serve to develop the research instrument (second stage), which is administrated to the population (third stage). This design was deemed appropriate for exploring a relatively new phenomenon (i.e., online learning) in Albania as it allows the refinement of existing instruments. Accordingly, first, we surveyed 470 bachelor's and master's students to explore better idiosyncrasies of the online learning experience in the Albanian context. While the survey provided some interesting descriptive data, the instrument included many open questions to identify specific factors that might affect outcomes during the particular circumstances of the lockdown following the COVID-19 pandemic. Based on the first stage findings, and after some validation from online interviews, we developed indicators to capture phenomena such as different types of constraints or barriers to online learning, expanding the theory-based questionnaire. Finally, in the third stage, we administered the enriched questionnaire, i.e., including existing, theory-based constructs and the ones we developed to the population of undergraduate and graduate students. The findings of this study are based on the results of this second survey.

3.2. Data

An online survey was used to collect data from bachelor's and master's students attending different programs in 26 faculties of 12 universities. Before disseminating the questionnaire to students, we pre-tested it with 13 of them. Accordingly, some questionnaire items were modified.

Three uncompleted questionnaires were removed from the dataset. From the remaining 1822 cases, 16 were removed due to unengaged responses. Additionally, we excluded 55 cases of students who had never used online platforms. Finally, using the modified Z-score method (Iglewicz & Hoaglin 1993), we removed 53 outliers. The final dataset consists of 1698 cases.

3.3. Bias examination

Since data were collected using a self-reporting questionnaire by individual students, we controlled for non-response (NRB) and common method bias (CMB).

We tested for the NRB using wave analysis (Van der Stede et al., 2006) by comparing early versus late respondents depending on when online questionnaires were filled out. The chi-square tests indicated no difference between the groups for students' attributes, such as residence area (urban vs rural) (χ^2 test, p -value = 0.307), gender (χ^2 test, p -value = 0.121), attendance year (χ^2 test, p -value = 0.320) employment status (χ^2 test, p -value = 0.203). Furthermore, there are no differences between the two groups regarding the three learning outcomes. Independent T-test results indicate no differences of means for satisfaction (p -value = 0.579), perceived learning (p -value = 0.685) and quality (p -value = 0.550). Thus, we concluded that NRB is not a problem in our study.

Following Podsakoff et al. (2003), the questionnaire was pre-tested to improve the clarity and avoid ambiguity. Further, students were informed that the survey would only be used for research purposes. Finally, using Harman's single-factor technique, we determined that a single factor extracted accounted well below the indicated threshold of 50% (at around 22.7%). The ex-ante remedies and ex-post analysis suggest that CMB is not a threat in our study.

3.4. Measures

3.4.1. Dependent variable

Following Sebastianelli et al. (2015), we operationalise satisfaction, perceived learning and quality using a two-item construct for satisfaction and a single item for the last two learning outcomes. The standardised Cronbach's alpha coefficient of satisfaction is acceptable at 0.739 (Nunnally, 1978).

3.4.2. Independent variables

Interaction with content, peers, and the instructor was measured using multi-item scales developed by Ravenscroft et al. (2017) and Alqurashi (2018). The Cronbach's alpha of the three constructs, respectively, at 0.861, 0.915, and 0.795, meet the recommended criteria of Nunnally (1978).

Technical constraints is a construct composed of four items. Following the conceptualisation of Bolliger and Martindale (2004) and the results of the exploratory factor analysis, we measured this construct using the following items: the extent of use of inappropriate hardware and equipment (e.g., computers, cell phones), problems with internet connection, the high costs of the internet connection and lack of suitable learning space (e.g., a quiet room for attending classes). The Cronbach's alpha coefficient of the construct is excellent at 0.809.

Similar to technical constraints, time constraints is a construct that emerged from the exploratory phase of the study. It is composed of two items. Students assessed the extent to which inappropriate timing for lecturing and schedule flexibility represented a barrier to learning. The construct's Cronbach's alpha coefficient is acceptable at 0.743.

Attitude towards online learning was measured using Taylor and Todd's three-item scale (1995) on students' perceptions of whether online tools were the right ones for an interesting class. One item was removed following the factor analysis's indications. The Cronbach's alpha of the two-item constructs is excellent at 0.872.

Ease of use was measured using a two-item construct, following Li and Yu (2020), on students perceived ease of using online learning software and hardware. The Cronbach's alpha coefficient of the construct is excellent at 0.880.

3.4.3. Control variables

Five binary variables describing principal respondents' attributes were used in this study, namely gender, employment status (employed vs unemployed), level of study (master vs bachelor), university type (public vs. non-public), residence (urban vs. rural area) and last

year's average grade. Class attendance can affect quality and learning (James & Seary, 2019). Hence, we included this variable as a control. Details on the operationalisation of the variables are presented in Appendix I.

3.5. Construct validity

Factor analysis with Promax rotation was performed to test the validity of multi-item constructs (see Appendix II). The results showed that all items for the eight constructs load reasonably high, above the acceptable standard of 0.4 (Hinkin, 1995), with few exceptions. AT3, SII4 and SCI4, respectively for attitudes, student-instructor interaction and student-content interaction, were removed due to low and cross-loadings. All the other items did not show significant cross-loadings, indicating the discriminant validity of our measures. Moreover, we tested the convergent and discriminant validity of our two new constructs, namely, technical and time constraints. Exploratory factor analysis showed that there are no cross-loadings with items of other constructs, and loadings of each item within the construct are usually above 0.6, with one exception at 0.57.

3.6. Model

A two-stage hierarchical multiple regression analysis was used to test our hypothesis. We aimed to examine the contribution of different dimensions above and beyond the control variables – respondent's attributes and behaviour (e.g., class attendance) (see Pedhazur, 1997). Respondents' attribute variables were entered in the first stage, while all the other variables representing different dimensions of the online learning experience were entered in the second stage.

3.7. Assumptions testing

Following George and Mallery (2010), we tested for normality, linearity, autocorrelation, heteroscedasticity, and multicollinearity. First, our data are substantially normal, with levels of kurtosis and skewness within the -2 to +2 range. Also, the quantile-quantile (q-q) plot showed a straight line, indicating that the residuals are normally distributed. Taken together, these analyses showed univariate and multivariate normality of our data. Second, the scatter plot of residuals and y values followed a linear pattern, showing that the linearity assumption is met. Third, Durbin Watson's test statistic value around 2 showed (see table 1 below) that there is no autocorrelation between the residuals. Fourth, upon visual inspection of the residual errors, we concluded that the data are spread consistently and equally through the plot, indicating homoscedasticity. Finally, variance inflation factor values around 1 indicated no multicollinearity-related issues in our analysis.

4. Analysis and results

Table 1 presents the results for our three regression models, with satisfaction as the outcome in model 1, perceived learning in model 2, and quality in model 3.

Model 1 results show that interaction-related factors significantly affect satisfaction, except for student-to-student interaction ($p > 0.1$). As expected, the effect is positive for both student-content ($\beta = 0.179, p < 0.001$) and student-instructor interaction ($\beta = 0.061, p < 0.01$); thus, hypotheses 2a and 3a are supported while hypothesis 1a is rejected. Further,

among the two learners' cognitive factors, attitude has a positive significant effect on satisfaction ($\beta = 0.318, p < 0.001$), while the effect of ease of use is not significant ($p > 0.1$), supporting hypothesis 5a and rejecting hypothesis 4a. Among the environmental factors, both technical constraints and time constraints decrease satisfaction ($\beta = -0.136, p < 0.001$ and $\beta = -0.154, p < 0.001$, respectively). Thus, hypotheses 6a and 7a are supported.

Table 1
Regression results

Variables	Model 1 (satisfaction) Value (std.err.)	Model 2 (perceived learning) Value (std.err.)	Model 3 (quality) Value (std.err.)
First step (control variables only)			
Gender	0.102 (0.106)	0.179 (0.111)	0.153 (0.115)
Level of study	0.459*** (0.091)	0.213* (0.095)	0.279** (0.098)
Employment status	0.032 (0.094)	0.078 (0.099)	0.027 (0.102)
University type	-0.185 [†] (0.095)	-0.094 (0.100)	-0.668*** (0.103)
Residence	-0.028 (0.084)	-0.029 (0.088)	0.013 (0.091)
Average grade	-0.009 (0.034)	0.011 (0.035)	-0.050 (0.037)
Class attendance	0.487*** (0.032)	0.566*** (0.034)	0.420*** (0.035)
R ²	0.145	0.155	0.114
Adjusted R ²	0.142	0.151	0.110
Second step (all variables)			
Gender	-0.018 (0.082)	0.110 (0.094)	0.063 (0.092)
Level of study	0.248*** (0.071)	0.025 (0.082)	0.044 (0.080)
Employment status	0.065 (0.073)	0.057 (0.084)	0.026 (0.082)
University type	0.220** (0.075)	0.220* (0.086)	-0.295** (0.085)
Residence	0.007 (0.066)	-0.022 (0.076)	0.006 (0.074)
Average grade	-0.050 [†] (0.026)	-0.026 (0.030)	-0.089** (0.030)
Class attendance	0.140*** (0.027)	0.278*** (0.031)	0.085** (0.031)
Student-content interaction	0.184*** (0.027)	0.238*** (0.031)	0.217*** (0.030)
Student-instructor interaction	0.071* (0.033)	0.078* (0.038)	0.108** (0.037)
Student to student Interaction	0.029 (0.022)	0.053* (0.025)	0.100*** (0.025)
Attitude	0.304*** (0.026)	0.251*** (0.030)	0.298*** (0.029)
Ease of use	0.025 (0.030)	0.004 (0.034)	-0.039 (0.034)
Technical constraints	-0.142*** (0.022)	-0.101*** (0.025)	-0.115*** (0.024)
Time constraints	-0.133*** (0.018)	-0.005 (0.021)	-0.032 (0.020)
F	116.372***	95.674***	134.574***
R ²	0.492	0.396	0.432
Adjusted R ²	0.488	0.391	0.427
Durbin-Watson	1.899	1.872	1.951

Note. Std. err.: Standard error; Value: Unstandardized beta; * $0.01 \leq p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; [†] $0.05 \leq p < 0.1$

Model 2 results indicate that all three interactions, student-content ($\beta = 0.220, p < 0.001$), student-instructor ($\beta = 0.062, p < 0.05$) and student-to-student interaction ($\beta = 0.053, p < 0.05$), have a significant positive effect on perceived learning supporting

hypothesis 1b, 2b and 3b. Similarly to model 2, attitude has a positive effect on perceived learning ($\beta = 0.249, p < 0.001$), while ease of use does not ($p > 0.1$). Thus, hypothesis 5b is supported, while hypothesis 4b is rejected. Technical constraints have a negative effect on this outcome ($\beta = -0.091, p < 0.001$), while the time constraints effect is not significant ($p > 0.1$), thus supporting hypothesis 6b and rejection hypothesis 7b.

Model 3 results are similar to the ones of Model 2. All three interaction measures, student-content ($\beta = 0.198, p < 0.001$), student-instructor ($\beta = 0.086, p < 0.05$) and student-to-student interaction ($\beta = 0.101, p < 0.001$), attitude ($\beta = 0.293, p < 0.001$), and technical constraints ($\beta = -0.104, p < 0.001$) have a significant effect on quality, supporting hypothesis 1c, 2c, 3c, 5c, 6c. However, the effect of ease of use and time constraints on quality are not significant ($p > 0.1$). Thus, hypotheses 4c and 7c are rejected.

In our study, we controlled for the effect of students' attributes. Gender, employment status and being a resident in an urban area do not affect any learning outcomes. Attending a public university has a positive effect on satisfaction ($\beta = 0.056, p < 0.01$) and perceived learning ($\beta = 0.053, p < 0.05$) but a negative one on quality ($\beta = -0.071, p < 0.01$). Attending a master's program has a positive effect on satisfaction ($\beta = 0.066, p < 0.001$), while there is no significant relationship with either perceived learning or quality ($p > 0.1$). The average grade of the student has a negative effect on satisfaction ($\beta = -0.035, p < 0.1$) and quality ($\beta = -0.059, p < 0.01$) but no significant effect on perceived learning ($p > 0.1$). Finally, class attendance has a significant positive effect on satisfaction ($\beta = 0.101, p < 0.001$), perceived learning ($\beta = 0.190, p < 0.001$) and quality ($\beta = 0.057, p < 0.001$).

Regression results show that the student's attributes and class attendance explain 14.2%, 15.1% and 11% of satisfaction, perceived learning and quality variations. Adding the other determinants resulted in the increase of each of the learning outcomes' variations to 48.8%, 39.1%, and 42.7% for models 1, 2, and 3, respectively.

To better understand the differences between the population of master's and bachelor's students, we analysed the two subsamples (see Appendix III). While the results should be interpreted with caution due to the different sample sizes, they indicate small differences between the populations and between these subsamples and the entire population of students. A significant difference is that student-instructor interaction appears to be an essential determinant for the three learning outcomes of bachelor students ($\beta = 0.065, p < 0.001$; $\beta = 0.208, p < 0.001$; and $\beta = 0.175, p < 0.001$ for satisfaction, perceived learning and quality, respectively) but not master students. Further, student-to-student interaction is more important for the perceived quality of learning of master compared to bachelor students; the results are significant for the two subsamples and the entire population of students, although there are differences regarding the size effect. Technical constraints affect all learning outcomes among bachelor students but have a strong negative impact only on learning quality ($\beta = -0.155, p < 0.01$) among master students. Finally, time constraints affect bachelor students' satisfaction ($\beta = -0.162, p < 0.001$) only while not affecting any learning outcomes for master students. The results for the rest of the determining factors are similar to the one presented above, with attitude being the determinant with the largest size effect.

5. Discussion

This study explores the differentiated effect of several determinants on online learning outcomes: satisfaction, perceived learning and quality of online courses. It also aims to provide a nuanced understanding of the investigated effects by comparing the population of students attending the master's and bachelor's programs. By including in our models, the individual, interaction and cognitive factors, and the emerging environmental variables from our exploratory analysis as determinants of various learning outcomes, our study contributes to the research stream investigating the differentiated effect of various factors on learning outcomes (e.g., Arbaugh, 2002; Sebastianelli et al., 2015). While corroborating some of the previous research findings, our study results show some differences that indicate the importance of the context in shaping students' experience with online learning.

Our results confirm some of the previous research findings regarding the crucial role of attitudes in determining various online learning outcomes. Applying a more nuanced interpretation, the effect is more substantial on satisfaction, followed by perceived quality and learning. These findings are partly in line with Arbaugh's (2002) work, which supported the hypothesis on the positive effect of attitude on satisfaction with the delivery medium but not for perceived learning. Further, the analyses of our two subsamples (i.e., master and bachelor students) show similar results. Taken together, our results strengthen the theoretical arguments on attitudes' pivotal role in active participation in self-directed and collaborative learning environments (Nam & Zellner, 2011) and their impact on actual learning (Ajzen & Fishbein, 1980; Venkatesh & Davis, 2000).

In line with previous research (e.g., Alqurashi, 2018; Joksimović et al., 2015; Sebastiaianelli et al., 2015), which highlights the importance of the course content in determining various learning outcomes, our research confirms interaction with content as the second most important determinant of all learning outcomes in terms of effect size for both subsamples and the pooled sample with some subtleties worth mentioning. More specifically, interaction with content has a stronger impact on perceived learning and the weakest on satisfaction. Such an effect size acquires more relevance considering the context in which the shift to online learning occurred. Anecdotic evidence suggests that some instructors were unprepared to adjust the curricula and the relevant content for a technology-mediated modality. Furthermore, learning management systems did not always facilitate optimal student interactivity with the content. Hence, the interaction variability with content is relatively high, leading to such an effect across learning outcomes.

Our pooled sample regression results indicate that interaction with the instructors positively affects all learning outcomes, but the effect is weak. Interaction with the instructor has the most robust impact on learning quality, followed by satisfaction and learning, which differs from Sebastianelli et al. (2015) findings, who determined a more substantial effect of interaction with the instructors on satisfaction than quality. This difference in size effect can be attributed to the experience of instructors with online learning in the context analysed by Sebastianelli et al. (2015). The Albanian professors had little time to improve didactics and pedagogy after the lockdown and the abrupt switch from face-to-face to online learning. Thus, the impact on satisfaction, for example, is not high. When comparing different student groups, we found that student-instructor interaction is significant for bachelor's students only, suggesting that younger and less experienced learners rely more on instructors for guidance. In contrast, more experienced master's students, who tend to be more independent, rely less on such interaction. This lack of significant impact for the master's student sub-sample aligns with previous research

findings (e.g., Moore, 1989), further supporting the notion that student-instructor interaction is not among this group's most important determinants of learning outcomes, at least for this group.

Interaction with peers is more critical for master's than bachelor's students, especially regarding its effect on perceived quality. This result might be explained by the teaching methodology usually followed in smaller master classes, where group work for assignments applies and peer learning opportunities among experienced classmates are higher. In line with Sabasatianelli et al. (2015) and Arbagouh (2002), the effect of peer interaction on quality is more substantial than that of perceived learning, showing that cooperative learning enriches the gaps associated with this new learning format. Besides, as previous research suggests (Alqurashi, 2018), our study shows that this interaction does not affect satisfaction.

Our study seems to validate Anderson's (2003) theorem on interaction in online/distance learning: *"Deep and meaningful formal learning is supported as long as one of the three forms of interaction (student-teacher; student-student; student-content) is at a high level. The other two may be offered at minimal levels or even eliminated without degrading the educational experience. High levels of more than one of these three modes will likely provide a more satisfying educational experience."* In the Albanian higher education context, interaction with content is the primary and most important type of interaction, consistent with Bernard et al. (2009) meta-analysis on the most effective types of interaction in distance education. However, the other types of interaction affect the two subsamples differently, with interaction with peers affecting quality and interaction with the instructor having an effect across outcomes. Therefore, subsample analysis shows that *"the right mix"* or *"trade-offs"* between types of interaction can be optimised to maximise the desired effect on selected online learning outcomes.

Our research confirmed environmental factors as the third block of online learning outcome determinants. Inappropriate timetables (i.e., time constraints) are a strong constraint, negatively impacting the satisfaction of bachelor students but having no effect on perceived learning and quality. These findings indicate that the schedule for online learning sessions and other irregularities and changes in class schedules create discomfort (lowering satisfaction). However, such discomfort is not evidenced among master students. This group appears to be unaffected by flexible timetables. Our results seem to contradict some research suggesting that students might benefit from flexibility in terms of learning and perceived quality, as Panigrahi et al. (2018) suggested. However, these results should be interpreted with caution. The frequent change of online learning schedule was temporary, occurring only in the first weeks of the lockdown, enough to affect satisfaction but perhaps not long enough to affect actual learning and quality.

Our findings for the pooled sample highlight the critical role of access to proper devices, the internet and software, as suggested by many authors (Bolliger & Martindale, 2004; Filius et al., 2019; Fredericksen et al., 2000; Piccoli et al., 2001), negatively affecting all learning outcomes, mostly quality. The subsample analysis shows that the constraint is perceived as a more substantial barrier for bachelor students compared to master students, affecting all three outcomes. However, the technical constraints negatively affect the perceived quality of learning of master students, too. Further, in contrast with recent research on COVID-19 pandemic-impacted learning environments (e.g., Nikou & Maslov, 2021) and in line with earlier research (e.g., Arbaugh, 2002), our study results suggest that the fact that platforms and systems are easy to use does not affect either affective or objective online learning outcomes. This inconsistency with recent research may be

attributed to the limited functionalities of commonly used platforms during the lockdown period, such as Zoom and Google Meet, compared to Microsoft Teams, which were widely used by many Albanian Universities the following year. These platforms were primarily employed for synchronous video communication rather than fostering a highly interactive class environment or supporting content management that allows for quality learning.

6. Implications

The study has some important theoretical implications regarding the critical role played by the context when investigating the online learning phenomenon. Education systems in countries such as Albania were not adequately prepared to face the challenges of online learning, exacerbated by the abrupt shift to this modality caused by the COVID-19 crisis. Therefore, there are additional barriers to online learning's intended outcomes compared to other countries that have acquired more experience with such modalities. Hence, a qualitative investigation of context idiosyncrasies was warranted. The exploratory sequential mixed methods research design allowed us to develop new valid measures and increase our models' explanatory power. Future research can employ a similar approach to identify environmental barriers, such as technical and time constraints, which can be adapted and refined to other contexts.

This research has some significant practical implications for policymakers, University decision-making bodies and individual instructors. It highlights how diverse factors impacting online learning can produce distinct and converging effects on various learning outcomes. With regards to distinct effects, if the objective of online learning is to improve bachelor student satisfaction, addressing the infrastructure and time constraints is critical, followed by enhanced interaction with the instructor. In case the quality of online learning at the master level is an aspired objective, addressing technical constraints is essential, followed by participatory teaching and learning methodologies that allow for peer interaction. Hence, developing peer-to-peer learning methods such as group project-based learning, peer mentoring, and peer assessment (see Raymond et al., 2016) should be explored. In the case of actual learning as the ultimate learning outcome, especially for bachelor students, after addressing infrastructure constraints as a barrier, designers should allow for effective interaction with the teacher, which is far more critical than interaction among peers.

Concerning the convergent effects, our study findings emphasise the indispensable role of cultivating a positive attitude toward online learning to achieve any learning outcome. Therefore, institutions must understand students' perspectives, beliefs, emotions, and prerequisites for enthusiastic engagement in online learning. In this regard, regular student surveys and other instruments for quality assurance purposes should include dimensions of online learning (Dibra et al., 2023; Zhao, 2003). Faculties, especially the ones with the proper pedagogical competencies, should conduct action research to provide evidence on students' attitudes, motivations, and other antecedents for improved online learning outcomes (Acharya, 2019). Further, given the strong effect of student-content interaction on all learning outcomes, the access to technologies (software and hardware), the selection, development and improvement of user-friendly and especially useful digital learning platforms (see Venkatesh & Davis, 2000) should be considered, implying that additional funds need to be dedicated rather than using mainstream cost-efficient solutions. Promoting active learning while highlighting the benefits of online learning can be another action to pursue (see Molinillo et al., (2018), for more).

Finally, from the instructor's perspective, our study results highlight the critical role of instructors in achieving higher levels of online learning effectiveness. As noted above, many face challenges in changing teaching methods and preparing content suitable for an online learning modality under such circumstances. Therefore, given the substantial effect of student-instructor and student-content interaction on all learning outcomes, teaching methods that actively involve students should be applied, especially at the bachelor level. The improved teacher-student interaction experience might determine the attitudes and students' future decisions when choosing online courses at higher study levels. Based on the experience with online learning during the pandemic, instructors would require institutional support, access to external continuing education on online learning and technical pedagogical support in redesigning their course, which all together create a culture of support for online learning as indicated by Marek (2009).

7. Limitations and further research

Despite its contributions, our study has some limitations. Some of these shortcomings can provide starting points for future research. First, the data for this study were collected immediately after the lockdown following the COVID-19 pandemic. Consequently, there are limitations in generalising findings to other non-emergency circumstances and contexts. Hence, future research can validate our findings by replicating and extending our three models. Second, the sample was not randomly selected, limiting the generalisation of findings to the entire student population. Finally, the substantial effect of attitudes on the three outcomes calls for further research, as Johnson et al. (2007) pointed out. Examining the antecedents of attitudes, including the effect of ease of use or other factors such as personal involvement, purpose and personal achievement (Anghelache, 2013), social interaction, experience with online learning, and the possibility for self-regulated learning (Zhu et al., 2020), would constitute some additional areas of research that in turn, would inform effective policies for national and University decision-making bodies.

Author Statement

The authors declare that there is no conflict of interest.

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Appendix I

Measurement items

Item	Literature
Interaction-related factors	
Student – Student interaction (SSI)	Ravenscroft et al. (2017)
This course included activities and assignments that allowed students to interact with one another (SSI1)	
I felt comfortable interacting with other students in this course (SSI2)	
Generally, I am good at exchanging ideas with peers in this course (SSI3)	
I work with peers to cope with tasks or projects required by this course (SSI4)	
Student – Instructor interaction (SII)	Ravenscroft et al. (2017)
The professor motivated me to do my best work (SII1)	
I am responsive to those messages placed by the teacher (SII2)	
I felt comfortable asking questions about issues that were not clear to me (SII3)	
The teacher offered no opportunity to interact during the course (SII4)	
The instructions on interacting with the teacher were clear and precise (SII5)	
Student – Content interaction (SCI)	Ravenscroft et al. (2017)
This course included interactive assignments and links to examples from the Web that directly involved me in the learning process (SCI1)	Alqurashi (2018)
This course used activities that simulated real-world tasks (SCI2)	
This course provided good examples and explanations that helped to understand concepts and skills (SCI3)	
When the need arises, I could pose questions (SCI4)	
Environment factors	
Technical constraints (TEC)	Bolliger & Martindale (2004)
Use of inappropriate hardware and equipment (e.g., computers, cell phones) (EQUIP)	conceptualisation and our own operationalisation
Problems with internet connection (WIFIS)	
High costs to ensure internet connection (WIFIC)	
Lack of suitable learning space (e.g., a quiet room for attending classes) (LS)	
Time constraints (TIC)	Own conceptualisation and operationalisation following the exploratory research.
Inappropriate timetable for online learning sessions (TIMET)	
No fixed schedule for online learning sessions (FLEXT)	
Learners cognitive factors	
Attitude	Taylor & Todd (1995)
The use of platforms/applications from the instructor made the class more interesting (ATT1)	
The use of platforms/applications from the instructor was the right choice (ATT2)	
(Use of platforms/applications from the instructor was annoying (R) (ATT3)	
Easy to use (EOU)	Li & Yu (2020)
It is easy for me to use platforms/systems (EOU1)	
It is easy for me to use the equipment for online learning (EOU2)	
Learning outcomes	
Satisfaction (SAT)	Sebastianelli et al. (2015)
I am very happy with the subjects delivered online (SAT1)	
Generally, I am disappointed with subjects delivered online (R) (SAT2)	
Perceived learning (PL)	
I learned a lot in courses delivered online (PL1)	
Quality (QUA)	
Courses delivered online are of high quality (QUA1)	

Appendix II

Factor analysis

Items of seven constructs	F1	F2	F3	F4	F5	F6	F7
EQUIP		.570					
WIFIC		.760					
WIFIS		.880					
LS		.646					
TIMET						.724	
FLEXT						.817	
ATT1							.935
ATT2							.694
SCI1				.803			
SCI2				.926			
SCI3				.652			
SSI1	.779						
SSI2	.917						
SSI3	.906						
SSI4	.806						
SII1			.405				
SII2			.571				
SII3			.956				
SII5			.547				
EOU1					.873		
EOU2					.886		
Percentage of variance explained	35.870	12.284	5.197	4.849	3.038	2.289	1.669

Note. Underlying dimensions in eight factors: F1 = Interaction with peers; F2 = Technical constraints; F3 = Interaction with instructor; F4 = Interaction with content; F5 = Ease to use; F6 = Time constraints; F7 = Attitudes

Appendix III

Regression results for bachelor and master students

Variables	Model 1 (satisfaction)		Model 2 (perceived learning)		Model 3 (quality)	
	Bachelor	Master	Bachelor	Master	Bachelor	Master
	Value (std.err.)	Value (std.err.)	Value (std.err.)	Value (std.err.)	Value (std.err.)	Value (std.err.)
First step (control variables only)						
Gender	0.206 [†] (0.121)	-0.197 (0.214)	0.309 (0.129)	-0.209 (0.213)	0.166 (0.131)	0.080 (0.233)
Employment status	-0.115 (0.120)	0.194 (0.155)	-0.232 (0.128)	0.454** (0.155)	-0.158 (0.130)	0.153 (0.170)
University type	-0.057 (0.112)	-0.466* (0.180)	-0.030 (0.120)	-0.216 (0.179)	-0.455*** (0.121)	-1.137*** (0.196)
Residence	-0.016 (0.097)	-0.075 (0.164)	-0.002 (0.103)	-0.086 (0.164)	0.053 (0.105)	-0.091 (0.179)
Average grade	-0.002 (0.038)	-0.043 (0.072)	-0.036 (0.041)	0.126 [†] (0.072)	-0.073 [†] (0.041)	0.002 (0.078)
Class attendance	0.501*** (0.037)	0.437*** (0.066)	0.614*** (0.039)	0.433*** (0.065)	0.451*** (0.039)	0.309*** (0.072)
Adjusted R ²	0.137	0.096	0.176	0.105	0.106	0.119
Second step (all variables)						
Gender	0.051 (0.093)	-0.216 (0.170)	0.213 [†] (0.109)	-0.180 (0.186)	0.062 (0.107)	0.059 (0.182)
Employment status	-0.068 (0.093)	0.231 [†] (0.126)	-0.218 (0.108)	0.464** (0.138)	-0.122 (0.106)	0.096 (0.135)
University type	0.231** (0.087)	0.204 (0.151)	0.223* (0.102)	0.209 (0.166)	-0.177 [†] (0.100)	-0.517** (0.162)
Residence	-0.013 (0.076)	0.052 (0.132)	0.009 (0.089)	-0.061 (0.144)	-0.003 (0.087)	0.013 (0.141)
Average grade	-0.040 (0.029)	-0.093 (0.058)	-0.062 [†] (0.034)	0.062 (0.063)	-0.096** (0.034)	-0.073 (0.062)
Class attendance	0.143*** (0.031)	0.126* (0.056)	0.300*** (0.036)	0.216*** (0.061)	0.128*** (0.036)	-0.033 (0.060)
Student-content interaction	0.168*** (0.030)	0.243*** (0.058)	0.230*** (0.035)	0.258*** (0.063)	0.188*** (0.034)	0.308*** (0.062)
Student-instructor interaction	0.074* (0.037)	0.046 (0.068)	0.103* (0.044)	0.008 (0.075)	0.087* (0.043)	0.110 (0.073)
Student to Student Interaction	0.007 (0.025)	0.066 (0.043)	0.056 [†] (0.030)	0.044 (0.047)	0.069* (.0029)	0.173*** (0.046)
Attitude	0.335*** (0.030)	0.235*** (0.050)	0.244*** (0.035)	0.261*** (0.055)	0.344*** (0.034)	0.201*** (0.054)
Ease of use	0.046 (0.035)	-0.019 (0.056)	0.062 (0.041)	-0.105 [†] (0.062)	-0.042 (0.041)	-0.033 (0.060)
Technical constraints	-0.121*** (0.025)	-0.200 (0.046)	-0.119*** (0.029)	-0.041 (0.050)	-0.084** (0.028)	-0.178** (0.049)
Time constraints	-0.141*** (0.021)	-0.106 (0.036)	0.007 (0.025)	-0.056 (0.040)	-0.032 (0.024)	-0.017 (0.039)
Adjusted R ²	0.494	0.437	0.420	0.327	0.408	0.473
N. Cases	1214	484	1214	484	1214	484

Note. Std. err.: Standard error. Value: Unstandardized beta; *0.01 ≤ *p* < 0.05; ***p* < 0.01; ****p* < 0.001;[†]0.05 ≤ *p* < 0.1