Active Learning and the Development of 21st Century Skills in Online STEM Education: A Large-Scale Survey

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Abstract
While the benefits of active learning to student experiences are well documented, less is known about active learning in online education, especially regarding the development of 21st century skills (e.g., communication, collaboration, critical thinking, creativity). Specifically, open questions remain concerning the contribution of different active learning pedagogies to different sets of skills in online Science, Technology, Engineering, and Mathematics (STEM) education. The current research addresses this gap. We surveyed 744 undergraduate students to evaluate the relationship between learning design, 21st century skill development, and satisfaction in the context of a course taken remotely during the COVID-19 pandemic (Spring 2020). Using an exploratory and a confirmatory factor analysis as well as several multiple linear regressions, we extracted the relationship between various properties of course design (e.g., frequency of groupwork) and the self-reported development of key 21st century skills. Results show that these skills can be grouped into three sets: communication and collaboration skills, domain-general skills, and STEM-specific skills. We further found that designs for active learning explain variance in students' development of 21st century skills. Specifically, individual work, group work, long-term work, and synchronous work explain variance in students' reports of skill development. Moreover, supporting students in skill development was associated with greater satisfaction with the course. Our findings suggest that activities in the higher levels of the Interactive, Constructive, Active, and Passive framework (ICAP; Chi et al., 2018) are associated with greater learning of key 21st century skills and increase students' satisfaction. We discuss implications for design and institutional support.

Keywords: Active learning, 21st century skills, STEM education, remote teaching and learning.

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Leading organizations (e.g., UNESCO, OECD, APEC; Ananiadou & Claro, 2009) call for educational systems to prepare their students to be “full participants in a dynamic, ever-changing world and industry” (Kennedy & Sundberg, 2020, p. 482). Accordingly, students should be taught skills and competencies that go beyond any specific content-based professional curricula. Achieving this is particularly important in Science, Technology, Engineering, and Mathematics (STEM) education as there is often a gap between the curricula and the skills students are expected to demonstrate upon graduation (Jang, 2016; Kennedy & Sundberg, 2020). These skills are often referred to as 21st century skills. The Partnership for 21st Century (2011) defines these skills as “The Four Cs”: i) Communication, ii) Collaboration, iii) Critical Thinking, and iv) Creativity (Christensen & Knezek, 2015).

Recent work shows an association between instructional approaches emphasizing active learning and the development of 21st century skills (Christensen & Knezek, 2015; Lavi, Tal & Dori, 2021). Learning opportunities that include complex problem-solving, collaboration, and critical thinking, improve students’ domain-specific performances (Freeman et al., 2014; Hattie, 2010) as well as 21st century competencies (Buitrago-Flórez et al., 2021; Lopatto, 2007). However, most studies on active learning and 21st century skills focus on a face-to-face instructional context. Thus, it is still unclear if the advantages of active learning instruction in a face-to-face context are transferable to an online educational context. This is particularly relevant as the COVID-19 pandemic introduced new challenges to online teaching and learning (Basdogan & Birdwell, 2023; Hadi Mogavi et al., 2021). Here we explore the relationships between active learning, 21st century skill development, and student satisfaction in the context of online STEM education. For this purpose, we surveyed the undergraduate student community of a leading technological university in Israel. The survey focused on remote learning during the first wave of the COVID-19 pandemic (Spring 2020).

Background

Active Learning and 21st Century Skills

Active, student-centered learning builds on constructivist theories of learning. This theoretical framing refers to learning opportunities in which students actively construct their knowledge and take control and responsibility over their learning processes (Chi et al., 2018; Duffy & Cunningham, 1996). Such learning opportunities allow learners to think critically, practice their communication skills, and find creative ways to solve problems (Hmelo-Silver et al., 2007). Furthermore, learning activities differ in the degree of learners’ participation as well as in the cognitive processes that they facilitate (Chi et al., 2018). When considering participation and cognitive engagement, instructional activities can be classified based on the learners’ level of engagement into a learning activity taxonomy known as the ICAP framework: *Interactive*, *Constructive*, *Active*, and *Passive* learning (Chi et al., 2018). The ICAP framework is organized hierarchically so that more advanced learning activities produce deeper, more meaningful learning (Interactive > Constructive > Active > Passive). While ICAP refers to student activity, different instructional designs can call for different levels. For example, collaborative activities, such as group projects, facilitate joint attention and the synthesis of different learners’ contributions and thus support *interactive* learning. Next, activities that facilitate *constructive* learning ask learners to produce outputs that are additional to the instructional material, for example, producing summaries. *Active* learning refers to overt learner behaviours such as highlighting, copying text, forwarding, or rewinding a video. These behaviours, while active, do not produce novel outputs. The provision of instructional materials enables learners to engage in this level of activity. *Passive* learning does not include any overt student activity, as when listening to a lecture or watching a video linearly and is contrasted with the three prior types of activities. While this taxonomy was originally developed for face-to-face instructional contexts, recent work suggests that it is applicable for online educational contexts with some adaptations (Prince et al., 2020). For example, a "think-pair-share" activity is classified as a constructive and an interactive activity that requires students to interact with the course's content, their peers, and the instructor. Further, according to Prince and colleagues, such an activity can be adapted to an online synchronous, asynchronous, or blended contexts. These studies suggest that activities at the higher level of the ICAP framework are also likely to require skills similar to those detailed in 21st century frameworks (collaboration, argumentation, etc.; Dede 2010). It is thus likely that designing curricula to support active learning could also support the development of 21st century skills.

Further support of the association between active learning and 21st century skill development comes from Lavi, Tal, and Dori (2021) who surveyed recent STEM graduates about the development of 14 specific skills. They classified the skills into three sets: (1) key competencies, (2) STEM-specific skills, and (3) STEM-general skills. Key competencies included creativity, collaboration, communication, and entrepreneurship. STEM-specific skills were engineering design, experiment and testing, STEM knowledge application, and systems thinking. Domain-general skills were complex problem-solving, critical thinking, individual learning, and posing questions. Lavi et al. asked recent graduates to elaborate on the pedagogies that contributed to the development of one of the skills. Their analysis revealed that both active and passive pedagogies had a similar, medium-sized effect on all perceived skill development. However, when looking into the development of key competencies and STEM-specific skills, active methods contributed more than passive methods. Likewise, Lopatto (2007) surveyed undergraduate science students and found that those who participated in research work reported a positive learning experience, and increased technical and personal skills (i.e., 21st century skills). Similarly, Buitrago-Flórez et al. (2021) found that active learning improved 11th grade students' computation thinking skills from a pre- to a post-test, domain-specific communication skills, collaboration skills, and creativity. Together, these findings show that higher-level ICAP instructional activities, which include collaboration and novel output production, can support students' 21st century skill development.

Active Learning in an Online Context: STEM and Non-STEM Subjects

Active learning and its advantages have been predominantly studied in the physical classroom with fewer studies examining its effect in an online context. In one such work, Koedinger and colleagues (2015) found that learners in a more active version of an introduction to psychology Massive Open Online Course (MOOC) participated more and outperformed MOOC-only learners on the final exam. They further showed that these differences are due to student uptake of available active learning opportunities. Similarly, Soffer and Cohen (2019) found that students' participation in online learning activities (watching videos, entering the course's webpage, forum visits) differentiates completers from non-completers in non-STEM online courses. They also found small but significant correlations between students' active participation and exam grades. These studies show the importance of providing students with active learning opportunities online.

The work reviewed above points to the importance of designs for active learning in online education, but does the same apply to STEM fields that require specific training in problem-solving and advanced calculations? Several studies suggest that the answer is yes. For example, Chen et al., (2018) surveyed students' perceptions of designs for learning in online STEM courses. They found that the perceived efficacy of the course's activities and assessments were positively and significantly associated with students' satisfaction. For example, students perceived frequent formative quizzes as a practice that improved their final exam score. Similarly, Cho et al., (2021) found that course design contributed to students' learning outcomes for some, but not all exams. They further found a positive and statistically significant correlation between students' video viewing time and exam scores. These findings highlight the importance of students' prior preparation and participation with online resources to their success in the course. Similar results were found for students at the secondary level who studied geometry online following the transition to emergency remote teaching during the COVID-19 pandemic (Ruiz-Palmero et al., 2023).

Despite these conclusive findings, the road to active learning for all online learners is still long. Cinque (2017) pointed to the challenges in developing an instructional platform that will support 21st century skill development online and will "fit all" learners (e.g. MOOCs). Additional work points to specific barriers for the implementation of active learning online. Hadi Mogavi and colleagues (2021) mapped barriers that may hinder the use of active pedagogies in online learning. Their list of barriers starts from technical issues such as time-zone differences and bandwidth but extends to include mental exhaustion, low self-efficacy, and even sexual harassment. These findings suggest that it may be challenging to support students' 21st skill development in an online context. Thus, active learning opportunities may be less effective. For example, Usher and colleagues (2021) found that students' innovation scores were higher in a F2F version of a course compared to its online version.

As demonstrated above, designs that support active learning and 21st century skill development are promising in a face-to-face context. However, there are still open questions around the degree to which such designs support skill development in an online context in STEM subjects. It is of interest to evaluate whether there are specific designs that contribute to specific skills within STEM education. The current work begins to address this gap through the following research questions:

(RQ1) What is the relationship between different designs for active online learning and the development of key 21st century competencies in STEM courses?

(RQ2) What is the relationship between designs that support active learning, 21st century skill development, and students' satisfaction of STEM courses?

To answer these questions, we conducted an institute-wide survey asking undergraduate students about their experiences during the Spring 2020 term. We recognize that the Spring 2020 term, taking place between March and June of 2020, was not a typical one. Specifically, instructional designs during that term were often responsive to developments with the pandemic and might have been less careful. Therefore, the topic of this paper is not the rate or adoption of active learning in the emergency online semester. However, the scale of the shift to online learning allows us to study the relationship between online instructional design and skill development. Here we begin by documenting learning designs and opportunities for active learning during that period, to better understand the context for this work. We then continue to evaluate the relationships among these designs, reported skill development, and overall student satisfaction.

Method

Design

We used a survey to map teaching and learning practices during the Spring 2020 term at the Technion, Israel Institute of Technology. The survey asked students to choose one "particularly challenging" course they took and to fill out the survey about that course. Students were instructed to choose a STEM course that included lectures (either synchronous or asynchronous) and to avoid referring to lab-based courses or workshops. Notably, students did not report the course's name or subject. To address potential biases resulting from this survey design, we grouped responses by the overall characteristics of the courses as explained in the next section under "Course Characteristics." This grouping allows the evaluation of course designs within STEM disciplines and beyond specific subject matters. In addition, we invited several instructors, administrators, and students to review the survey to evaluate its face validity (similarly to Chen et al., 2018). The survey was revised based on their feedback.

The survey was delivered using Qualtrics Experience Management Software and distributed via email to the university undergraduate community. The survey was administered a few months after the term was over, so grades had already been submitted.

Materials

The survey included five components: (1) learning design, (2) 21st century skill development, (3) learning experience, (4) demographics, and (5) course characteristics.

Learning Design

Learning design questions targeted the frequency of use of active learning in different educational contexts (similarly to Chen et al., 2018). Students reported the frequency of educational activities in the course on a four-point scale ("Never" = 0; "Sometimes" =1; "Often" =2; "Always" =3). Twelve designs in four categories were included: preparatory activities before lectures (readings and videos; quizzes and exercises), lecture activities (discussions and clicker questions, groupwork in breakout rooms), individual and group home assignments (short and long-term), and tutorial activities (demonstrations, individual work, groupwork, and recordings instead of a synchronous tutorial). See Appendix A for the items and Table 1 for the classification of activities into common features.

21st Century Skills

Students rated the degree to which the course contributed to the development of their 21st century skills on a 5-point Likert scale (adopted from Lavi et al., 2021). The 15 items were: 1) knowledge application, 2) intercultural communication, 3) posing questions, 4) critical thinking, 5) entrepreneurship, 6) creativity, 7) self-directed learning, 8) complex problem-solving, 9) multidisciplinary collaboration, 10) written communication, 11) verbal communication, 12) experimenting and testing, 13) systems thinking, 14) engineering design, and 15) ethical awareness (see Appendix B). The last item, ethical awareness, was added in the current work. To avoid survey fatigue, each participant received seven randomly selected items out of the 15. This design generated data that was missing completely at random. These missing data were handled using the full information maximum likelihood framework, as explained in the Data Analysis section.

Learning Experience

Students rated the overall quality of the course on a 5-Point Likert scale. See Appendix B.

<u>Demographics and Course Characteristics</u>

We collected the following demographic information: gender, student seniority, GPA, student discipline (grouped into: Science and Mathematics, Engineering, or "Other"), and language proficiency (main language used at the institution). Course context variables were the course's discipline (Sciences and Mathematics, Engineering, or "Other"), number of students registered to the course (1= up to 10 students; 2 = 10-25 students, 3 = 25-100 students; 4 = +100 students), whether the course was elective or compulsory, and whether the course was a "service course," i.e. compulsory Sciences and Mathematics foundation for non-science majors.

Academic Context

The Technion, Israel Institute of Technology is a large technological university, specializing in science, engineering, and medicine with strong ties to industry. During the Spring 2020 term, 10,759 undergraduate students (40% women) were enrolled to the different faculties: 69% Engineering, 5% Sciences and Mathematics, and 26% in other faculties (e.g., medical school, architecture).

Procedure

Data was collected via two email invitations sent by the office of undergraduate studies on November and December of 2020. To encourage participation, we raffled 5 gift cards worth ~ $50 each. The survey was delivered after the review and approval of the Institutional Review Board. Additionally, the first page of the survey included an informed consent form

Sample

Our sample is made of 744 students who answered all relevant survey items. Gender: 43% identified as women and 57% as men. This is rather representative of the institute's population, with 40% women enrolled at the undergraduate level. Student discipline: 89% were Engineering students, with the rest distributed over the other disciplines. This shows a slight overrepresentation of Engineering students compared to the 69% of Engineering students enrolled in the institution. Seniority: 17% were first year students and for them, the Spring 2020 was their first or second term as undergraduate students. GPA: 56% reported their GPA is above 85 (B+ or higher), 40% reported it to be between 70 and 85 (C to B), and four percent reported it to be less than 70 (C- or lower). Language proficiency level: 93% of the responders had either native language or full proficiency in Hebrew. Ethnicity/race data was not collected to not trigger stereotype threat (Steele, 2011) and in accordance with guidelines for best practices in the field of inclusive designs for research (e.g., The Centre for Teaching, Learning and Technology, The University of British Columbia, n.d.).

Course Characteristics Descriptive Statistics

Eighteen% of students reported they are referring to an elective course, while 82% referred to compulsory courses; 54% referred to large-enrollment courses (+100 students); 36% referred to medium-sized courses (26 -100 students enrolled), and 10% referred to courses with less than 26 students. Twenty-seven % of respondents referred to service courses.

Data Preparation and Analysis

Data Preparation of Course Characteristics Variables

We excluded courses from "Other" faculties from analysis due to a low number of responses (10% of survey respondents) and high diversity in faculties (e.g., education, medicine, architecture). While architecture is a STEM profession, and taught at our university, courses delivered at the Faculty of Architecture include a variety of courses such as studio courses and design courses. Since survey respondents did not report course names, we had no way of knowing if they were referring to a course similar to other STEM courses or unique to the faculty.

Student Background

The "Student Seniority" variable was restructured to distinguish first year students and students of other academic years. Additionally, as there is little variance in students' discipline (89% Engineering students), we excluded students' discipline from the analysis.

Analysis of Learning Design

There are many forms for active online learning varying in their operational definitions (Chi et al., 2018), and the 12 survey items asking about learning design only sampled this space. The goal of this work is to identify features of productive designs, rather than to perform a competition between specific implementations. To be able to generalize beyond specific classroom implementations, active learning designs were grouped based on whether they included or not seven common design features. These features were group work, individual work, synchronous work, asynchronous work, long-term work, short-term work, and the use of resources only. Our classification looked into each type of survey item and categorized it to either include or not the above-mentioned features. So, for example, preparatory readings and videos were classified as a type of activity that includes individual work, asynchronous work, is short-termed, and can include the use of resources only. Long-term group homework on the other hand, was classified as including groupwork, asynchronous work and long-term work. This grouping allowed us to study the features of different activities, beyond the specific implementation of the activity in a given classroom.

Table 1 presents this classification of learning activities into active learning design features. For each such raw variable (the rows in Table 1), we report the mean and SD of frequency of our sample (e.g., mean frequency of quizzes, mean frequency of TA demos etc.). Further, for each column (e.g., activity feature), we report the mean and SDs for that feature within the sample and its maximum possible value based on the items included in the survey. In both cases these values are based on the reported frequency in the survey (0=never, 1= Sometimes, 2 =Often, 3=Always).

Table 1

Classification of Learning Activities into Learning Constructs

Instructional context	Type of activity	*M* (*SD*)	Group work	Ind. work	Sync. work	Async. work	Long term	Short term	Resources only
Preparatory activities									
	Readings and videos	0.65 (1.16)	0	1	0	1	0	1	1
	Quizzes and exercises	0.48 (1.02)	0	1	0	1	0	1	0
Lecture activities									
	Class discussions clicker questions	0.59 (0.99)	0	1	1	0	0	1	0
	Groupwork in breakout sessions	0.14 (0.52)	1	0	1	0	0	1	0
Homework									
	Short-term individual work	2.01 (1.26)	0	1	0	1	0	1	0
	Long-term individual work	0.83 (1.18)	0	1	0	1	1	0	0
	Short-term groupwork	0.25 (0.74)	1	0	0	1	0	1	0
	Long-term groupwork	0.54 (1.07)	1	0	0	1	1	0	0
Tutorials									
	Individual work	0.47 (0.84)	0	1	1	0	0	1	0
	Groupwork in breakout sessions	0.10 (0.47)	1	0	1	0	0	1	0
	TA demos	2.59 (0.72)	0	0	1	0	0	1	1
	Recordings only	0.73 (1.17)	0	1	0	1	0	1	1
Mean for activity beyond instructional context (SD)			1.03 (1.72)	5.69 (3.59)	3.73 (2.04)	5.42 (3.21)	1.35 (1.60)	7.80 (3.94)	3.77 (1.97)
Max possible value			12	21	15	21	6	30	9

Data Analysis

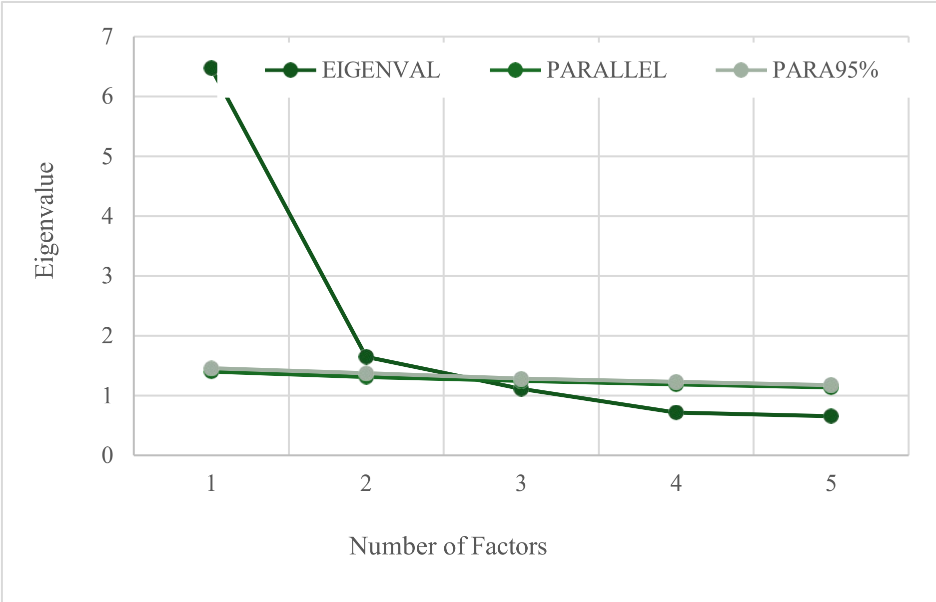
Analysis of 21st Century Skills

The survey included 15 items asking about specific 21st century skills, with each participant receiving seven randomly selected items out of the 15. This procedure produced data that was missing completely at random (Bar, 2017). To address this, we used the Exploratory Structure Equation Modeling (ESEM) procedure in Mplus V.8.3 (Stalikas et al. 2018) which works within the Full Information Maximum Likelihood Framework (FIML; Enders, 2010; Cham et al., 2017) and uses correlated data to extract the factor scores regardless of the missing values.

To reduce the number of items into parsimonious indicators, we used an exploratory and confirmatory factor analysis (EFA, CFA). In this process, a first exploratory lookup at the data indicated two to three potential factors, yet the three-factor option received higher goodness of fit (χ^2=72.02, df=63, p=.204) and advanced the two-factor solution. See Figure 1 for eigenvalue test versus parallel analysis. The parallel analysis was set to 100 simulation repeats and shows superior value in the intersection with the actual eigenvalue between two and three factors. We applied the preliminary results to the exploratory structural equation (ESEM) modeling procedure and readjusted loadings with the *Target* rotation option. This yielded three factors, for which we had loadings, and consequentially, confirmed this factor structure within a confirmatory framework (CFA). Table 2 shows EFA and CFA loadings and model goodness-of-fit. These results were within required thresholds and provided construct validity to the three factors. However, correlations between factors were high which challenged desired distinct factors. We used the Average Variance Extracted (AVE) measure for internal consistency versus the Maximum Shared Variance (MSV), to determine discriminant and convergence validity (Henseler, et al., 2015). The maximum shared variance which is the squared largest correlation was slightly lower in comparison to the AVE across the three factors, which suggested discriminant and convergence validity, beyond the construct validity.

Figure 1

Parallel Analysis Versus Scree Plot to Determine Optimal Number of Factors



Final factors were labeled: i) Communication and collaboration (ii) Domain-general skills, and iii) STEM-specific skills. See Table 2 for the CFA results and variables loading on each factor. Notably, these factors echo similar grouping by Lavi and colleagues (2021). Table 2 presents the results of EFA and CFA with final factor loadings.

Table 2

Exploratory and Confirmatory Factor Loadings

Item	Factor 1	Factor 2	Factor 3	CFA
F1: **Communication and collaboration**				
Intercultural communication	0.879***	-0.028	0.013	0.782
Entrepreneurship	0.469***	0.155*	0.194**	0.719
Multidisciplinary collaboration	0.621***	0.012	0.160*	0.706
Verbal communication	0.660***	0.171**	-0.022	0.740
Experimenting and testing	0.413***	0.055	0.347***	0.692
Ethical awareness	0.533***	0.203**	0.019	0.674
F2: **Domain general skills**				
Posing questions	-0.018	0.639***	0.199**	0.773
Critical thinking	0.039	0.704***	0.021	0.734
Creativity	-0.035	0.784***	-0.029	0.717
Self-directed learning	-0.135	0.626***	0.017	0.533
Complex problem solving	-0.252***	0.631***	0.302***	0.677
Written communication	0.088	0.500***	0.160*	0.673
F3: **STEM-specific skills**				
Knowledge application	0.047	-0.003	0.705***	0.692
Systems thinking	0.056	0.229**	0.496***	0.747
Engineering design	-0.071	-0.021	0.821***	0.690
AVE	.587	.537	.583	
MSV	.472	.543	.543	

*** p<.001, ** p<.01, * p<.05.
EFA Goodness-of-fit: χ^2=72.02, df=63, p=.204; CFI=.997, TLI=.995; RMSEA=.010, 95% CI[.00,.02]; SRMR=.024; CFA Goodness-of-fit: χ^2=186.31, df=87, p=.001; CFI=.966, TLI=.959; RMSEA=.028, 95%CI[.023,.034]; SRMR=.048;
Correlations: F1 WITH F2 r=.643, p<.001; F1 WITH F3 r=.687, p<.001; F2 WITH F3 r=.737, p<.001.

Explaining Variance in Skill Development

To answer our research questions, we conducted several multiple linear regression (MLR) analyses using stepwise inclusion criteria in IBM's SPSS Statistics 18. Our interpretation of the MLRs is based on common approach (e.g., Ziglari, 2017), where each variable's beta coefficient gives the change to Y-HAT given a one unit change in the variables (p. 14) and R2 gives information about the explained variance to Y by the different predictors (p.15).

For RQ1, we fitted three separate MLR models, one for each of the three 21st century facets as dependent variables. All models included three groups of Independent Variables: (1) learning design features (as explained in Table 1), (2) course context: service course, elective or compulsory, course size, and course discipline, and (3) student attributes: GPA, gender, seniority, and language.

For RQ2, we used a model with overall satisfaction with the course as the dependent variable, and the following variables as independent variables: (1) the three 21st century skill facets, (2) learning design features, (3) course context, and (4) student attributes.

Results

RQ1: Active Learning and 21st Century Skill Development

Communication and Collaboration Skills

Nineteen% of the variance in students' development of communication and collaboration skills is explained by the model. Specifically, the more individual and group work (β = + 0.13*** and β = + 0.15*** respectively), the more likely students were to report an improvement of this set of skills. However, short-term work (β = - 0.05***) as well as asynchronous work (β = - 0.06***) had a small yet significant negative beta coefficient, suggesting that the more short-term work and the more asynchronous work, the less students feel improvement of their communication and collaboration skills. As for student attributes, the lower their language skills (β = - 0.11***) and the lower their GPA (β = - 0.09*), the more likely they are to report these skills improved. Additionally, students are more likely to report improvement of this skillset in smaller courses (β = - 0.10**). See Table 3 for the full model.

Table 3

Communication and Collaboration Skills Explained by Learning Design Features, Student Attributes, and Course Context

Factor 1: Communication and collaboration					95% confidence interval for B	
	Unstandardized B/ beta in for non sig. variables	Coefficient SE	Standardized Beta	Sig.	Lower bound	Upper bound
Constant	0.719	0.194		0.000	0.34	1.10
Learning design features:						
Individual work	**0.13**	**0.019**	**0.689**	**0.000**	**0.09**	**0.16**
Groupwork	**0.15**	**0.018**	**0.398**	**0.000**	**0.12**	**0.19**
Short-term work	**- 0.05**	**0.013**	**- 0.284**	**0.000**	**- 0.07**	**- 0.02**
Long-term work	- 0.11	-	-	0.164		
Synchronous work	- 0.13	-	-	0.164		
Asynchronous work	**- 0.06**	**0.016**	**- 0.310**	**0.000**	**- 0.10**	**- 0.03**
Resources only	0.02	-	-	0.685		
Student attributes:						
GPA	**- 0.09**	**0.039**	**- 0.073**	**0.029**	**- 0.16**	**- 0.01**
Gender (0=M; 1=W)	- 0.03	-	-	0.956		
Seniority (0= 1st year; 1 = other years)	- 0.04	-	-	0.864		
Language (0=poor; 4=Native)	**- 0.11**	**0.035**	**- 0.109**	**0.001**	**- 0.18**	**- 0.04**
Course context:						
Service course	- 0.04	-	-	0.680		
Elective or compulsory	0.04	-	-	0.771		
Course size	**- 0.10**	**0.033**	**- 0.101**	**0.003**	**- 0.16**	**- 0.03**
Course discipline (0 = Sci & Math; 1 = Eng.)	0.07	-	-	0.797		
Regression summary						
Explained variance (R^2)	0.19					
N	744					

Domain General Skills

Ten% of the variance is explained by the model. Courses that include individual work, long-term work, and synchronous work (β = + 0.02*, β = + 0.07***, and β = + 0.08***, respectively) are more likely to contribute to students' domain general skills. Further, first year students are more likely to report growth in these skills (β = - 0.22*). Additionally, students in smaller courses are also more likely to report the development of this skillset (β = - 0.14**). See Table 4.

Table 4

Domain General Skills Explained by Learning Design Features, Student Attributes, and Course Context

Factor 2: Domain-general skills					95% confidence interval for B	
	Unstandardized B/ beta in for non sig. variables	Coefficient SE	Standardized Beta	Sig.	Lower bound	Upper bound
Constant	- 0.10	0.130		0.428	- 0.36	0.15
Learning design features:						
Individual work	**0.02**	**0.010**	**0.087**	**0.042**	**0.001**	**0.04**
Groupwork	0.05	-	-	0.251		
Short-term work	- 0.02	-	-	0.836		
Long-term work	**0.07**	**0.019**	**0.133**	**0.000**	**0.03**	**0.11**
Synchronous work	**0.08**	**0.017**	**0.186**	**0.000**	**0.04**	**0.11**
Asynchronous work	- 0.02	-	-	0.836		
Resources only	- 0.04	-	-	0.440		
Student attributes:						
GPA	- 0.03	-	-	0.365		
Gender (0=Men; 1=Women)	- 0.06	-	-	0.108		
Seniority (0= 1st year; 1 = other years)	**- 0.22**	**0.085**	**-0.095**	**0.011**	**- 0.38**	**- 0.05**
Language (0=poor; 4=Native)	- 0.03	-	-	0.379		
Course context:						
Service course	- 0.04	-	-	0.346		
Elective or compulsory	- 0.02	-	-	0.595		
Course size	**- 0.14**	**0.047**	**-0.110**	**0.003**	**- 0.23**	**- 0.05**
Course discipline (0 = Sci & Math; 1 = Eng.)	0.05	-	-	0.216		
Regression summary						

Explained variance (R2)	0.10
N	744

STEM-Specific Skills

The model explains 15% of variance. Individual work, groupwork, and long-term activities increase the likelihood of students to report an improvement of this skillset (β = + 0.10***, β = + 0.09***, and β = + 0.06**, respectively). Further, asynchronous activities are associated with a decrease in the development of this skillset (β = - 0.08***). Additionally, students are also more likely to report growth in small courses (β = - 0.10*) and Engineering courses (β = + 0.21***). See Table 5.

Table 5

STEM-Specific Skills Explained by Learning Design Features, Student Attributes, and Course Context

Factor 3: STEM-specific skills					95% confidence interval for B	
	Unstandardized B/ beta for non sig. variables	Coefficient SE	Standardized Beta	Sig.	Lower bound	Upper bound
Constant	- 0.25	0.084		0.003	- 0.42	- 0.09
Learning design features:						
Individual work	**0.10**	**0.02**	**0.48**	**0.000**	**0.07**	**0.13**
Groupwork	**0.09**	**0.02**	**0.20**	**0.000**	**0.05**	**0.12**
Short-term work	- 0.04	-	-	0.790		
Long-term work	**0.06**	**0.02**	**0.14**	**0.001**	**0.03**	**0.10**
Synchronous work	-.020	-	-	0.790		
Asynchronous work	**- 0.08**	**0.02**	**-0.36**	**0.000**	**-0.12**	**-0.05**
Resources only	0.031	-	-	0.546		
Student attributes:						
GPA	- 0.05	-	-	0.165		
Gender (0=Men; 1=Women)	- 0.05	-	-	0.134		
Seniority (0= 1st year; 1 = other years)	- 0.05	-	-	0.152		
Language (0=poor; 4=Native)	- 0.04	-	-	0.245		
Course context:						
Service course	0.01	-	-	0.833		

Elective or compulsory	-0.01	-	-	0.748		
Course size	**- 0.10**	**0.04**	**-0.09**	**0.016**	**- 0.17**	**- 0.02**
Course discipline (0 = Sci & Math; 1 = Eng.)	**0.21**	**0.06**	**0.14**	**0.000**	**0.09**	**0.32**
Regression summary						
Explained variance (R^2)	0.15					
N	744					

See Appendix C for the full correlation matric between all variables.

RQ2: Active Learning, 21st Century Skill Development, and Student Satisfaction

The model explains that 27% of variance in students' overall satisfaction with the course. Students are more likely to report the course was good when they felt the courses contribute to the development of their domain-general skills (β = + 0.78***), and when the course includes synchronous activities (β = + 0.07***). Further, students with a higher GPA (β = + 0.25***) are more likely to be satisfied with the course. Further, students are less likely to be satisfied with the course in courses that support the development of STEM-specific skills (β = - 0.22*) and in courses that are not elective (β = - 0.22*). See Table 6.

Table 6

Student Satisfaction as a Function of Skill Development, Learning Design Features, Student Attributes, and Course Context

	Student satisfaction with the course				95% confidence interval for B	
	Unstandardized B/ beta for non sig. variables	Coefficient SE	Standardized Beta	Sig.	Lower bound	Upper bound
Constant	2.69	0.19		0.000	2.29	3.04
21st century skills						
Communication and collaboration	-.03	-	-	0.63		
Domain-general skills	**0.78**	**0.09**	**0.59**	**0.000**	**0.53**	**0.70**
STEM-specific skills	**-0.22**	**0.11**	**-0.14**	**0.04**		
Learning design features:						
Individual work	.05	-	-	0.20		
Groupwork	- 0.04	-	-	0.21		
Short-term work	.026	-	-	0.56		
Long-term work	- 0.01	-	-	0.73		

Synchronous work	**0.07**	**0.02**	**0.13**	**0.000**	**0.03**	**0.11**
Asynchronous work	.012	-	-	0.72		
Resources only	-0.05	-	-	0.16		
Student attributes:						
GPA	**0.25**	**0.07**	**0.13**	**0.000**	**0.13**	**0.39**
Gender (0=Men; 1=Women)	0.00	-	-	0.91		
Seniority (0= 1st year; 1 = other years)	- 0.04	-	-	0.20		
Language (0=poor; 4=Native)	0.03	-	-	0.37		
Course context:						
Service course	0.02	-	-	0.52		
Elective or compulsory	**- 0.23**	**0.10**	**-0.08**	**0.02**	**-0.39**	**-0.2**
Course size	.030	-	-	0.39		
Course discipline (0 = Sci & Math; 1 = Eng.)	-0.01	-	-	0.68		
Regression summary						
Explained variance (R^2)	0.27					
N	738					

Table 7 further shows the changes to explained variance with the addition of each variable that contributed significantly to the model. As seen by the table, the greatest contribution to R2 was by the domain-general skillset. However, the additional variables increased it by a total of four percent.

Table 7

Changes to R^2 with the Addition of Variables (Stepwise Inclusion Criteria)

Model number	Variables in the model	R^2	R Square Change	F Change	df1	df2	Sig. F Change
1	Domain-general skills	0.234	0.234	225.351	1	736	0.000
2	Domain-general skills + GPA	0.250	0.016	15.443	1	735	0.000
3	Domain-general skills + GPA + Synch. Work	0.262	0.012	11.925	1	734	0.001

4	Domain-general skills + GPA + Synch. Work + elective/required course	0.267	0.005	4.509	1	733	0.034
5	Domain-general skills + GPA + Synch. Work + elective/ required course + STEM-specific skills	0.271	0.004	4.384	1	732	0.037

Discussion

This study surveyed students about active online learning, 21st century skill development, and satisfaction in postsecondary STEM education during the Spring 2020 term. We found that opportunities for active learning online contributed to the development of students' 21st century competencies. The development of said competencies in turn increased students' satisfaction with the course.

Similarly to Lavi et al. (2021), we identified three main facets that encompass 15 common 21st century skills, providing further validation for their instrument. This study also demonstrates the important role active learning has in skill development even when learning takes place remotely and online, in an emergency response situation. Thus, our findings extend prior work (e.g., Buitrago-Flórez et al., 2021; Lopatto, 2007) to an online remote context. We next review our results in the context of the ICAP framework and the active learning literature, discuss the study limitations, and provide design recommendations.

Active Learning Designs That Are Associated with Skill Development

RQ1 focused on the association between learning design features and 21st century skill development. The regression models explained 10 to 19% of the variance in skill development. These percentages are non-trivial, considering that these models did not include the topic of the class, the type or content of activity, or the identity and proficiency of the lecturer. These findings are consistent with the vast literature pointing to the advantages of active learning for skill development (Buitrago-Flórez et al., 2021; Christensen & Knezek, 2015; Lopatto, 2007; Lavi et al., 2021).

Our analysis shows that long-termed activities are associated with skill development more than short-termed activities. Such activities are more likely to rank higher on the ICAP framework, as they are more constructive in nature and require students to generate outputs on their own and practice these over a prolonged period of time (e.g. as in a project due at the end of the term). Thus, these activities also likely give more room to practice the target skills. Not surprisingly, it is not merely being active that supports the development of these skills, but the opportunity to practice them over time.

Other elements that were strongly associated with skill development are self- or group-activities. It is interesting that there was almost no difference between these two, not even on the development of communication skills. One explanation may be that students work in groups even on individual activities. As discussed by Chi and colleagues (2018), the benefit of the activity depends not only on its design, but on students' engagement with it. Future work will need to look into how students engage with individual activities in an online context. Instructors often complain about students submitting identical assignments – this may be another hint at students' choice to work collaboratively, with its benefits.

Notably, asynchronous activities were negatively associated with 21st century skill development. One clear aspect is the relative lack of support compared with synchronous activities. Still, the negative value is interesting, given the strong and positive association with long-term activities, such as projects, which are often asynchronous. This may be a statistical artefact. Long-term activities are beneficial especially when synchronous (such as Problem-Based Learning). While still beneficial also asynchronously, there is some penalty associated with that implementation.

The only type of activity that was not associated with any skill development is the provision of resources. This, indeed, is not an activity in and of itself. Resources can afford, but not require, active learning. While using such resources may be beneficial for learning at the domain level (and such analysis is outside the scope of the current study), it seems to have no bearing on the development of 21st century competencies.

One of the main contributions of this study is the focus on design features (e.g., long-term vs. short-term; synchronous vs. asynchronous) as opposed to specific activities or technologies (e.g., clickers vs. quizzes; Zoom vs. Teams). Such focus allows the consideration of the features of an activity and the purpose it is set to serve in terms of skill development. Thus, our analysis highlights the importance of the fit between the instructional context and the desired learning outcome beyond specific activities or assignments. If for example, the goal is to support the development of critical thinking and creativity skills, both found in the "domain-general" skillset, our analysis suggests using learning activities that are long-termed, synchronous, and individual. However, the choice of whether to use projects, reports, or portfolios depends on the instructor's preferences, the class's content, and the constraints of the course.

Other Notable Relationships

Several other patterns can be noticed in the results. First, when student characteristics were significant it was only in favour of the less privileged students. Students with low GPA and lower language skills reported higher improvement of communication and collaboration skills. First year students reported higher improvement of domain-general skills. These are very important findings. Several studies have pointed at the growing gaps due to the shift to online learning (e.g., Stöhr et al., 2020). Other studies have shown that active learning pedagogies reduce these gaps (e.g., Theobald et al., 2020). These results suggest that while online learning introduces equity challenges (Means, & Neisler, 2021), they also present opportunities for skill development, especially for those who need it the most. Furthermore, we found no effect to gender although gendered differences often emerge in the context of STEM education (e.g., Ballen et al., 2017). It is possible that as various 21st century competencies are not domain specific, they do not present the same gendered-differences. Future work will be helpful in discovering if and how active learning methods contribute to this pattern.

Another interesting yet unsurprising finding is that the course's size explains variance in students' 21st century skill development, across the different skill sets. It is likely that instructional activities that invite active learning are easier to facilitate in smaller classes. It is thus reasonable to assume that students in smaller courses were more likely to enjoy the benefits of instructional designs that invite active learning.

We further found that the course's discipline contributed to explained variance in skill development. Engineering courses are more likely to support the development of communication and collaboration skills, and STEM-specific skills compared to sciences or mathematics courses. It may be that engineering courses have hands-on components, while science courses are more theoretical and are thus lecture-based.

Another interesting observation is that there were very little differences between the three skill facets. This is surprising, as the factor analysis showed that these facets are very distinct; hence, we did not anticipate a high correlation between them. It seems that while they are, indeed, supported differently by different courses, drawing clear relationship between features of active learning and specific facets may not be obvious. It may also be that clear relationships between some designs and specific skills (of the list of 15) were washed out during the dimension reduction process.

Course Satisfaction

Our results show that almost 30 percent of the variance in students' satisfaction with the course is explained by the model. Unsurprisingly, students are more satisfied with elective courses—courses they choose to take. Further, students appreciated more courses that supported the development of domain-general skills. Within these facets were skills such as critical thinking and asking questions, creativity, self-directed learning, and complex problem-solving. These experiences and activities are ones also found at the higher levels of the ICAP framework (Chi et al., 2018). Interestingly, we found that students were less likely to be satisfied with courses that highlighted STEM-specific skills: engineering design, systems thinking, and knowledge application. These skills are ones that may require students to deeply engage with the course content but not necessarily to interact with others or produce novel output. These results show that enabling students to practice learning activities higher on the ICAP taxonomy impacts their satisfaction with the course.

Limitations

Our research aimed to gain insights into the relationship between learning design and 21st century skill development in the context of higher online STEM education and at an institutional level. To achieve this aim, we targeted the entire student population at the Technion, that is, we invited over 10K undergraduate students to participate in our survey. Alas, only about 20 percent of students opened and answered at least one survey question. This number shrunk in the process of data cleanup and analysis, making our final sample over 700 students. In terms of response rate, 744 students make only seven percent of all undergraduate students in our institution. While this is a small response rate, prior work suggests that our sample is nonetheless sufficient. For example, Fosnacht and colleagues (2017) found that in higher education survey studies, when the sample is between five and ten percent of the population and larger than 500 participants it can be considered representative of the population. Furthermore, according to Holtom et al. (2022), when considering response rate, it is important to consider the responses' validity, their representativeness of the target population and the researchers' work process and methodological decision-making. As we invited students to participate in the study by sending two email invitations to the entire student body there are likely no biases resulting from this method. This is supported by the representativeness of our sample of the student body in terms of demographics. Finally, as seen in the results, we successfully replicated prior findings, further supporting the validity of the study and sampling method.

Furthermore, in terms of the sample's adequacy in addressing the RQs, according to Hair and colleagues (2010), MLR analysis requires 15-20 cases for each independent variable entered into the model. Our most complex analysis includes 18 independent variables with 738 cases (Table 6). This makes the minimum number of participants between 15*18 to 20*18 = 225 – 300. Our sample meets this criterion, and all other levels of analysis satisfy these requirements with an appropriate sample size to answer our RQs.

Another limitation to consider is that our survey design did not include demographic questions asking students about their ethnicity, race or religion. Thus, the study does not allow a discussion of the implications of designs for active learning, 21st century skills development, and these student attributes. This was a deliberate decision made in accordance to best practices for inclusive research design (e.g., The Centre for Teaching, Learning and Technology, The University of British Columbia, n.d.) and in an attempt not to trigger a stereotype threat in study participants (e.g., Steele, 2011). Future work can help consider if such data can help gain a more nuanced understanding of the interaction between demographics and learning design on 21st century skill development in online STEM education.

Finally, it is important to remember that the Spring 2020 term was unique in the quick response it required of teaching staff. This likely produced less than optimal designs for learning, so it is possible that our findings offer an underrepresentation of the actual contribution of designs for active learning to 21st century skill development in the context of online STEM education.

Summary and Design Implications

The study suggests several design considerations. Its first lesson learned is that active learning in STEM education works—also online, also as an emergency response, and across course contexts. It further suggests that certain features of active learning are more beneficial. Patterns for productive implementation include groupwork, individual work, synchronous activities (as in lecture or tutorial activities) and long-term endeavours such as group projects. Such activities all could be facilitated in a digital environment (Prince et al., 2020).

When considering these benefits, more work would be helpful in mapping barriers to the implementation of such designs in remote or hybrid STEM education (cf. Børte et al., 2020). For example, universities should make these tools readily available to instructors, including integration into their instructional technological landscape, and provide technical and pedagogical support. Such infrastructure will reduce the overload for both instructors and students, and support more common application of these pedagogies.

This study has two unique properties that support generality of its results. First, to improve the external validity of our results and generalize beyond a specific use of a task or a technology, we classified the twelve designs into design features that could be relevant in other contexts. Future work will need to evaluate whether such predictions about other types of activities hold. Second, the study did not ask learners to draw direct links between activities, active learning, skill development or their satisfaction with the course. Instead, we asked learners for their overall course evaluation, to avoid analyzing students' opinions about the different designs. Alas, these choices also introduce a limitation. For example, it may be that there are aspects of active learning that are not included in this analysis. Notably, this analysis focused on *learning designs* that invite active learning. Students may apply active learning also on other designs, such as when listening to a lecture. Similarly, correlation is not causation. It is possible that instructors that offer active learning opportunities are more engaging instructors in general. Further, our survey asked about a "particularly challenging course." Less challenging courses were likely underreported in the survey. Last, these results may be specific to STEM disciplines.

While these concerns are valid, results show clear association between active learning opportunities and self-reported skill development. At one level, this is to be expected. For example, students who had a chance to practice groupwork should have improved their collaboration skills. Results of this study corroborate this intuition in data. However, results go deeper than that, for example, by showing the benefit of synchronous activities, possibly due to the supported environment. Results also generalize these findings across STEM disciplines and specific activity implementation. Thus, this study is a call for action—to offer more active learning in online settings in higher STEM education.

Statements and Declarations

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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Ethics

This work was reviewed and approved by the Institutional Behavioral Sciences Research Ethics Committee.

References

Ananiadou, K. and M. Claro (2009). "21st century skills and competences for new millennium learners in OECD countries," OECD Education Working Papers, No. 41, *OECD Publishing*. http://dx.doi.org/10.1787/218525261154

Ballen, C. J., Wieman, C., Salehi, S., Searle, J. B., & Zamudio, K. R. (2017). Enhancing diversity in undergraduate science: Self-efficacy drives performance gains with active learning. *CBE—Life Sciences Education*, *16*(4), ar56. https://doi.org/10.1187/cbe.16-12-0344

Bar, H., (2017). Missing data—mechanisms and possible solutions / Datos ausentes: mecanismos y posibles soluciones. *Cultura y Educación*, 29:3, 492-525

Basdogan, M. & Birdwell, T. (2023). Faculty transition from in-person to online teaching: Qualitative investigation for active learning. *Online Learning*, *27*(1), 428-450. https://doi.org/10.24059/olj.v27i1.3229

Børte, K., Nesje, K., & Lillejord, S. (2020). Barriers to student active learning in higher education. *Teaching in Higher Education*, 1–19. https://doi.org/10.1080/13562517.2020.1839746

Buitrago-Flórez, F., Danies, G., Restrepo, S., & Hernández, C. (2021). Fostering 21st century competences through computational thinking and active learning: A mixed method study. *International Journal of Instruction*, *14*(3), 737-754. https://doi.org/10.29333/iji.2021.14343a

Cham, H. Reshetnyak, E. Rosenfeld, B. & Breitbart, W. (2017). Full information maximum likelihood estimation for latent variable interactions with incomplete indicators. *Multivariate Behavioral Research*, 52(1), 12–30. https://doi.org/10.1080/00273171.2016.1245600

Chi, M. T. H., Adams, J., Bogusch, E. B., Bruchok, C., Kang, S., Lancaster, M., Levy, R., Li, N., McEldoon, K. L., Stump, G. S., Wylie, R., Xu, D., & Yaghmourian, D. L. (2018). Translating the ICAP theory of cognitive engagement into practice. *Cognitive Science*, *42*(6), 1777–1832. https://doi.org/10.1111/cogs.12626

Chen, B., Bastedo, K., & Howard, W. (2018). Exploring design elements for online STEM courses: Active learning, engagement & assessment design. *Online Learning*, *22*(2) 59-76. https://doi.org/10.24059/olj.v22i2.1369

Christensen, R., & Knezek, G. (2015). Active learning approaches to integrating technology into a middle school science curriculum based on 21st century skills. In *Emerging technologies for STEAM education* (pp. 17-37). Springer. https://doi.org/10.1007/978-3-319-02573-5_2

Cinque, M. (2017). MOOCs and soft skills: A comparison of different courses on creativity. *Journal of e-Learning and Knowledge Society*, *13*(3). https://doi.org/10.20368/1971-8829/1386

Dede C. (2010). Comparing frameworks for 21st century skills. In Bellanca J., Brandt R. (Eds.), *21st century skills* (pp. 51–76). Solution Tree Press.

Duffy, T. M., & Cunningham, D. J. (1996). Constructivism: Implications for the design and delivery of instruction. In D. H. Jonassen (Ed.), *Handbook of research for educational communications and technology*. Macmillan Library Reference USA.

Enders, C. K. (2010). *Applied missing data analysis.* Guilford.

Fosnacht, K., Sarraf, S., Howe, E., & Peck, L. K. (2017). How important are high response rates for college surveys? *Review of Higher Education*, *40*(2), 245–265. https://doi.org/10.1353/rhe.2017.0003

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, 111(23), 8410–8415. https://doi.org/10.1073/pnas.1319030111

Hadi Mogavi, R., Zhao, Y., Ul Haq, E., Hui, P., & Ma, X. (2021, June). Student barriers to active learning in synchronous online classes: Characterization, reflections, and suggestions. In *Proceedings of the Eighth ACM Conference on Learning@ Scale* (pp. 101-115). https://doi.org/10.1145/3430895.3460126

Hair, J., Anderson, R., Babin, B., & Black, W. (2010). Multivariate Data Analysis.pdf. In *Australia : Cengage: Vol. 7 edition* (p. 758).

Hattie, J. (2010). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement* (Reprinted). Routledge.

Henseler, J., Ringle, C.M. & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science,* 43: 115 - 135.

Hmelo-Silver, C. E., Duncan, R. G., & Chinn, C. A. (2007). Scaffolding and achievement in problem-based and inquiry learning: A response to Kirschner, Sweller, and Clark (2006). *Educational Psychologist*, *42*(2), 99–107. https://doi.org/10.1080/00461520701263368

Holtom, B., Baruch, y., Aguinis, H. & Ballinger, G. A. (2022) Human relations survey response rates: Trends and a validity assessment framework. *Human Relations*, *75*(8), 1560 –1584.

Jang, H. (2016). Identifying 21st century STEM competencies using workplace data. *Journal of Science Education and Technology*, *25*(2), 284–301. https://doi.org/10.1007/s10956-015-9593-1

Kennedy T.J., Sundberg C.W. (2020) *21st century skills*. In: Akpan B., Kennedy T.J. (eds) Science education in theory and practice. Springer Texts in Education. Springer, Cham. https://doi.org/10.1007/978-3-030-43620-9_32

Koedinger, K. R., Kim, J., Jia, J. Z., McLaughlin, E. A., & Bier, N. L. (2015, March). Learning is not a spectator sport: Doing is better than watching for learning from a MOOC. In *Proceedings of the second (2015) ACM conference on learning@ scale* (pp. 111-120). https://doi.org/10.1145/2724660.2724681

Lavi, R., Tal, M., & Dori, Y. J. (2021). Perceptions of STEM alumni and students on developing 21st century skills through methods of teaching and learning. *Studies in Educational Evaluation*, 70, 101002. https://doi.org/10.1016/j.stueduc.2021.101002

Lopatto, D. (2007). Undergraduate research experiences support science career decisions and active learning. *CBE—Life Sciences Education*, *6*(4), 297–306. https://doi.org/10.1187/cbe.07-06-0039

Means, B., & Neisler, J. (2021). Teaching and learning in the time of COVID: The student perspective. *Online Learning*, *25*(1) https://doi.org/10.24059/olj.v25i1.2496

Prince, M. Felder, R., Brent, R. (2020). Active student engagement in online STEM classes: Approaches and recommendations. *Advances in Engineering Education. 8*(4), 1-25. https://advances.asee.org/wp-content/uploads/Covid%2019%20Issue/Text/2%20AEE-COVID-19-Felder.pdf

Ruiz-Palmero, J., Guillén-Gámez, F. D., Colomo-Magaña, E., & Sánchez-Vega, E. (2023). Effectiveness of the flipped classroom in the teaching of mathematics in an online environment: Identification of factors affecting the learning process. *Online Learning*, *27*(2). 304-323. https://doi.org/10.24059/olj.v27i2.3239

Stalikas, A., Kyriazos, T. A., Yotsidi, V., and Prassa, K. (2018). Using bifactor efa, bifactor cfa and exploratory structural equation modeling to validate factor structure of the meaning in life questionnaire, Greek version. *Psychology*, 9: 348—371. https://doi.org/10.4236/psych.2018.93022.

Steele, C. M. (2011). *Whistling Vivaldi: How stereotypes affect us and what we can do* (reprint edition). W. W. Norton & Company. https://doi.org/10.1176/appi.ajp.2011.11010005

Stöhr, C., Demazière, C., & Adawi, T. (2020). The polarizing effect of the online flipped classroom. *Computers and Education*, *147*. https://doi.org/10.1016/j.compedu.2019.103789

Soffer, T., & Cohen, A. (2019). Students' engagement characteristics predict success and completion of online courses. *Journal of Computer Assisted Learning*, *35*(3), 378–389. https://doi.org/10.1111/jcal.12340

The Centre for Teaching, Learning and Technology, The University of British Columbia, (n.d.). Equity and inclusion in data collection: General guideline on asking for demographic information. https://isotl.sites.olt.ubc.ca/files/2020/02/EIOGuidelines_2020.pdf

Theobald, E. J., Hill, M. J., Tran, E., Agrawal, S., Arroyo, E. N., Behling, S., ... & Freeman, S. (2020). Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. *Proceedings of the National Academy of Sciences*, *117*(12), 6476-6483. https://doi.org/10.1073/pnas.1916903117

Usher, M., Barak, M., & Haick, H. (2021). Online vs. on-campus higher education: Exploring innovation in students' self-reports and students' learning products. *Thinking Skills and Creativity*, 100965. https://doi.org/10.1016/j.tsc.2021.100965

Ziglari, L. (2017). Interpreting multiple regression results: β weights and structure coefficients. *General Linear Model Journal*, 43(2), 13–22. https://doi.org/10.31523/glmj.043002.002