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Carolin Flerlage*, Andrea Bernholt and Ilka Parchmann

Motivation to use digital educational content – differences between science and other STEM students in higher education

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Abstract: Digitalization leads to an increased importance of digital educational content for learning in higher education as well as in the sciences. The investigation of individual factors (e.g., motivation, self-efficacy, attitudes) influencing the intention to use digital educational content is a major research interest in design and implementation of suitable content (Hsu, J.-Y., Chen, C.-C., & Ting, P.-F. (2018). Understanding MOOC continuance: An empirical examination of social support theory. *Interactive Learning Environments*, 26(8), 1100–1118), yet to date without differentiation by discipline. A questionnaire following the *Theory of Planned Behavior* (Fishbein, M., & Ajzen, I. (2010). Predicting and changing behavior: The reasoned action approach. Psychology Press. <http://site.ebrary.com/lib/alltitles/docDetail.action?docID=10462474>) was developed to analyze relationships between STEM students' individual beliefs and their personal motivation to use digital educational content. In November 2021, a total of 662 STEM students from 8 universities in Germany participated in the study. Analyses showed differences within the group of STEM students: science students rated their digital skills lower and expected more difficulties compared to other STEM students, but did not differ in terms of their motivation. For science students, unlike other STEM students, motivation was predicted only by attitudes and digital skills. Moreover, the present results suggest that, first, the focus of the design should be on learning environment rather than on digital tools, and second, the potential of collaboration is largely unrecognized by students.

Keywords: digital educational content; motivation; science students; STEM students

1 Introduction

The importance of digital learning resources in higher education is increasing due to digitalization's impact on society, professions, and daily-life, and most recently due to the COVID-19 pandemic. Learning enhancing technologies are increasingly being used in (higher) education, even in disciplines such as chemistry or science in general, which are characterized by an experiment-based approach. These technologies include, for example, augmented reality (Xu et al., 2022), computer simulations (Develaki, 2019), databases (Tuvi-Arad & Blonder, 2019), virtual laboratories (Sypas & Kalles, 2018), or learning analytics (Kubsch et al., 2022). In most cases, such tools and digital content are integrated in learning materials or even entire learning units and made available to learners and teachers for a fee, but also in the spirit of open access free of charge. Here, we refer to the many freely available digital resources ranging from individual learning materials such as explanatory videos, simulations, or

***Corresponding author: Carolin Flerlage**, Chemistry Education, Leibniz Institute for Science and Mathematics Education at the University of Kiel, Olshausenstraße 62, 24118 Kiel, Germany, E-mail: flerlage@leibniz-ipn.de

Andrea Bernholt, Educational Research and Educational Psychology, Leibniz Institute for Science and Mathematics Education at the University of Kiel, Olshausenstraße 62, 24118 Kiel, Germany, E-mail: abernholt@leibniz-ipn.de

Ilka Parchmann, Chemistry Education, Leibniz Institute for Science and Mathematics Education at the University of Kiel, Olshausenstraße 62, 24118 Kiel, Germany, E-mail: parchmann@leibniz-ipn.de

Open Educational Resources (OER) in general, to online courses such as Massive Open Online Courses (MOOCs). These resources will be referred to here by the term digital educational content (DEC).

A key issue of the scientific discussion related to DEC is the appropriate design of these learning resources (Zhu et al., 2020). What design characteristics make DEC effective for learning? What kind of features engage the intended learners? What didactic design of DEC can motivate learners to their use? Research addressing such DEC design issues has repeatedly highlighted the importance of focusing on the needs of users (Hsu et al., 2018). This results in a great research interest to examine individual factors (e.g., motivation, self-efficacy, attitudes) influencing the level of intention to use DEC. Many studies have already identified motivation and attitudes as major factors influencing the intention to use DEC (Badali et al., 2022; Hew & Cheung, 2014; Howarth et al., 2016; Hsu et al., 2018). Disciplinary differences in students' motivation and attitudes toward the use of DEC—induced by discipline-specific practices, educational approaches, and learning goals—might also prove important to design appropriate educational content.

Differences between disciplines could already be expected within the often combined areas of STEM study programs. While sciences base their explanations and scientific developments on a successful interplay between experiments, mental models, and representations (Talanquer, 2011), mathematics does not need experiments due to a deductive reasoning approach (Khan, 2015). The technical or engineering sciences develop and test engineered prototypes and aim to optimize them rather than developing a fundamental understanding of nature (DiGironimo, 2010). Such (simplified) differences might lead to different interests and requirements of students with regard to explanations and scaffolds of their learning processes. In terms of the way technology is used in teaching, science courses often use digital media to support traditional learning formats, whereas in computer science, for example, the technology itself is the subject of learning (Riplinger & Schiefner-Rohs, 2017). In addition, more skepticism seems to exist in the sciences regarding online education than in other STEM fields (Allen & Seaman, 2012). Given these disciplinary differences in practices, learning goals, and use of technology already in STEM subjects, potential disciplinary differences in students' attitudes and motivation to use DEC could be expected. When comparing STEM and non-STEM, some studies did indeed find differences in students' motivation (e.g., Christensen et al., 2013), while others could not support these findings (e.g., Williams et al., 2018). A more specific investigation of disciplinary differences within STEM fields has not been addressed in studies to date.

The sciences are of particular interest as a first step toward addressing this research gap, as not only do they differ from the other STEM fields by an experimental approach and goal of explaining natural phenomena, but at the same time sciences are the subject area with the least affinity for technology and online teaching within the STEM field (Allen & Seaman, 2012). Consequently, science students need to be considered separately from non-science STEM students (hereafter referred to as TEM students) in order to identify science-specific needs and to draw conclusion for designing DEC for them. We examined an exemplary cohort of science and TEM students in higher education to identify individual factors (e.g., attitudes, expectations, self-efficacy) influencing their motivation to use DEC and compared them to TEM students.

2 Theoretical framework

In the emerging field of DEC, there is a lack of established models that describe predictions of motivation to use DEC (Otto et al., 2021; Zhu et al., 2020). Therefore, a theoretical framework following Ajzen's (1985) *Theory of Planned Behavior* (TPB) was developed to investigate students' motivation to use DEC. The TPB is widely used to predict a specific behavior of individuals in different contexts and situations and also in the context of digital learning environments (Lee et al., 2010; Sugar et al., 2004; Vogelsang et al., 2019). According to the TPB, a particular behavior (e.g., the use of DEC) is predicted by intention, which in turn is influenced by behavioral, normative, and control beliefs of individuals (Fishbein & Ajzen, 2010). Behavioral beliefs are defined as beliefs about the likely consequences of behavior that result in negative or positive attitudes toward this behavior (Ajzen, 2002). Other people's expectations that lead to perceived social norms are called normative beliefs. Control beliefs are beliefs about existing facilitating or inhibiting factors that affect behavior. These beliefs are associated with perceived

behavioral control, that is, the expectation of ability to perform a behavior easily or with difficulty (Ajzen, 2002). Overall, these three factors lead to the formation of a behavioral intention, which is assumed to be the immediate precursor of behavior (Fishbein & Ajzen, 2010). Forming a behavioral intention requires a concrete situation with a possible short-term implementation and for this reason makes it more difficult to measure intention in studies on less concrete or only medium-to long-term situations. Therefore, Vogelsang et al. (2019) extended the TPB to consider motivation as a central predictor of behavioral intention (see Figure 1).

Due to the *FutureSkills* project structure, it was not possible to investigate the use of a specific DEC as authentically planned behavior in line with the TPB. We therefore included motivation instead of intention in the theoretical framework as suggested by Vogelsang et al. (2019). Previous studies have shown that motivation, both in general and in relation to the use of DEC, is a complex issue (Badali et al., 2022; Zheng et al., 2015). To provide a more detailed understanding of motivation in this context, this study differentiated three facets of motivation (see Figure 2): Flexibility due to independence in terms of content, time, and location (Hew & Cheung, 2014; Zheng et al., 2015); Networking and collaboration beyond regional and national boundaries (Badali et al., 2022); and an expected usefulness for professional or personal development (Badali et al., 2022; Howarth et al., 2016).

Considering Eccles et al. (1983) *Expectancy-Value Theory* (EVT), wherein motivation is determined by subjective expectations of success and subjective value toward the behavior, perceived behavioral control and attitudes toward the behavior appeared to be important predictors of motivation. Regarding social norms, a number of studies found that normative beliefs were predictors of behavior or behavioral intentions only if the relevant behavior was clearly defined (Lee et al., 2010) or if the use of the investigated technology was mandatory (Venkatesh et al., 2003). Other studies found no significant effect on motivation in voluntary settings with less

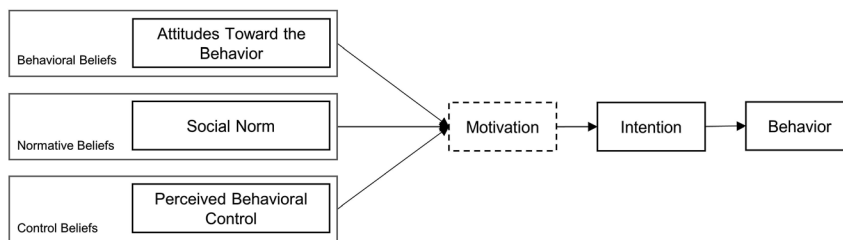


Figure 1: Theory of planned behavior (continuous line) according to Fishbein and Ajzen (2010) extended by the “motivation” component (dashed line) according to Vogelsang et al. (2019).

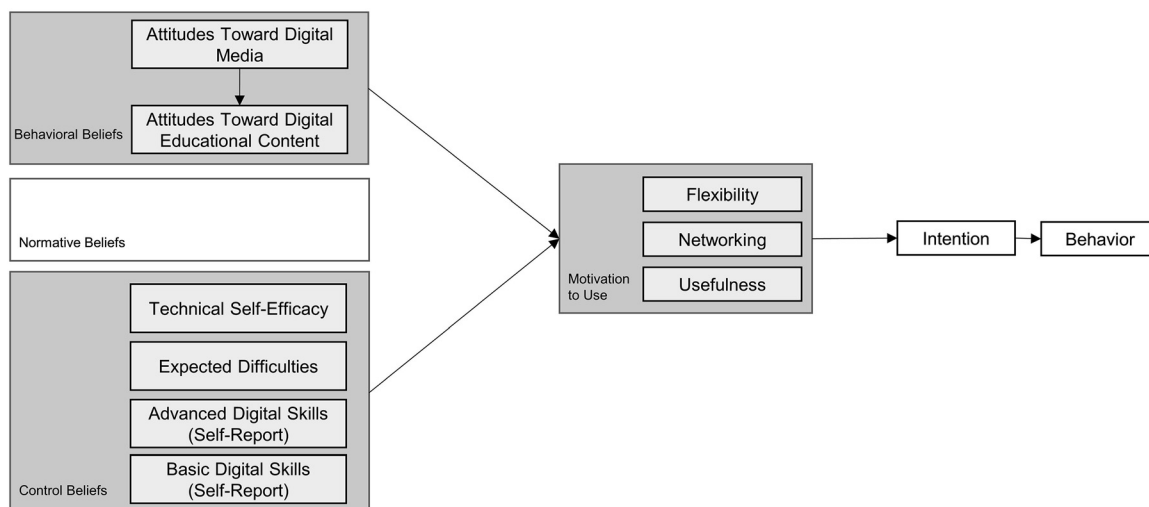


Figure 2: Theoretical framework of the study (in gray) following the theory of planned behavior (Fishbein & Ajzen, 2010) and an adapted version of Vogelsang et al. (2019).

clearly defined behaviors (Sugar et al., 2004; Vogelsang et al., 2019). Taking into account these findings and the EVT, this study focused on behavioral and control beliefs that influence motivation to use DEC and did not investigate normative beliefs (see Figure 2).

Overall, combining both theories—the TPB and the EVT—provides an appropriate foundation for our theoretical framework because it focuses on the individual influences and beliefs predicting behavioral intention instead of enabling conditions or ease of use. While more specific models in the technology acceptance field (e.g., *Technology Acceptance Model* or the *Unified Theory of Acceptance and Use of Technology*; Venkatesh et al., 2003) characterize technology use as a tool, the TPB's more general approach allowed us to concentrate on the use of educational content and learning (in a digital environment).

2.1 Attitudes and motivation of science, STEM, and other students

As presented in the introduction, STEM disciplines differ in terms of practices, learning goals, didactic approaches, and technology use. Consequently, differences in attitudes and motivation regarding the use of DEC can be expected between science and TEM students, though this issue has rarely been addressed in previous studies. To our knowledge, only few studies have examined individual characteristics (e.g., motivation, attitudes, self-efficacy) related to the use of DEC for science, TEM, or general STEM students (Thongsri et al., 2020). In a study conducted by Thongsri et al. (2020) on e-learning, STEM students demonstrated significantly higher technical self-efficacy, perceived e-learning as easier, and held more positive attitudes toward e-learning compared to non-STEM students. However, the study did not differentiate between STEM disciplines within the STEM student group.

Taking a reverse perspective, some research exists on DEC (especially on online courses) from science fields examining motivation and attitudes toward usage, but learners did not necessarily have science or even STEM backgrounds (Barak et al., 2016; Formanek et al., 2019; Li & Canelas, 2019; Otto et al., 2016). In the case of two chemistry MOOCs, a study revealed positive attitudes related to open access, free content selection, and high flexibility during participation (Li & Canelas, 2019). MOOCs were seen as a helpful complement to traditional education and an opportunity to democratize education by providing freely available resources (Li & Canelas, 2019). Studies of online courses in science consistently showed that motivation to use DEC is primarily intrinsic (Formanek et al., 2019; Li & Canelas, 2019; Otto et al., 2016). For example, motivation to participate in a chemistry MOOC was related to the relevance to one's own professional development or personal interest in the topic (Li & Canelas, 2019). The latter motive was also the most frequently cited reason for participation in a MOOC about astronomy or climate change, while the chance of a certificate or the instructor's reputation rarely played a role (Formanek et al., 2019; Otto et al., 2016). Enrolment in a Nanotechnology MOOC was motivated either by expected professional usefulness, interest in current developments in the field, or networking and becoming part of the community (Barak et al., 2016).

These findings from studies in science contexts align with those from STEM context, where the primary motives for participating in a STEM MOOC were personal interest and expected professional benefits, with networking, certificates, and the instructor's reputation having less importance (Christensen et al., 2013; Williams et al., 2018). While in non-STEM courses, curiosity was the main driver, usefulness played an equally important role in STEM courses (Christensen et al., 2013). However, some studies reported no differences in motivation for taking STEM or non-STEM courses (Williams et al., 2018).

Even research without considering disciplinary differences or STEM students showed that interest in the course topic and chances for professional development were more important for using DEC than opportunities for networking and the promise of certificates (Hew & Cheung, 2014; Howarth et al., 2016; Zheng et al., 2015). Additionally, the flexibility of DEC in terms of time and location was also listed as a motivation for its use (Zheng et al., 2015). At this point, it should be noted that collaboration is only a secondary motivator for the use of DEC, regardless of whether the field is science, STEM, or general. However, according to the self-determination theory, relatedness as a basic need is one of the factors underlying motivation (Deci & Ryan, 1993). Therefore, investigating successful ways of interaction and collaboration in digital learning environments aligns with the interests of DEC research (e.g., Bonafini, 2017; Radtke et al., 2020; Tawfik et al., 2017).

Overall, current research primarily focuses on students' motivation and attitudes toward DEC from a general or a disciplinary-specific perspective. The few comparisons across disciplines have been mostly at a level comparing STEM and non-STEM students. However, more comprehensive investigations into disciplinary differences in relation to DEC are required, as multiple studies emphasize (Riplinger & Schiefner-Rohs, 2017; Thongsri et al., 2020).

2.2 Research questions

Based on previous research and the theoretical framework of Ajzen (1985) and Vogelsang et al. (2019), this study aims to address the lack of a discipline-specific perspective among science students compared to TEM students, who are often grouped together. The following research questions were posed in order to compare individual beliefs as well as their influence on motivation:

- RQ 1: To what extent do behavioral beliefs, control beliefs, and motivation regarding the use of DEC differ between science and TEM students?
- RQ 2: Which individual beliefs influence science students' motivation to use DEC, and how do these beliefs differ from those of TEM students?

The results will be used to propose initial approaches for designing DEC in higher education programs to meet the individual needs of science and TEM students in order to increase the motivation to use DEC.

3 Methods

3.1 Participants

In November 2021, a total of 662 STEM students from 8 universities in Germany participated in the survey.¹ This study was part of the *FutureSkills* project, in which a digital cross-university educational platform with freely available online courses on the topics of digitalization and artificial intelligence is being set up. An online questionnaire was advertised to students via email lists at each university, and motivation to voluntarily participate in the study was based entirely on the opportunity to communicate beliefs and needs regarding DEC. The study was conducted in German and was not linked to use of the project platform, nor did it require prior experience with DEC. Therefore, the study is independent of the content offered on the project platform. On average, participants were in their 7th semester ($Md = 7$; $M = 6.48$, $SD = 4.04$, range: 1 to > 15). The total sample included 255² science students (62 % female) and 407 TEM students (41 % female), with the latter consisting of 173 students from mathematics and computer science, and 239 students from technology and engineering.³ Due to the survey methodology, it is not possible to differentiate science students into specific disciplines such as biology, chemistry, physics, or earth science.

3.2 Measures

The scales used to measure the constructs of the theoretical framework were a mixture of adaptations from already existing instruments and literature-based newly created constructs (see Table 1). Behavioral beliefs were assessed using items about (1) general attitudes toward the use of digital media in higher education and (2) attitudes toward DEC, including issues such as openness, sharing, and educational equity. Control beliefs were measured with the constructs of (3) technical self-efficacy, self-reported digital skills (subdivided into (4) basic digital skills and (5) advanced digital skills), and (6) expected difficulties. Motivation was divided into (7) flexibility, (8) networking, and (9) usefulness as different reasons for using DEC. In addition, gender, semester of study, and field of study were collected as control variables.

¹ The response rate is less than 3 %.

² Some of the science students ($n = 39$) also study another program in the TEM field.

³ The numbers do not add up to 407 because 5 students are taking study programs in both areas of TEM. But no student in the TEM sample is studying a science program.

Table 1: Number of items, mean value, standard deviation, example items, Cronbach's alpha, and literature of the instruments from the STEM student sample ($N = 662$).

	Variable	<i>n</i> items	<i>M</i>	<i>SD</i>	Example item	Cronbach's alpha	Literature
Behavioral beliefs	1. Attitudes toward digital media ^a	7	3.05	0.65	Digital media in general should be given a strong emphasis in higher education teaching.	0.84	Adaptation of Vogelsang et al. (2019)
	2. Attitudes toward digital educational content ^b	8	4.40	0.84	I value digital educational content as helpful for my learning – even after graduation.	0.78	Self-construction according to Hüther et al. (2020) and Mishra et al. (2016)
Control beliefs	3. Technical self-efficacy ^c	3	4.12	0.80	When I am confronted with technical problems, I find ways to solve them.	0.88	Adaptation of Janneck et al. (2012)
	4. Basic digital skills (self-report) ^d	6	4.36	0.56	I can prepare and write papers (e.g., protocols, reports, essays) using digital media.	0.78	Adaptation of Janschitz et al. (2021)
	5. Advanced digital skills (self-report) ^d	5	3.61	0.79	I can make simple video edits (e.g., trim videos, insert text) using digital tools.	0.65	Adaptation of Janschitz et al. (2021)
	6. Expected difficulties ^a	7	1.92	0.52	I expect to spend a lot of time if I want to use digital educational content.	0.65	Self-construction according to Gil-Jaurena et al. (2017) and Vogelsang et al. (2019)
Motivation to use	7. Motivation to use – flexibility ^a	3	3.46	0.60	I would use digital educational content for learning because I can flexibly choose the time and place of learning.	0.63	Self-construction according to Hew and Cheung (2014) and Zheng et al. (2015)
	8. Motivation to use-networking ^a	3	2.73	0.77	I would use digital educational content for learning if I can use it to make contacts for my studies.	0.69	Self-construction according to Hew and Cheung (2014) and Zheng et al. (2015)
	9. Motivation to use – usefulness ^a	3	3.19	0.71	I would use digital educational content for learning if I can get credit for it towards my degree.	0.68	Self-construction according to Hew and Cheung (2014) and Zheng et al. (2015)

Note. These items are translated from German. ^ascale, 1 – disagree to 4 – agree; ^bscale, 1 – disagree to 6 – agree; ^cscale, 1 – disagree to 5 – agree; ^dscale, 1 – “I can’t and won’t learn”; 2 – “I can’t but will seek help if needed”; 3 – “I can’t but will figure it out if needed”; 4 – “I can do this”; 5 – “I can do this and can also solve any problems that arise”.

3.3 Analyses

All reported data analyses were conducted using R software, version 4.0.4 (R Core Team, 2021), and IBM SPSS Statistics 26. The scales were tested using confirmatory factor analysis (see Appendix Table A1) and evaluated using common model fit values (chi-square test, comparative fit index, Tucker-Lewis index, root-mean-square error of approximation, root-mean-square residual; Gäde et al., 2020). *T*-tests were used to test for differences between science students ($n = 255$) and TEM students ($n = 407$) in the mean scores of behavioral beliefs, control beliefs, and motivation (RQ 1). Path analyses (individually for science and TEM students) were calculated using the package *lavaan* in R (Rosseel, 2012) to clarify to what extent the motivation was influenced by behavioral and control beliefs (RQ 2). The missing data were treated using the full information maximum likelihood (FIML) approach.

4 Results

Mean comparisons were made using χ^2 -tests and *t*-tests to statistically verify the assignment of the 39 students who studied both a science and a TEM program to the subsample of science students. Results showed only a significant difference in gender ($\chi^2(2, N = 637) = 41.83, p < 0.001$), with a higher proportion of male students studying another TEM program in addition to science (for *t*-tests results see Appendix Table A2). Therefore, the division into sub-samples remains appropriate for the subsequent analyses.

4.1 Differences in individual beliefs and motivation between science and TEM students

Regarding the control variables, the TEM student sample showed significantly higher proportion of male students ($\chi^2(1, N = 637) = 33.97, p < 0.001$), while the two samples did not differ with respect to the number of semesters (see Appendix Table A3). Consistent with expectations, the semester of study is positively correlated particularly with digital skills in both samples (see Appendix Table A4). Analyzing the individual variables, science students had lower attitudes toward digital media ($t(623) = -4.88, p < 0.001, d = 0.40$), while attitudes toward DEC were quite similar (see Figure 3). In terms of control beliefs, science students showed lower expectations of their technical self-efficacy ($t(555) = -2.73, p = 0.006, d = 0.24$), rated their advanced digital skills lower ($t(660) = -6.37, p < 0.001, d = 0.51$), and expected more difficulties ($t(493) = 2.58, p = 0.010, d = 0.24$). Finally, no significant differences were found between science and TEM students in terms of motivation to use DEC.

4.2 Influence of individual factors on motivation for science and TEM students

The path analyses conducted on science students' motivation to use DEC yielded good model fit values (see Figure 4). Controlling for gender and semester of study revealed that female science students showed higher motivation for reasons related to flexibility and usefulness. Additionally, students in higher semesters of study were less motivated for networking reasons. As expected, attitudes toward DEC, which were influenced by attitudes toward digital media ($B = 0.72, p < 0.001$), had a positive effect on all facets of motivation, with flexibility-related motivation being the most affected ($B = 0.48, p < 0.001$). Contrary to expectations, no significant effect was found from technical self-efficacy and expected difficulties on motivation to use DEC. However, self-reported advanced digital skills had an impact on flexibility-based motivation ($B = 0.20, p = 0.008$), while self-reported basic digital skills had a small effect on usefulness as a facet of motivation ($B = 0.19, p = 0.025$). Overall, attitudes toward DEC and self-reported advanced digital skills were the most significant predictors of science students' motivation. For flexibility as a reason for use, 46 % of the variance was explained, while the variance clarification for usefulness and networking was less than 20 %.

For TEM students, the path analyses for motivation to use DEC also showed good model fit values (see Figure 5). Gender and semester of study did not have any significant impact on the motivation after controlling for these variables. Attitudes toward DEC and digital media were significant predictors of both flexibility and usefulness as facets of motivation, but here the more general attitudes toward digital media showed the largest effects (flexibility: $B = 0.33, p = 0.001$; usefulness: $B = 0.26, p = 0.006$). In addition, self-reported advanced digital skills negatively affected flexibility-based motivation ($B = -0.11, p = 0.032$), while basic digital skills and technical self-efficacy did not have a significant impact. Expected difficulties had a significant effect on socially-shaped motivation ($B = 0.21, p = 0.002$). Overall, attitudes toward digital media and expected difficulties were the most significant predictors of TEM students' motivation. The explained variance was 27 % for flexibility, while the variance clarification was low for networking (10 %) and usefulness (16 %).

5 Discussion

The aim of our study was to examine the individual factors that influence science students' motivation to use DEC and compare them to those of TEM students. Therefore, *t*-tests and path analyses were used to identify disciplinary differences. In general, the individual factors (including digital skills and attitudes) of science and TEM students differ in mean scores and also in their impact on motivation to use DEC.

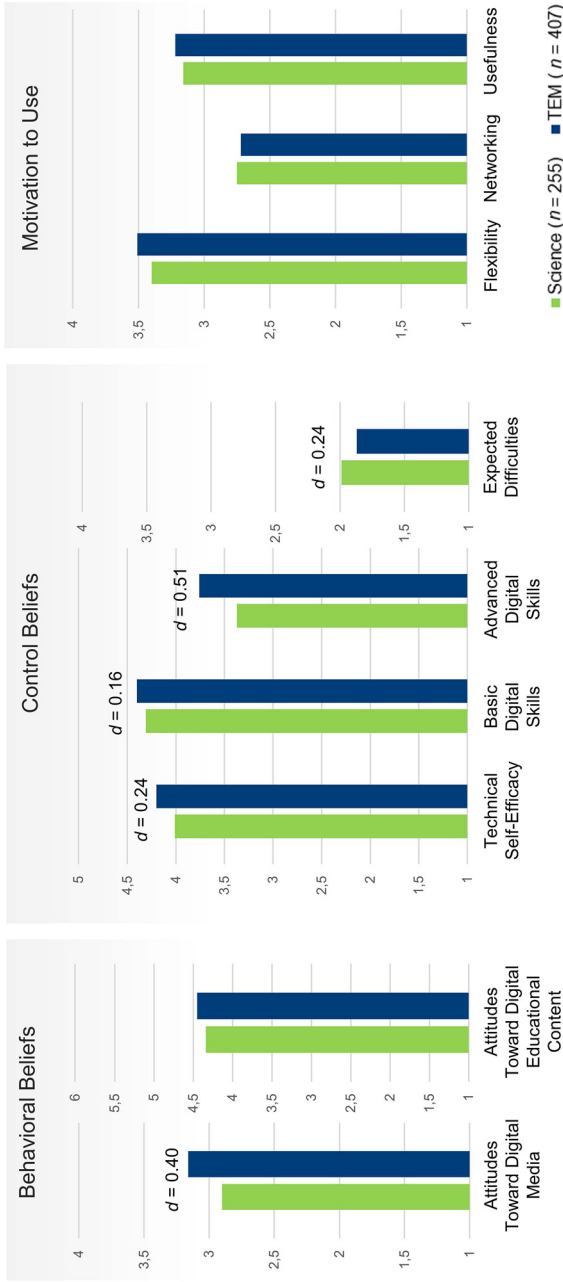


Figure 3: Mean scores of behavioral beliefs, control beliefs, and motivation, divided by science (n = 255) and TEM students (n = 407). For significant t-tests (p < 0.05) Cohen's d effect sizes are given.

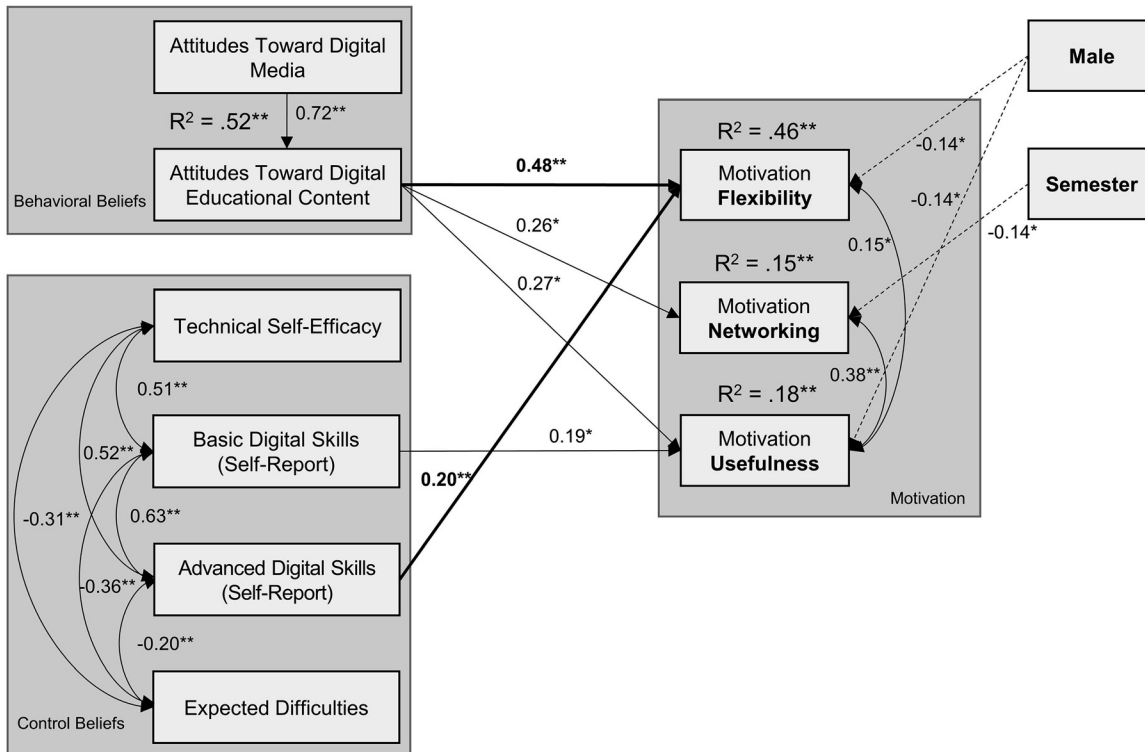


Figure 4: Path analysis of science students ($n = 255$). Only significant paths are shown with indication of standardized coefficients of path analysis (MLR estimator and FIML); * indicates $p < 0.05$; ** indicates $p < 0.01$; model fit: χ^2 (df) = 5.51 (6); $p = 0.480$; CFI = 1.00; TLI = 1.01; RMSEA = 0.00; SRMR = 0.02.

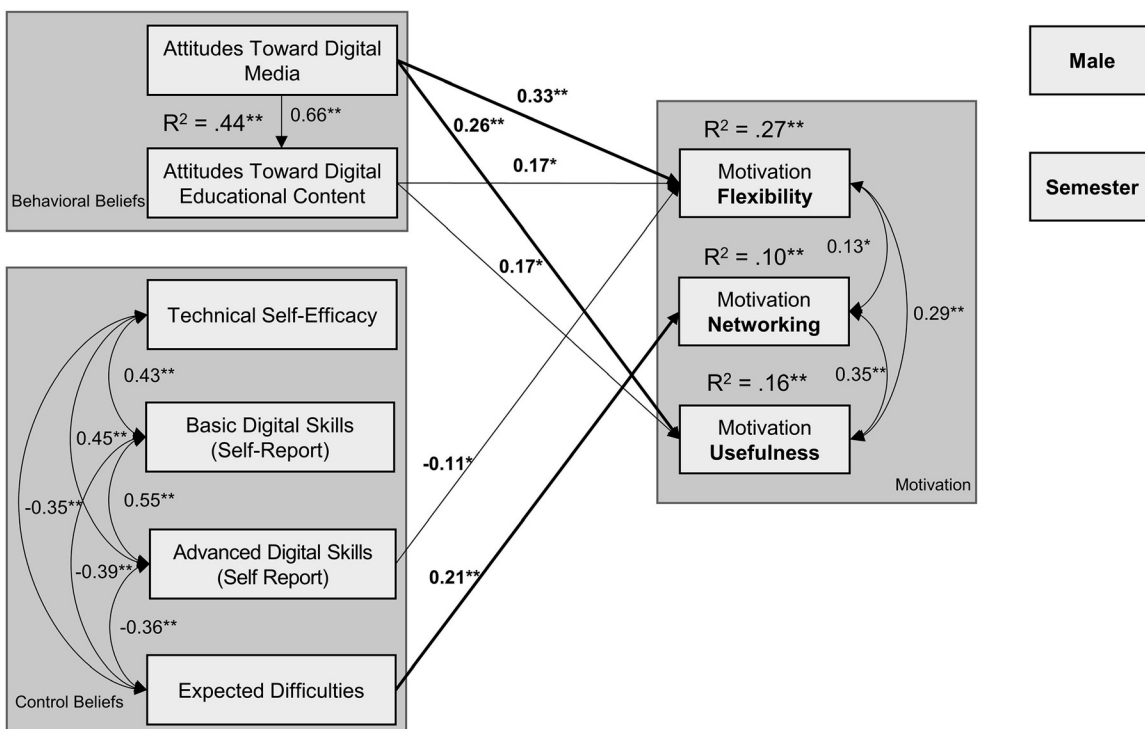


Figure 5: Path analysis of TEM students ($n = 407$). Only significant paths are shown with indication of standardized coefficients of path analysis (MLR estimator and FIML); * indicates $p < 0.05$; ** indicates $p < 0.01$; model fit: χ^2 (df) = 3.79 (6); $p = 0.706$; CFI = 1.00; TLI = 1.04; RMSEA = 0.00; SRMR = 0.01.

5.1 Beliefs and motivation to use DEC among science and TEM students

Looking at the science students, the lower attitudes towards digital media, lower self-reported technical self-efficacy and digital skills, and greater expected difficulties can be explained by considering the comparison group of TEM students. The TEM students' sample included significantly more male students, and male students typically showed higher technical self-efficacy than females, even within the same study program (Janneck et al., 2012). In addition, previous studies have shown that science students are the most skeptical of online education within the group of STEM students (Allen & Seaman, 2012). Considering that disciplinary practices influence students' technical abilities and, in turn, their self-efficacy (Thongsri et al., 2020), it is reasonable that students from TEM fields scored higher in technical self-efficacy, digital skills, and attitudes toward digital media. However, it should be noted that there were no differences between science and TEM students in terms of attitudes towards DEC. Also in the study of Li and Canelas (2019), students of chemistry MOOCs demonstrated positive attitudes towards aspects of DEC such as openness, learning opportunities, and equity. Thus, attitudes related to ideas of Open Education seem to be less influenced by prior technical background.

The motivation of science and TEM students to use DEC did not differ in the current study, which is consistent with previous findings. Flexibility in content, time, and location, as well as perceived usefulness for their own professional development were identified as the most important motivation for using DEC (Formanek et al., 2019; Hew & Cheung, 2014; Li & Canelas, 2019; Williams et al., 2018). This is also in line with the results of Christensen et al. (2013), where usefulness plays an important role mainly for STEM courses. However, one interesting finding is the low motivation to use DEC for networking or collaboration found among all STEM students. Other studies from STEM fields and cross-disciplinary research support this finding (Williams et al., 2018; Zheng et al., 2015). Consider this as an example of how the user perspective should not be the only guide for course design, but rather can be seen as a starting point for development. Efforts to increase collaboration in MOOCs by providing discussion forums have proven less successful so far, as the interactions were at a low level and mostly driven by only a few engaged learners (Tawfik et al., 2017; Zheng et al., 2015). A way forward could be teaching users why and how collaboration in digital contexts is useful. Successful examples for networking and collaboration in DEC also exist in the area of science education, such as the collaborative environment for personalized teaching and learning (PeTeL;⁴ Aviran et al., 2020). Another promising approach to promote collaboration in DEC could be the implementation of escape rooms (or parts of them). Escape rooms are renowned not only for their entertainment and team-building value but also for positive effects in terms of collaboration and other cognitive, behavioral, and affective domains as documented in the systematic literature review by Makri et al. (2021). However, the challenge of transferring interaction into a digital format must also be addressed, and suitable solutions must be found to enable collaboration in digital escape room formats (Haimovich et al., 2022). In particular, the need for communication in escape room formats could be a way to motivate STEM students to collaborate in a digital environment and convince them of its potentials.

5.2 Effects of individual beliefs on motivation to use DEC

Overall, attitudes became the most significant predictor of science and TEM students' motivation, consistent with the findings of Hsu et al. (2018). In contrast to TEM students, path analyses of science students revealed that attitudes toward DEC were more important than attitudes toward digital media in predicting motivation to use digital content. This suggests that content and the learning environment are more crucial for science students than the tools themselves. This may be because the content-oriented curricula of science programs, e.g., in the case of chemistry, prioritize developing conceptual understanding and experimental skills. Digital tools can serve as scaffolds but do not represent important tools themselves (so far). In contrast, computer

⁴ <https://stwwww1.weizmann.ac.il/petel/en/home-en/>.

science often emphasizes innovative tools to provide learning opportunities through analysis and optimization (Riplinger & Schiefner-Rohs, 2017). Therefore, when designing DEC for science students the focus should be on appropriate learning environments and content supported by digital elements rather than digital tools.

The weak influence of control beliefs, particularly technical self-efficacy, is surprising given that self-efficacy has been identified in previous studies as a significant predictor of motivation or behavioral intention (Alsharida et al., 2021; Hsu et al., 2018; Pan, 2020; Thongsri et al., 2020). In our study, the lack of influence of technical self-efficacy may result from digital skills being surveyed using self-report items, which could assume and find a correlation with technical self-efficacy. Overall, the small effect of the control beliefs should be viewed positively as low self-reported digital skills and technical self-efficacy initially have little influence on motivation. This means that students with lower self-efficacy and digital skills are still motivated to use DEC. At the same time, promoting digital skills provides an opportunity for science students to recognize the potential of DEC in terms of flexibility and usefulness, and thereby become motivated to use it in their study programs.

The low variance clarification in networking and usefulness indicates that the beliefs examined in this study are insufficient predictors of these two facets of motivation for both science and TEM students. This could be due to the operationalization of the constructs or the broadly defined concept of DEC, but it also suggests that our theoretical framework needs to be reviewed and developed further. Looking at other studies, constructs such as prior experience, use of digital media, facilitating conditions, outcome expectations, and social influence (especially in terms of networking) may have an impact on motivation to use DEC (Chroustová et al., 2022; Venkatesh et al., 2003; Vogelsang et al., 2019). Investigating these constructs could lead to a better understanding of motivation in general.

6 Limitations and conclusion

It is important to consider the limitations of our study when interpreting the results. The sample may not be representative due to the response rate and possible positive sample selection bias, as students who responded to the online survey had already engaged with the topic of DEC or were interested in it. From a methodological perspective, the results are limited by certain aspects of the survey design, including self-report, a large number of constructs combined with a necessary restriction on the number of items, and the use of scales that are not yet established. This may explain the lower reliability scores in some cases and the associated low variance clarification. Moreover, the wide definition of DEC and the lack of specific use cases may have led to differences in participants' interpretation of the questions. Future studies should use specific learning materials and situations to investigate effects on using DEC to address this issue, especially in the context of higher education. Furthermore, our data do not provide insights into actual behavior or behavioral intentions toward the use of DEC; therefore, this also needs to be explored in future studies. Such further investigations, guided by the theoretical assumptions of the TPB, could lead to important findings about the effects of attitudes and motivation on intentions and, in particular, on actual behavior in this field.

Nevertheless, this study contributes to the scientific discussion in the context of DEC in three ways. First, the results support the development of theoretical models for investigating motivation to use DEC. Second, the methodological approach employed in this study, which considers both the extend and influence of individual factors on motivation, is proven to be useful. Therefore, this approach should be considered in future research with the aim of identifying disciplinary differences. Third, the results have practical implications that can be implemented in the design of DEC to meet the needs of science (and TEM) students. Taking a closer look at the practical implications, the results indicate that science students differ somewhat from students in technology, mathematics, and computer science, even though they are often grouped together under the broader term STEM. Furthermore, when developing suitable digital content in higher education, it is important to consider users' needs regarding discipline-specific attitudes, digital skills, and expected difficulties. In general, but particularly

for science students, educational content design should focus on the fit between didactic content and learning-enhancing technologies rather than on the specific tool used. In other words, it is less important which tool is used, but rather important whether the technology fits the educational goal. Additionally, users will need to be convinced of the potential of digital environments for collaboration, regardless of their STEM discipline. Although some approaches and best practices have been discussed, further research and development is needed to fully realize the potential of digital collaboration. In short, the content needs to be adapted to the user and also the user to the content—in the sense that users need to learn how to use the content in a helpful and successful way.

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Appendix: Motivation to use digital educational content – differences between science and other STEM students in higher education

All reported data analyses were conducted with the R software, version 4.0.4 (R Core Team, 2021) and IBM SPSS Statistics 26.

Table A1: Testing of the scales using confirmatory factor analysis.

Scale	<i>n</i> Items	χ^2 (df) <i>p</i> -value	AIC	BIC	CFI	TLI	RMSEA	SRMR	Cronbach's alpha
Attitudes toward digital media									
One-dimensional	8	54.33 (20) < 0.001			0.98	0.97	0.06	0.03	0.85
Attitudes Toward Digital Educational Content									
One-dimensional	12	199.68 (54) < 0.001	17,839.69	17,938.53	0.86	0.83	0.08	0.07	0.79
One-dimensional (short)	8	44.36 (20) 0.001	11,544.10	11,610.13	0.97	0.96	0.06	0.04	0.78
Technical self-efficacy									
One-dimensional	4	9.10 (2) 0.011	4650.15	4684.70	0.99	0.96	0.13	0.02	0.90
One-dimensional (short)	3	0 (0) –	3428.51	3454.42	1.00	1.00	0.00	0.00	0.88
Digital skills (self-report)									
One-dimensional	11	104.48 (44) < 0.001	17,723.22	17,821.88	0.94	0.93	0.06	0.05	0.82
Two-dimensional (basic/advanced)	6/5	77.75 (43) 0.001	17,682.21	17,785.36	0.97	0.96	0.04	0.04	0.78/0.65
Expected difficulties									
One-dimensional	10	114.54 (35) < 0.001	12,243.65	12,327.42	0.84	0.80	0.07	0.06	0.71
One-dimensional (short)	7	21.25 (14) 0.095	8727.19	8785.88	0.98	0.96	0.04	0.03	0.65
Motivation to use									
One-dimensional	13	494.87 (78) < 0.001	15,756.62	15,866.72	0.71	0.65	0.12	0.08	0.82
Three-dimensional (flexibility/networking/usefulness)	3/3/3	82.84 (24) < 0.001	10,924.41	11,013.62	0.94	0.91	0.07	0.05	0.63/0.69/0.68

Note. Good [and acceptable] cut-off values according to Gäde et al. (2020), $\chi^2/df \leq 2$ [3]; $p > 0.05$; CFI, comparative fit index ≥ 0.95 [0.90]; TLI, Tucker-Lewis index ≥ 0.95 [0.90]; RMSEA, root mean square error of approximation ≤ 0.05 [0.08]; SRMR, standardized root mean square residual ≤ 0.05 [0.10]. Models with lower Akaike information criterion (AIC) and Bayesian information criterion (BIC) are generally preferred.

Table A2: Comparison using unpaired *t*-tests between exclusively science/TEM students and science students studying an additional TEM program.

Exclusively science vs. S + TEM	t-test				Group statistics			
	<i>T</i>	<i>df</i>	<i>p</i> (2-sided)	Cohen's <i>d</i>	eS		S + TEM	
					<i>N</i>	<i>M</i>	<i>N</i>	<i>M</i>
Semester of study	−0.17	251	0.864	−0.03	214	6.77	39	6.90
Attitudes toward digital media	1.26	244	0.207	0.22	207	2.92	39	2.78
Attitudes toward digital educational content	1.23	195	0.221	0.25	168	4.37	29	4.16
Technical self-efficacy	−0.23	226	0.820	−0.04	193	4.00	35	4.04
Basic digital skills (self-report)	0.32	253	0.747	0.06	216	4.31	39	4.28
Advanced digital skills (self-report)	0.16 ^a	46.32	0.871	0.03	216	3.37	39	3.35
Expected difficulties	−0.09	205	0.927	−0.02	175	1.99	32	2.00
Motivation to use – flexibility	0.58 ^a	38.91	0.565	0.13	185	3.42	33	3.33
Motivation to use – networking	0.50	216	0.616	0.10	185	2.76	33	2.69
Motivation to use – usefulness	1.02 ^a	38.75	0.313	0.24	185	3.18	33	3.01
Exclusively TEM vs. S + TEM					eTEM		S + TEM	
Semester of study	−0.74 ^a	42.59	0.463	−0.15	403	6.29	39	6.90
Attitudes toward digital media	3.54	416	<0.001	0.59	379	3.16	39	2.78
Attitudes toward digital educational content	1.32 ^a	31.03	0.195	0.34	274	4.45	29	4.16
Technical self-efficacy	1.14	362	0.256	0.20	329	4.20	35	4.04
Basic digital skills (self-report)	1.28	444	0.202	0.21	407	4.40	39	4.28
Advanced digital skills (self-report)	2.62 ^a	42.88	0.012	0.52	407	3.76	39	3.35
Expected difficulties	−1.35	318	0.179	−0.25	288	1.87	32	2.00
Motivation to use – flexibility	1.23 ^a	35.86	0.227	0.29	306	3.51	33	3.33
Motivation to use – networking	0.23	337	0.818	0.04	306	2.72	33	2.69
Motivation to use – usefulness	1.24 ^a	35.86	0.221	0.29	306	3.22	33	3.01

Note. eS, students studying exclusively a natural science program; eTEM, students studying exclusively a TEM program; S + TEM, students studying a TEM program in addition to a natural science program. ^aDue to unequal variance, the Welch test was used.

Table A3: Comparison using unpaired *t*-tests between science and TEM students.

Exclusively science vs. S + TEM	t-test				Group statistics			
	<i>T</i>	<i>df</i>	<i>p</i> (2-sided)	Cohen's <i>d</i>	eS		S + TEM	
					<i>N</i>	<i>M</i>	<i>N</i>	<i>M</i>
Semester of study	1.56	654	0.119	0.13	253	6.79	403	6.29
Attitudes toward digital media	−4.88	623	<0.001	−0.40	246	2.90	379	3.16
Attitudes toward digital educational content	−1.37	469	0.172	−0.13	197	4.34	274	4.45
Technical self-efficacy	−2.73	555	0.006	−0.24	228	4.01	329	4.20
Basic digital skills (self-report)	−2.01	660	0.045	−0.16	255	4.31	407	4.40
Advanced digital skills (self-report)	−6.37	660	<0.001	−0.51	255	3.37	407	3.76
Expected difficulties	2.58	493	0.010	0.24	207	1.99	288	1.97
Motivation to use – flexibility	−1.92	522	0.055	−0.17	218	3.40	306	3.51
Motivation to use – networking	0.44	522	0.663	0.04	218	2.75	306	2.72
Motivation to use – usefulness	−0.95	522	0.342	−0.08	218	3.16	306	3.22

Note. S, students studying at least one natural science program; TEM, students studying a TEM program (mathematics, computer sciences, technology, and engineering) and not a natural science program.

Table A4: Correlation between variables and covariates (gender, semester of study) of science ($n = 255$) and TEM students ($n = 407$).

	Science		TEM	
	Male	Semester of study	Male	Semester of study
Attitudes toward digital media	−0.11	−0.14 ^a	−0.02	0.03
Attitudes toward digital educational content	−0.11	−0.09	−0.02	0.02
Technical self-efficacy	0.11	0.09	0.26 ^b	0.09
Basic digital skills (self-report)	0.05	0.05	0.04	0.19 ^b
Advanced digital skills (self-report)	0.15 ^a	0.19 ^b	0.19 ^b	0.25 ^b
Expected difficulties	0.03	−0.04	−0.06	−0.14 ^a
Motivation to use – flexibility	−0.19 ^b	−0.13	−0.01	0.05
Motivation to use – networking	−0.17 ^a	−0.20 ^b	−0.11	−0.07
Motivation to use – usefulness	−0.17 ^a	−0.17 ^a	−0.07	0.02

Note. ^a $p < 0.05$; ^b $p < 0.01$.

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