International Journal of Mathematical Education in Science and Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tmes20

Self-efficacy and approaches to learning mathematics among engineering students: empirical evidence for potential causal relations

Yusuf F. Zakariya , H. K. Nilsen , Simon Goodchild & Kirsten Bjørkestøl

INTERNATIONAL JOURNAL OF MATHEMATICAL EDUCATION IN SCIENCE AND TECHNOLOGY
https://doi.org/10.1080/0020739X.2020.1783006

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

Self-efficacy and approaches to learning mathematics among engineering students: empirical evidence for potential causal relations

Yusuf F. Zakariya, H. K. Nilsen, Simon Goodchild and Kirsten Bjørkestøl

Department of Mathematical Sciences, University of Agder, Kristiansand, Norway

ABSTRACT

Theories of self-efficacy and approaches to learning are well-established in the psychology of learning. However, studies on relationships between the primary constructs on which these theories are developed are rarely reported in mathematics education research. Thus, the purpose of the current study is to provide empirical evidence for a potential causal relationship between perceived self-efficacy and approaches to learning. The present study adopts a cross-sectional survey research design that includes 195 engineering students enrolled on a first-year introductory calculus course. The data are collected using two well-developed and validated instruments with established high psychometric properties. Two hypotheses are formulated and tested using a structural equation modelling approach coupled with a weighted least square mean and variance adjusted estimator. The findings show that a high sense of perceived self-efficacy has a strong tendency to induce a deep approach to learning mathematics. In contrast, a low sense of perceived self-efficacy induces a surface approach to learning mathematics with a strong effect. This study represents a shift from the usual correlational studies that characterize quantitative research in mathematics education literature to causal relation research. Therein, causal assumptions are made and tested against the collected data, and some recommendations are made for future studies.

ARTICLE HISTORY
Received 25 March 2020

KEYWORDS
Self-efficacy; deep approach; surface approach; causal relation; empirical evidence

1. Introduction

Mathematics instruction that leads to satisfactory learning outcomes in terms of high performance as measured in examinations, understanding that supports future progression, engaged, motivated and enthusiastic students, has not been an easy task. Students, teachers, parents, researchers, policymakers, and other education stakeholders seek possible solutions to the global trend of poor performance in mathematics. The utility of mathematics transcends several educational levels, employment, and career opportunities, which explains why engineering students value the subject (Tossavainen et al., 2019). Mastery of introductory first-year mathematics courses is crucial to successful performance on core

CONTACT Yusuf F. Zakariya yusuf.zakariya@uia.no Department of Mathematical Sciences, University of Agder, Kristiansand, Norway

engineering courses at later years in the university. However, many first-year engineering students struggle with these courses, and their poor performance compels some of them to develop negative attitudes toward mathematics and change their career aspirations (Braathe & Solomon, 2015; Martínez-Sierra & García-González, 2016). Since students suffer most of the associated effects of poor performance in mathematics, a study that focuses on factors that emanate from the students is equally important. Several empirical studies have linked a variety of factors to poor performance in mathematics. These factors include but are not limited to mathematics anxiety (Dowker et al., 2016), attitudes toward mathematics (Dowker et al., 2019), academic motivation (Tossavainen et al., 2019), perceived self-efficacy (Williams & Williams, 2010), approaches to learning (Maciejewski & Merchant, 2016), conception of mathematics (Yang et al., 2019), prior mathematics knowledge (Zakariya, 2016), and self-concept (Pajares & Miller, 1994).

Two of these factors (perceived self-efficacy and approaches to learning) have received increased attention recently. The reason for this increased attention may lie in their satisfactory prediction of students' performance in mathematics (Loo & Choy, 2013; Maciejewski & Merchant, 2016; Williams & Williams, 2010). Perceived self-efficacy is linked to Albert Bandura's self-efficacy theory, which is grounded in the agentic social cognitive theory (Bandura, 1997). Perceived self-efficacy encapsulates 'beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments' (Bandura, 1997, p. 3). With a particular focus on engineering students, perceived self-efficacy has been defined as 'a person's belief that he or she can successfully navigate the engineering curriculum and eventually become a practicing engineer' (Jordan et al., 2010, p. 2). It is an important personal factor that facilitates improved students' performance in mathematics and boosts perseverance when undertaking difficult tasks (Bandura, 2012). Empirical studies have revealed that students with a high sense of perceived self-efficacy have low mathematics anxiety, high motivation to learn, positive attitudes toward mathematics, and increased interest in the subject (Bandura, 1997). Perceived self-efficacy has also been reported to predict students' performance in mathematics better than mathematics self-concept and prior knowledge of mathematics (Pajares & Miller, 1994). Efficacy beliefs have also been found to exert a more substantial direct effect on students' performance in a mathematics problem-solving activity than mental ability, mathematics anxiety, and high school mathematics content level (Pajares & Kranzler, 1995).

Students approach their learning of mathematics in different ways. However, these diverse ways of learning have been postulated by the approaches to learning theory to converge to two main approaches (Marton & Booth, 1997). Some engineering students learn mathematics with the motives of developing a deep understanding of its concepts (deep approach). In contrast, other students are extrinsically motivated to learn mathematics, such as satisfying the curriculum requirement, and thereby concentrate on crucial points (surface approach) to pass the course (Zakariya et al., 2020). Deep approaches to learning have generally been associated with an improved performance of first-year students on mathematics tasks more than surface approaches (Maciejewski & Merchant, 2016). However, there are some studies where a surface approach to learning mathematics has been reported to have a slightly higher positive correlation with performance than the deep approach to learning among engineering masters students (Svedin et al., 2013). Approaches to learning are strongly related to attitudes toward mathematics, conceptions of mathematics, and enjoyment of mathematics. Prior studies have shown a positive correlation between deep approach and attitudes toward mathematics and a negative correlation between surface approach and the latter (Alkhateeb & Hammoudi, 2006). The surface approach to learning predicts performance better than the enjoyment of mathematics, mathematics anxiety, motivation, the utility of mathematics, and gender (García et al., 2016).

Despite the success and satisfactory performance of both approaches to learning and perceived self-efficacy in predicting students' mathematics achievement, studies on causal relations between these constructs are rarely reported in the literature. Admittedly, some correlational studies are available which focus on science courses e.g. chemistry (Ardura & Galán, 2019), students enrolled on earth science programmes (Shen et al., 2016), and teachers in training (Phan, 2011). Thus, the purpose of the current study is to provide evidence for a potential causal relationship between perceived self-efficacy and approaches to learning among engineering students enrolled on a first-year calculus course. The present study is significant because if such a causal relation is revealed, then it is worth seeking interventions on one of the two constructs that can be designed to boost the other construct, which will, in turn, enhance students' performance. It is important to remark that the current study is not aimed at discovering an outright causal relation between the research constructs. Instead, causal assumptions are made therein to develop a model, and data are collected to test the causal model such that empirically-based arguments can be articulated to justify the plausibility of the model. As such, the main research question that this study attempts to address is: Does perceived self-efficacy influence the adoption of either deep or surface approach to learning mathematics among first-year engineering students?

2. Conceptual framework

A conceptual framework that can justify the relationship between approaches to learning mathematics and perceived self-efficacy among engineering students, rests on ideas from two psychological theories. Namely, approaches to learning theory and self-efficacy theory. The ontological and epistemological postulates of these theories and arguments that result in hypothesis formulations are presented in this section.

3. Student approaches to learning (SAL) theory

SAL theory can be linked to several studies of Marton and his colleagues on explorations and characterizations of approaches that university students adopt while reading some passages of prose and extracts of newspaper articles before being examined on their understanding of the presented materials (Marton & Säljö, 1976, 2005). Their qualitative analyses reveal diverse approaches to students' learning, which are highly motivated by prior experience, social factors, and the meanings that the students attached to learning (Marton & Booth, 1997). According to SAL theory, learning – a change in the experience of people about the world – forms a non-dualistic relationship between an individual and everything outside of it that is neither individually constructed nor environmentally imposed (Marton & Booth, 1997). Thus, it can be argued that students' approaches to learning vary because of the feedback relationship between students' motivation to learn, intentions, and learning context. However, these various students' approaches to learning can be generally classified into deep and surface approaches (Marton & Säljö, 2005).

Biggs (2012) describes deep approaches to learning as 'activities that are appropriate to handling the task so that an appropriate outcome is achieved' while surface approaches to learning, on the other hand, encapsulate 'activities of an inappropriately low cognitive level, which yields fragmented outcomes that do not convey the meaning of the encounter' (p.42). As such, considering the nature of engineering programmes in which students are being trained to solve practical problems, it is expected, if not required, that students adopt approaches that will facilitate the development of high cognitive skills required to solve these problems. Furthermore, approaches to learning according to SAL tradition (Marton & Booth, 1997) are predictable from students' learning conception – 'a qualitatively distinct manner in which the subjects were found to voice the way they thought about learning' (p.36), motives, intents, and the learning situations. For instance, engineering students who conceive calculus tasks as something useful and which proper understanding of it is necessary for intellectual development are likely to adopt deep approaches to learning the course. On the other hand, students who conceive calculus tasks as a mere requirement to move to the next level of study are likely to adopt surface approaches to learning the course. Thus, a deep approach to learning is intrinsically motivated, while a surface approach to learning is extrinsically motivated (Hounsell, 2005; Marton & Säljö, 2005).

It is important to remark that learning situations in the context of mathematics learning also include the nature of mathematics tasks. Such that the approaches students adopt to learning the subject are highly influenced by the nature of the tasks. Maciejewski and Merchant (2016), in an empirical cross-sectional study, show that there is a strong correlation between a deep approach to learning and students' first-year grades on mathematics tasks while a surface approach to learning has no significant correlation. However, for year-two, year-three, and year-four students, there is a strong negative correlation between the surface approach to learning and students' grades in which a deep approach shows no significant correlation. These discrepancies and inconsistencies in strength and direction of correlation coefficients between approaches to learning mathematics and students' grades are argued, using Bloom's taxonomy, to stem from the different nature of mathematics tasks at the different years of study (Maciejewski & Merchant, 2016). As such, considering its task specificity, approaches to learning mathematics are best investigated by focusing on a set of students who are following a common mathematics course.

4. Self-efficacy theory

Perceived self-efficacy is an essential component of the agentic social cognitive theory that describes behavioural changes of an individual as continuously being modified and regulated through a feedback interaction with social factors (Bandura, 2001). Unlike the traditional social cognitivism, it is argued that both social structure and personal agency 'function interdependently rather than as disembodied entities' (Bandura, 2012, p. 15). Thus, a rejection of an ontological position of dualism between social structure and personal agency. As such, agentic social cognitive theory relies on an epistemological proposition called 'reciprocal determinism' introduced by Bandura (1986, 2012). Reciprocal determinism describes human functioning as a triadic feedback causal model between personal, environmental, and behavioural factors. Therefore, it can be argued that perceived self-efficacy of engineering students on mathematics tasks is not a fixed construct since it an integral part of the personal factors that are embedded in the reciprocal deterministic model. Instead, it is causally affected by changes in the model. Borgonovi and Pokropek (2019) elaborate more on this concept when they write 'reciprocal determinism describes the sets of relationships underlying the interactions between: (a) individuals' exposure to mathematics tasks, (b) mathematics self-efficacy beliefs, and (c) mathematics ability' (p. 269).

Perceived self-efficacy contributes significantly to regulating affective, cognitive, decisional, and motivational processes of human functioning (Bandura, 2001, 2002). It is an essential construct in the learning process as it serves as a stimulus for students not to give up on difficult learning situations such that desired outcomes are achieved. It makes the individual's involvement very active and boosts morale to see to the attainment of a desirable outcome (Bandura, 1997, 2012). Since self-efficacy beliefs regulate some decisional processes of a learner, it can be argued that there is a causal relationship between perceived self-efficacy and approaches to learning mathematics. This is because students' approaches to learning a content are crucial components of their decisional processes (Biggs, 1993). Another proxy construct through which perceived self-efficacy can be causally linked with approaches to learning is students' motivation. Intrinsic motivation has been shown to induce a deep approach to learning while extrinsic motivation to induce a surface approach to learning (Marton & Booth, 1997). As such, it is expected that perceived self-efficacy is causally related to deep and surface approaches through motivation as an intervening construct since self-efficacy beliefs regulate motivational processes (Bandura, 1997).

To substantiate the argument on the causal relationship between approaches to learning mathematics and perceived self-efficacy, one could also turn to some findings that have been reported in other fields. For instance, Diseth (2011), in a study involving 177 first-year undergraduate students following a psychology course used a causal model to expose a negative relation between self-efficacy and surface approaches to learning, and an indirect positive relationship between self-efficacy and deep approaches to learning. The study by Shen et al. (2016) also reports a strong positive relationship between the deep approach to learning earth sciences and perceived self-efficacy. After an extensive search of the literature, the only quantitative study the authors could find on approaches to learning mathematics, and perceived self-efficacy is a correlational study by Zakariya et al. (2019). Therein, deep approaches to learning mathematics are found to have a positive correlation with perceived self-efficacy on calculus tasks, and a negative correlation is found between the latter and surface approaches to learning. Thus, based on the aforementioned discussion, the following hypotheses are formulated.

Hypothesis one: There is a positive causal effect of perceived self-efficacy on deep approaches to learning a first-year introductory calculus course among engineering students.

Hypothesis two: There is a negative causal effect of perceived self-efficacy on surface approaches to learning a first-year introductory calculus course among engineering students.

5. Methodology

5.1. Participants

The focus of the current study, using a cross-sectional survey research design, is on first-year engineering students at a leading Norwegian university. Even though they are enrolled on different engineering programmes, they followed a common introductory first-semester calculus course at the university. A total of 195 (47 females) students who voluntarily gave their consent took part in the study. The sample corresponds to about 65% of the total population of first-year engineering students who were invited to participate in the study. This response rate is considered high in the literature (Babbie, 1990).

5.2. Materials

Two well-developed survey instruments were used for collecting the research data. The first instrument was a Norwegian language adaptation of the revised two-factor study process questionnaire (R-SPQ-2F). This instrument was initially conceptualized and operationalized based on SAL theory to measure students' approaches to learning by Biggs et al. (2001) and was adapted to mathematics learning context among Norwegian first-year engineering students by Zakariya et al. (2020). The Norwegian adaption of the R-SPQ-2F is a 19-item questionnaire that measures two dimensions (deep and surface) of approaches to learning mathematics on a five-point Likert scale from (1) *never or only rarely true of me*, through (3) *it is true of me about half the time,* to (5) *it is always or almost always true of me.* The deep approach subscale has ten items with a reliability coefficient of .81, and the surface approach subscale has nine items with a reliability coefficient of .72 (Zakariya et al., 2020). The construct validity of the Norwegian adaption of R-SPQ-2F has been studied involving several comparisons of competing models using confirmatory factor analyses (Zakariya, 2019). Despite the availability of other measuring instruments of students' approaches to learning, such as the approaches and study skills inventory for students (ASSIST), R-SPQ-2F was adopted in the current study for a few reasons. First, it has been validated and available in Norwegian, which is the main language of instruction in the university undergraduate programmes. Second, it is concise with only 19 items, unlike the ASSIST, with 52 items and has strong psychometric characteristics. Third, given that approaches to learning are context-specific, an adapted R-SPQ-2F into mathematics context is likely to possess a high predictive power.

The second instrument used for collecting data in the current study was a calculus self-efficacy inventory (CSEI) developed by (Zakariya et al., 2019). The CSEI is a 13-item instrument developed based on guidelines for constructing perceived self-efficacy scales as explicated by the Bandura's self-efficacy theory (Bandura, 2006). The inventory contains calculus final exam-like questions in which the students are required to rate how much confidence they have in solving the questions correctly on a scale from 0 to 100. It was found to have high construct validity with unidimensionality of its items, high discriminant validity, and a high reliability index of .90 (Zakariya et al., 2019). The CSEI was adopted in the current study not only for its strong psychometric properties and because its theoretical foundation suits our conceptual framework but also for its specificity in measuring student perceived self-efficacy on calculus tasks. The Norwegian adaption of R-SPQ-2F and the CSEI were embedded in an on-line survey tool and administered to the students via their email addresses. The data collection exercise took about two weeks, and the collected data were screened for outliers and missing values. There was no case of outliers, and few data were missing at random, which were less than 1% of the total data collected and, as such, do not pose any challenge to the analyses.

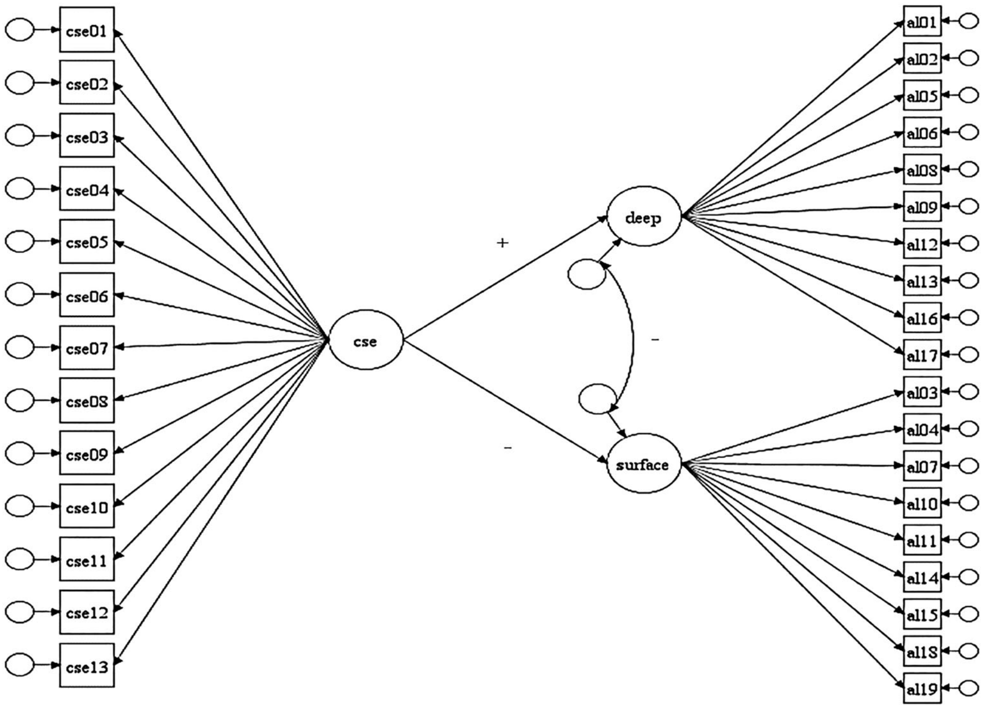

Figure 1. A hypothesized causal model of the relations between perceived calculus self-efficacy and approaches to learning mathematics.

5.3. Data analysis

The collected data were analysed using a structural equation modelling (SEM) approach. This involved testing the plausibility of the hypothesized causal relations between perceived self-efficacy and approaches to learning mathematics, as shown in Figure 1. As succinctly put by Bollen and Pearl (2013), 'SEM is an inference engine that takes in two inputs, qualitative causal assumptions, and empirical data, and derives two logical consequences of these inputs: quantitative causal conclusions and statistical measures of fit for the testable implications of the assumptions' (p.309). It is thus argued that the use of SEM in exposing the causal relationship between the current research constructs is justified, and an alternative statistical model that can do a satisfactory job in evaluating these causal claims is unlikely (Bullock et al., 1994). All the model parameters such as factor loadings, effect weights, residuals, and intercepts were evaluated using the weighted least square mean and variance adjusted (WLSMV) estimator with theta parameterization. WLSMV was used because of its satisfactory high performance in the analysis of categorical data such as the ones obtained using the Likert scale (Suh, 2015).

Figure 1 presents a graphical representation of the hypotheses one and two of the current study. The big oval shape with a label 'cse' represents the latent variable of the students' perceived calculus self-efficacy (henceforth refers to as self-efficacy) as measured by its 13 observed variables (rectangles with labels 'cse01' to 'cse13') accompanied by the small oval shapes with small arrows pointing to each rectangle indicating the associated errors in predicting each observed variable. In a similar manner, the big oval shapes with the labels 'deep' and 'surface' represent the latent variables of deep and surface approaches to learning mathematics, respectively, each of which is measured by its respective number of observed variables ('al01'-'al19'). The single-headed arrow between 'cse' and 'deep' and the one between 'cse' and 'surface' both indicate the hypothesized causal relations between these latent constructs with their respective signs as postulated in the hypotheses one and two. The double-headed arrow with a negative sign is an expected negative correction between deep and surface approaches. This is because a student with a high score on surface approach items of the R-SPQ-2F is expected to have a low score on the deep approach items.

The causal model presented in Figure 1 carries with it a few assumptions that are subject to testability. Prominent assumptions are represented by causal arrows from the self-efficacy to the two dimensions of approaches to learning. The observed variables are also assumed to relate to their respective latent constructs in a linearly causal manner. The errors of the observed variables are assumed to be uncorrelated with each other and with any of the latent constructs. It is also assumed that none of the observed variables exhibits a cross-loading i.e. each observed variable is assumed to expose only one latent construct. These qualitative assumptions are the elements that make a whole of the causal model presented in Figure 1 on which data are collected, analysed, and their plausibility is ascertained using some goodness of fit (GOF) indices. The following GOF indices are used to judge an acceptable fit: Tucker-Lewis index (TLI) and comparative fit index (CFI) with values close to or greater than .90 (Bentler, 1990), standardized root mean square residual (SRMR) with a value less than .80 (Hu & Bentler, 1999), and root mean square error of approximation (RMSEA) with a value less than or equal to .10 (MacCallum et al., 1996). Chi-square statistics are reported, and its ratio to the degree of freedom of less or equal to 3 (Brown, 2015) is used to assess a model fit. Also, chi-square statistics are also used to compare competing models using a difference test.

6. Results

6.1. Measurement model evaluations

The evaluation of the hypothesized causal model presented in Figure 1 proceeds in two steps. The first step concerns fitting a separate measurement model for both CSEI and R-SPQ-2F. This step is a preliminary step to the structural equation modelling of the relations between the research constructs. The ensuing results are presented in Table 1 with Model 1 for the CSEI measurement model and Model 2 for the R-SPQ-2F measurement model. Table 1 also presents improved results for both Model 1 and Model 2.

The results presented in Table 1 reinforce a rejection of Model 1. Consequently, a rejection of some assumptions associated with this model. This is evident with a high ratio of chi-square value to *df* (higher than 3), a low TLI value (lower than .90), and a high RMSEA value (higher than .10). Thus, the results show some inconsistency between the data collected and the hypothesized model. As such, Model 1 was improved upon by adding two error covariances between 'CSE09' and 'CSE11' as well as between 'CSE12' and 'CSE13', the results of which are presented in Table 1 (Improved Model 1). There is a significant improvement in Model 1 after modifying it, as shown in Table 1 with a reduced ratio of

Table 1. Selected GOF indices for the evaluations of CSEI and R-SPQ-2F measurement models.

	CSEI		R-SPQ-2F	
Fit statistics	Model 1	Improved Model 1	Model 2	Improved Model 2
Chi-square value (χ^2)	250.18	184.92	461.92	300.15
Degree of freedom (*df*)	65	63	151	148
χ^2 / *df*	3.85	2.94	3.06	2.03
TLI	.88	.92	.77	.89
CFI	.90	.94	.80	.90
SRMR	.07	.06	.09	.07
RMSEA	.12	.10	.10	.07

chi-square value to *df*, improved TLI and CFI, and reduced SRMR and RSMEA. The chi-square difference test exposes this improvement better as it returns a significant difference in chi-square values ($\chi^2(2) = 65.26, p < .001$) between Model 1 and Improved Model 1. These are all suggestive of the plausibility of the Improved Model 1.

Similarly, the results presented in Table 1 (Model 2) also show that the hypothesized measurement model for the R-SPQ-2F should be rejected. This is evident with a high ratio of chi-square value to *df* (higher than 3), a low TLI and CFI values (far lower than .90), and a high SRMR value (higher than .08). As such, Model 2 was improved upon by allowing 'al10' and 'al19' to cross-load on the deep approach to learning in addition to the surface approach to learning they were initially hypothesized. Also, an error covariance between 'al15' and 'al18' was included to achieve the model results presented in Table 1 (Improved Model 2). As it can be read from Table 1 (Improved Model 2), all the GOF indices are within the cutoff criteria coupled with a significant chi-square difference test ($\chi^2(3) = 161.77, p < .001$) which affirm the plausibility of the improved version of Model 2. The model modifications that have been carried out in this section are all guided by modification indices of the respective output during the analyses, and its conceptual implications are presented in the next section.

6.2. *Structural model evaluations*

After the validation of the measurement models, we proceed to the second step of the analyses, which concerns investigating the causal relations between self-efficacy and approaches to learning mathematics. The ensuing results of the selected fit statistics show the ratio of chi-square value to *df* to be 1.59, a TLI value to be .90, a CFI value to be .91, an SRMR value to be .07, and an RMSEA value to be .06 which are suggestive of an acceptable fit of the model. The causal estimates, as well as the associated standardized model parameters such as factor loadings, factor variance, and error covariance, are presented in Figure 2.

The results presented in Figure 2 show all the significant standardized factor loadings and error covariances. Figure 2 shows that there is a significant positive causal effect of the self-efficacy on deep approaches to learning a first-year introductory calculus ($\beta = .54, p < .001$) with a medium significant effect size of .29, and a significant negative causal effect of self-efficacy on surface approaches to learning a first-year introductory calculus ($\beta = -.47, p < .001$) with a medium significant effect size of .22. The results confirm the hypotheses one and two, respectively. These results can be interpreted to mean, given a unit metric increase in self-efficacy (e.g. $cse + 1$) there is a corresponding effect of a .54

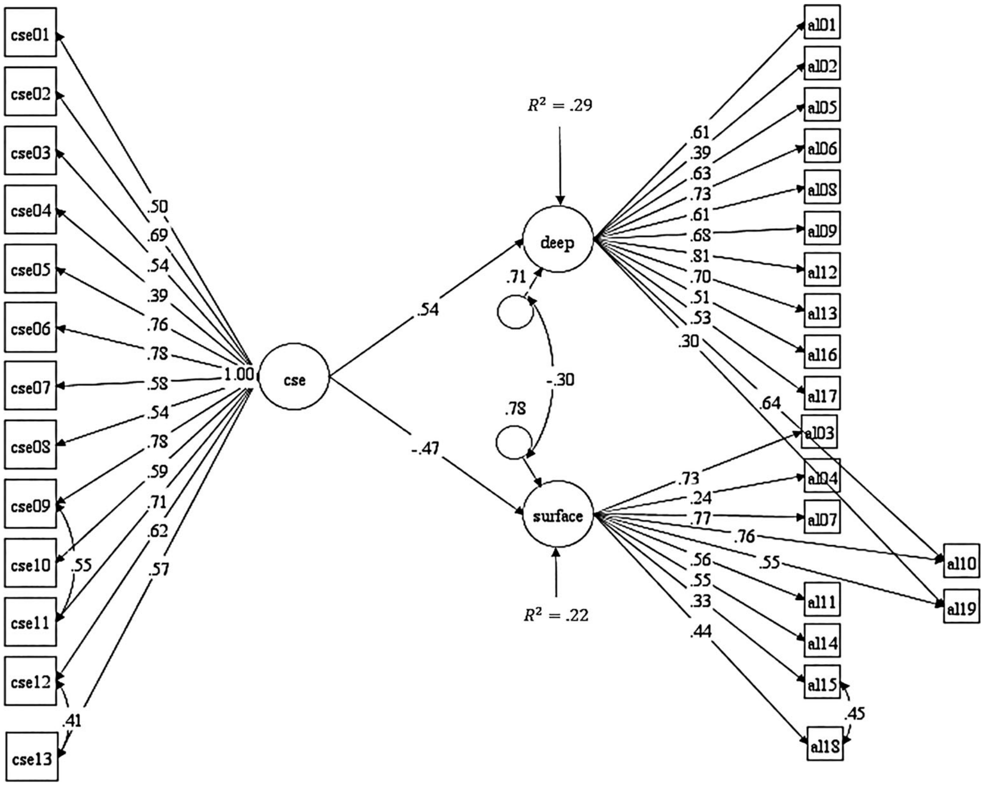

Figure 2. A validated causal model of the relations between self-efficacy and approaches to learning mathematics.

times a unit metric increase on deep approaches to learning, and a corresponding effect of a .47 times a unit metric decrease in surface approaches to learning among engineering students. Further, the respective effect sizes show that self-efficacy accounts for 29% of the variability in deep approaches to learning and 22% variability in the surface approaches to learning. At this juncture, it is important to remark that the results presented in Figure 2 are valid up to the group level, and there could be some discrepancy when it comes to each individual student that took part in the study. Further discussion on these results is presented in the next section.

7. Discussion, limitations, and conclusion

7.1. Discussion

The current study attempts to provide evidence for possible causal relations between self-efficacy and approaches to learning an introductory calculus course among first-year engineering students. In order to achieve this, both measurement and structural evaluations of models based on data collected using CSEI and R-SPQ-2F are reported in the current study. We improved on the CSEI measurement model by adding two error covariances. The first error covariance was between ‘CSE09’ and ‘CSE11’. These two items measure students' confidence in solving two different indefinite integral tasks. As such, an error covariance between these items could account for any error source from the common topic from which these two items have been drawn. The second error covariance was between 'CSE12' and 'CSE13', which can also be justified from a common topic (applications of integral calculus) from which the two items have been drawn. The addition of these two error covariances negates the lack of it that was initially assumed in the CSEI measurement model. Thus, it demonstrates how the plausibility of model assumptions can be tested in the SEM framework, which is contrary to those who think SEM assumptions are never tested (e.g. Freedman, 1995). Further, the addition of these error covariances also shows a marked difference between SEM framework and regression models because, in the latter, errors are always assumed to be orthogonal i.e. uncorrelated with each other (Bollen & Pearl, 2013).

The measurement model of the R-SPQ-2F was also improved upon by allowing items al10 ('I find I can get by in most assessments by memorizing key sections rather than trying to understand them') and al19 ('I find the best way to pass examinations is to try to remember answers to likely questions') that are initially on the surface approach dimension to cross-load on the deep approach dimension (Zakariya et al., 2020). A common aspect of these two items revolves around the memorization of key concepts. The finding of the current study suggests that the memorization technique is not peculiar to surface approach learners. Rather, students that adopt a deep approach to learning mathematics may also use the memorization technique. This finding, on the one hand, corroborates a report of widespread use of the memorization technique found among high achieving Asian students as a means of understanding (Kember, 1996). On the other hand, it suggests Entwistle (1997) could be right when he wrote: 'memorization is a necessary precursor to understanding, and for other purposes it is a way of reinforcing understanding'. Thus, a deep approach learner can as well use memorization techniques strategically to recall definitions of concepts, theorems, and procedures of carrying out some special differentiation or integration in a first-year calculus course.

Another model improvement of the R-SPQ-2F is the addition of an error covariance between al15 ('I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined') and al18 ('I see no point in learning material which is not likely to be in the examination') which are both measuring surface approaches to learning (Zakariya et al., 2020). This error covariance seems to be conceptually justified as both items share a common latent factor and emphasise skipping materials that are not going to be on students' examination questions. Moreover, this finding also fits into the body research that has advocated the inclusion of error covariances between some other items of surface approach dimension of the R-SPQ-2F (e.g. Önder & Besoluk, 2010).

Of prime importance in the current study is the established potential causal relation between self-efficacy and approaches to learning mathematics. It was found that self-efficacy has a positive effect on the deep approach to learning and a negative effect on the surface approach to learning. This seems to be the first time such a finding is being reported on mathematics learning of engineering students. However, our findings, on the one hand, do support a negative relation between self-efficacy and approaches to learning among psychology students reported by Diseth (2011). On the other hand, our findings establish a reverse relationship as compared to the report by Ardura and Galán (2019) on self-efficacy and approaches to learning Physics and Chemistry among secondary school students. Therein, Ardura and Galán (2019) proposed, tested, and found small effects (from − .12 to .25) between the dimensions of approaches to learning on self-efficacy. The reported potential causal effects between self-efficacy and approaches to learning mathematics in the current study are far away higher than the reverse effects by Ardura and Galán (2019). These suggest that our model establishes a better and more appropriate causal direction of the relationship between these constructs. Further, the estimates of the potential causal effects between self-efficacy and approaches to learning in the current study are higher than the correlation coefficients between these constructs in earth sciences (Shen et al., 2016) and in mathematics (Zakariya et al., 2019).

Even though, the percentages of explained variance in deep approaches to learning (29%) and surface approaches to learning (22%) that are accounted by the self-efficacy seem low in the current study they are substantially higher than reported values in the literature (e.g. Diseth, 2011). These percentages of explained variance are reflections of the fact that there are other factors e.g. motivation, nature of mathematics tasks, etc., that influence approaches to learning mathematics, which our proposed model does not account for. Admittedly, we do not seek to propose a model that explains every relation between self-efficacy and approaches to learning mathematics. Instead, the current study has attempted to provide evidence for a potential causal relationship between these constructs. The findings of the current study, therefore, will serve as justifications of designing self-efficacy interventions by university lecturers, engineering course coordinators, and other stakeholders who are directly involved in the teaching of mathematics to engineering students as proxies to induce desired learning approaches in their students.

7.2. Limitations

Despite the promising strength of the current study in providing evidence on the causal relation between the two important student-source factors, some limitations can be acknowledged. First, the current study is confined within the two research constructs without relating the ensuing effects to students' performance in the introductory calculus course. The authors acknowledge that it would have been more interesting to see how these effects translate either directly or indirectly from self-efficacy through approaches to learning to students' grades in the course. However, students' grades are not included in the model because of the unavailability of these grades to the researchers at the time of the study. A future study will be conducted with this intention. Second, given that the scope of the current study is limited to first-year engineering students at one university, its findings might be limited to this student population. Perhaps, the inclusion of students from year two, year three and year four or students following other programmes in the study and other institutions would have increased the generalization power of its findings. Third, and closely related to the second limitation is the lack of cross-validation of the established structural model of the relation self-efficacy and approaches to learning. To this end, we recommended replicated evaluations of this model in independent samples and across different student populations. Lastly, the authors declare that the model proposed and evaluated in the current study is neither an absolute model nor a simplification of reality between the research constructs. Rather, attempts have only been made to understanding the complex relationship between these constructs from a theoretical and empirical perspective. Future in-depth analyses are recommended using case studies, longitudinal design studies, and experimental design studies.

8. Conclusion

The current study was motivated by the dearth of studies on relationships between two well-established psychological theories that concern students' learning of mathematics in higher education. Therein, empirical evidence is provided for a potential causal relation between self-efficacy and approaches to learning a first-year calculus course among engineering students. A high sense of self-efficacy is found to induce the adoption of a deep approach to learning, while low sense self-efficacy induces an adoption of a surface approach to learning. We claim this to be an original contribution to the literature when it comes to the learning of mathematics among engineering students. As such, more studies are recommended using diverse methodological approaches and designs to understand further the relations between self-efficacy and approaches to learning mathematics.

Disclosure statement

The authors declare that there is no potential conflict of interest

ORCID

Yusuf F. Zakariya http://orcid.org/0000-0002-5266-8227

References

Alkhateeb, H. M., & Hammoudi, L. (2006). Attitudes toward and approaches to learning first-year university mathematics. *Perceptual and Motor Skills*, *103*(5), 115–120. https://doi.org/10.2466/PMS.103.5.115-120

Ardura, D., & Galán, A. (2019). The interplay of learning approaches and self-efficacy in secondary school students' academic achievement in science. *International Journal of Science Education*, *41*(13), 1723–1743. https://doi.org/10.1080/09500693.2019.1638981

Babbie, E. R. (1990). *Survey research methods*. Wadsworth.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman and Company.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, *52*(1), 1–26. https://doi.org/10.1146/annurev.psych.52.1.1

Bandura, A. (2002). Social cognitive theory in cultural context. *Applied Psychology: An International Review*, *51*(2), 269–290. https://doi.org/10.1111/1464-0597.00092

Bandura, A. (2006). Guide for constructing self-efficacy scales. In F. Pajares, & T. Urdan (Eds.), *Self-Efficacy beliefs of Adolescents* (Vol. 5., pp. 307–337). Information Age Publishing.

Bandura, A. (2012). On the functional properties of perceived self-efficacy revisited. *Journal of Management*, *38*(1), 9–44. https://doi.org/10.1177/0149206311410606

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Biggs, J. B. (1993). What do inventories of students' learning processes really measure? A theoretical review and clarification. *British Educational Research Journal*, *63*, 3–19. https://doi.org/10.1111/j.2044-8279.1993.tb01038.x

Biggs, J. B. (2012). What the student does: Teaching for enhanced learning. *Higher Education Research & Development*, *31*(1), 39–55. https://doi.org/10.1080/07294360.2012.642839

Biggs, J. B., Kember, D., & Leung, D. Y. P. (2001). The revised two factor study process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology*, *71*(1), 133–149. https://doi.org/10.1348/000709901158433

Bollen, K. A., & Pearl, J. (2013). Eight myths about causality and structural equation. In S. L. Morgan (Ed.), *Handbooks of Sociology and social research* (pp. 301–328). Springer.

Borgonovi, F., & Pokropek, A. (2019). Seeing is believing: Task-exposure specificity and the development of mathematics self-efficacy evaluations. *Journal of Educational Psychology*, *111*(2), 268–283. https://doi.org/10.1037/edu0000280

Braathe, H. J., & Solomon, Y. (2015). Choosing mathematics: The narrative of the self as a site of agency. *Educational Studies in Mathematics*, *89*(2), 151–166. https://doi.org/10.1007/s10649-014-9585-8

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. The Guilford Press.

Bullock, H. E., Harlow, L. L., & Mulaik, S. A. (1994). Causation issues in structural equation modeling research. *Structural Equation Modeling: A Multidisciplinary Journal*, *1*(3), 253–267. https://doi.org/10.1080/10705519409539977

Diseth, Å. (2011). Self-efficacy, goal orientations and learning strategies as mediators between preceding and subsequent academic achievement. *Learning and Individual Differences*, *21*(2), 191–195. https://doi.org/10.1016/j.lindif.2011.01.003

Dowker, A., Cheriton, O., Horton, R., & Mark, W. (2019). Relationships between attitudes and performance in young children's mathematics. *Educational Studies in Mathematics*, *100*(3), 211–230. https://doi.org/10.1007/s10649-019-9880-5

Dowker, A., Sarkar, A., & Looi, C. Y. (2016). Mathematics anxiety: What have we learned in 60 years? *Frontiers in Psychology*, *7*, 508. https://doi.org/10.3389/fpsyg.2016.00508

Entwistle, N. (1997). Reconstituting approaches to learning: A response to Webb. *Higher Education*, *33*(2), 213–218. https://doi.org/10.1023/A:1002930608372

Freedman, D. A. (1995). Causal diagrams for empirical research: Discussion of 'causal diagrams for empirical research' by J. Pearl. *Biometrika*, *82*(4), 692–693. https://doi.org/10.1093/biomet/82.4.692

García, T., Rodríguez, C., Betts, L., Areces, D., & González-Castro, P. (2016). How affective-motivational variables and approaches to learning predict mathematics achievement in upper elementary levels. *Learning and Individual Differences*, *49*, 25–31. https://doi.org/10.1016/j.lindif.2016.05.021

Hounsell, D. (2005). Understanding teaching and teaching for understanding. In F. Marton, D. Hounsell, & N. Entwistle (Eds.), *The experience of learning: Implications for teaching and studying in higher education* (3rd (Internet) ed., pp. 238–257). University of Edinburgh, Centre for Teaching, Learning and Assessment.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jordan, K. L., Sorby, S., Amato-Henderson, S., & Donahue, T. H. (2010). *Engineering self-efficacy of women engineering students at urban vs. rural universities* [Paper presented]. The 41st ASEE/IEEE Frontiers in Education Conference, Rapid City, South Dakota, USA.

Kember, D. (1996). The intention to both memorise and understand: Another approach to learning? *Higher Education*, *31*(3), 341–354. https://doi.org/10.1007/BF00128436

Loo, C. W., & Choy, J. L. F. (2013). Sources of self-efficacy Influencing academic performance of engineering students. *American Journal of Educational Research*, *1*(3), 86–92. https://doi.org/10.12691/education-1-3-4

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130–149. https://doi.org/10.1037/1082-989X.1.2.130

Maciejewski, W., & Merchant, S. (2016). Mathematical tasks, study approaches, and course grades in undergraduate mathematics: A year-by-year analysis. *International Journal of Mathematical Education in Science and Technology*, *47*(3), 373–387. https://doi.org/10.1080/0020739X.2015.1072881

Martínez-Sierra, G., & García-González, M. D. S. (2016). Undergraduate mathematics students' emotional experiences in Linear Algebra courses. *Educational Studies in Mathematics*, *91*(1), 87–106. https://doi.org/10.1007/s10649-015-9634-y

Marton, F., & Booth, S. A. (1997). *Learning and awareness*. Lawrence Erlbaum.

Marton, F., & Säljö, R. (1976). On qualitative differences in learning I: Outcome and process. *British Journal of Educational Psychology*, *46*(1), 4–11. https://doi.org/10.1111/j.2044-8279.1976.tb02980.x

Marton, F., & Säljö, R. (2005). Approaches to learning. In F. Marton, D. Hounsell, & N. Entwistle (Eds.), *The experience of learning: Implications for teaching and studying in higher education* (3rd (Internet) ed., pp. 39–58). University of Edinburgh, Centre for Teaching, Learning and Assessment.

Önder, I., & Besoluk, S. (2010). Adaptation of revised two factor study process questionnaire (R-SPQ-2F) to Turkish. *Education and Science*, *35*(157), 55–67.

Pajares, F., & Kranzler, J. H. (1995). Self-efficacy beliefs and general mental ability in mathematical problem-solving. *Contemporary Educational Psychology*, *20*(4), 426–443. https://doi.org/10.1006/ceps.1995.1029

Pajares, F., & Miller, M. D. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem solving: A path analysis. *Journal of Educational Psychology*, *86*(2), 193–203. https://doi.org/10.1037/0022-0663.86.2.193

Phan, H. P. (2011). Interrelations between self-efficacy and learning approaches: A developmental approach. *Educational Psychology*, *31*(2), 225–246. https://doi.org/10.1080/01443410.2010.545050

Shen, K.-M., Lee, M.-H., Tsai, C.-C., & Chang, C.-Y. (2016). Undergraduate students' earth science learning: Relationships among conceptions, approaches, and learning self-efficacy in Taiwan. *International Journal of Science Education*, *38*(9), 1527–1547. https://doi.org/10.1080/09500693.2016.1198060

Suh, Y. (2015). The performance of maximum likelihood and weighted least square mean and variance adjusted estimators in testing differential item functioning with nonnormal trait distributions. *Structural Equation Modeling: A Multidisciplinary Journal*, *22*(4), 568–580. https://doi.org/10.1080/10705511.2014.937669

Svedin, M., Balter, O., Scheja, M., & Pettersson, K. (2013). *A surface approach to learning rewards first-year engineering students*. [Paper presented]. The 2013 Learning and Teaching in Computing and Engineering.

Tossavainen, T., Rensaa, R. J., & Johansson, M. (2019). Swedish first-year engineering students' views of mathematics, self-efficacy and motivation and their effect on task performance. *International Journal of Mathematical Education in Science and Technology*, 1–16. https://doi.org/10.1080/0020739X.2019.1656827

Williams, T., & Williams, K. (2010). Self-efficacy and performance in mathematics: Reciprocal determinism in 33 nations. *Journal of Educational Psychology*, *102*(2), 453–466. https://doi.org/10.1037/a0017271

Yang, X., Leung, F., & Zhang, S. (2019). Junior secondary school students' conceptions of and approaches to learning mathematics and their relationships in mainland China. *Sustainability*, *11*(9), 2476. https://doi.org/10.3390/su11092476

Zakariya, Y. F. (2016). Investigating validity of Math 105 as prerequisite to Math 201 among undergraduate students, Nigeria. *International Journal of Instruction*, *9*(1), 107–118. https://doi.org/10.12973/iji.2016.919a

Zakariya, Y. F. (2019). Study approaches in higher education mathematics: Investigating the statistical behaviour of an instrument translated into Norwegian. *Education Sciences*, *9*(3), 191. https://doi.org/10.3390/educsci9030191

Zakariya, Y. F., Bjørkestøl, K., Nilsen, H. K., Goodchild, S., & Lorås, M. (2020). University students' learning approaches: An adaptation of the revised two-factor study process questionnaire to Norwegian. *Studies in Education Evaluation*, 100816. https://doi.org/10.1016/j.stueduc.2019.100816

Zakariya, Y. F., Goodchild, S., Bjørkestøl, K., & Nilsen, H. K. (2019). Calculus self-efficacy inventory: Its development and relationship with approaches to learning. *Education Sciences*, *9*(3), 170. https://doi.org/10.3390/educsci9030170