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PAPER

Improving Engineering Students' Motivation for Success in Statistics and Data Science: An Innovative Visualization of Four Mathematical Models in Higher Education in United Arab Emirates

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ABSTRACT

This study aims to analyze the factors that improve engineering students' motivation for success in statistics and data science courses at higher education institutions by using four mathematical models. The distinctiveness of this study was exemplified by the innovative graphical depiction of those models. The impact of certain factors, such as the importance of recognition and enjoyment of the course, students' self-concept, and future aspirations, on engineering students' motivation for achieving success in statistics and data science courses was examined. The proposed models are expected to provide beneficial academic insights to students, instructors, administrators of higher education, and societies worldwide. This paper employed a quantitative methodology, including a sample consisting of 144 female and 101 male engineering students enrolled in various statistics and data science courses at higher education institutions in the United Arab Emirates (UAE). A comprehensive survey questionnaire was developed to gather quantitative data, which were mathematically modeled via factor and regression analyses. The four mathematical models analyzed six variables derived from the survey items. According to the results, models IV, II, I, and III had the most significant influence on motivation, in decreasing order. Model IV explained 94.4% of the variation in the motivation for achieving success in statistics and data science courses, while models II and I explained 75.5% and 71.4%, respectively. The study's limitations stem from the fact that its findings might not apply universally and are dependent on the specific educational settings or cultural contexts in which the study was conducted.

KEYWORDS

statistics, data science, engineering students, motivation for success, mathematical modeling, higher education

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1 INTRODUCTION

The transdisciplinary significance of statistics and data science is evident in many aspects of contemporary life, highlighting their pivotal role in advancing human understanding across a wide range of professions [1, 2]. In engineering, concepts such as probability and statistics play a major role in solving various engineering problems [3]. Furthermore, statistics is used in medicine and health sciences to compare a patient's blood pressure readings in different positions of the patient [4]. Moreover, various phenomena in disciplines like business, sociology, sports, political science, and criminology have emerged through the application of statistical methodologies [5–7]. Thus, the interdependent relationship between statistics, data science, and other academic and professional domains highlights the importance of these subjects for advancing knowledge and fostering innovations.

Many generations of students have endured tedious statistics classes that focus more on teaching a set of formulas to be applied in various contexts than on understanding the reasoning behind using formulas or the challenges that arise when attempting to use data to answer problems [8, 9]. Educators who emphasize the connections between courses can help students find meaning and purpose in their education. It was reported that students' performance is optimized through the enhancement of their cognitive self-perception in mathematics by evaluating their belief in their mathematical ability, willingness to take more mathematics classes than necessary, confidence in their ability to study advanced arithmetic, and preference for receiving help when needed [10]. The mathematical and statistical anxiety of students was found to be one of the main factors resulting in negative performance in examinations of mathematics and statistics [11]. The situational engagement and motivation of students in a statistics classroom were investigated, and the findings indicated that students' intrinsic and utilitarian values have increased while their test anxiety has decreased [12]. According to the findings of [13], it is recommended to relate statistical exercises to students' real-life applications in the teaching and learning of statistics and data science. As a result, the learning environment and personal characteristics of each learner, such as motivation, engagement, pedagogical approaches, and character traits, become increasingly influential in explaining the differences in academic success.

Accordingly, several studies reported the effect of individual student's character traits and behavior, such as regularity in class attendance [14, 15], lifestyle [16, 17], social interactions [18], self-esteem [19], locus of control or satisfaction in life [20], self-efficacy [21], and the use of artificial intelligence (AI) [22]. On the other hand, pedagogical approaches were found to enhance students' academic achievement in statistics. Contrary to conventional approaches of teaching statistics, active learning, challenge-based gamification, automatic question generation, situation-problems in statistics textbooks, animation of algorithm in a graph form, educational approaches with AI, and the use of mobile learning applications, Android-based interactive e-modules were found to have a beneficial effect on student learning [23–29]. Although data science and statistics courses hold substantial importance, there has been a noticeable dearth of research investigating diverse motivational aspects and their impact on students' motivation and engagement with these subjects at higher educational levels [30, 31]. Therefore, this paper contributes to the existing academic literature by creating and incorporating four mathematical models designed to answer the following research question: What are the predictive factors that support improving engineering students' motivation to achieve success in data sciences and statistics courses? Subsequent to the introduction, the paper comprises several sections elucidating the importance of the research, a comprehensive literature review, the theoretical

framework, research methodology, questionnaire design, factor analysis, regression analysis, mathematical modeling, findings, and recommendations. The conclusion of the paper explains the study's limitations and provides a summary of the research.

2 RESEARCH SIGNIFICANCE

While numerous studies have examined various variables to predict students' academic performance in data science and statistics, scant attention has been devoted to understanding students' motivation for academic achievement in data science and statistics courses in engineering programs. Notably, achievement motivation encompasses a wide range of concepts, including interest, aspirations, and self-concept. Recently, achievement motivation has been widely investigated in different research studies in the form of a single construct [32–35]. Nevertheless, limited or nearly no studies have addressed the several building blocks of motivation in relation to students' achievement. This study addresses this gap by investigating the association between different motivation paths of engineering students, such as course importance recognition, interest, future ambitions, and self-concept, with their motivation for academic success in data science and statistics courses. A notable contribution of this paper is the development of four mathematical models, which creatively integrate graph-based visualizations to enhance engineering students' motivation for academic success in higher-education settings. These models provide a means to measure engineering students' mathematical motivation for academic achievement, providing administrators with valuable insights into students' attitudes and abilities. Through the discernment of students demonstrating elevated and diminished mathematical motivation, these models provide promising prospects for curbing failure and dropout rates in data science and statistics courses across diverse academic institutions. This study aimed to enhance engineering students' motivation for success in statistics and data science courses, ultimately leading to a positive impact on our educational systems.

3 THEORETICAL FRAMEWORK

The main focus of this study is on the social cognitive approach to motivation [36, 37] and achievement goal theory [38]. From a theoretical perspective of this approach, studies established the dependence of motivational dynamics on students' beliefs and interpretations of actual events as well as achievement context [37, 39]. It has been reported that several academic activities can be intrinsically and extrinsically motivated according to the expectancy-value theory [40]. In this regard, the social cognitive model broadly classifies the motivation constructs to expectancy components (e.g., self-concept) and value components (e.g., task value recognition). The former defines the belief of a student that he/she can accomplish a certain assigned task, and the latter comprises the students' rationale for choosing to complete this specific task [37]. Accordingly, the two factors relating to each category are evaluated in this study. Course importance recognition and interest levels relate to value components, whereas future ambitions and self-concept subsume expectancy components. Thus, it can be practically assumed that students who study statistics and data science not only are intrinsically motivated and enjoy studying these subjects, but also are extrinsically motivated owing to the possible future career opportunities with decent incomes. The achievement goal theory was employed to conceptualize

this study as it acknowledges that learners' goal orientations affect cognitive and affective outcomes. The types of goal orientations in relation to this theory are mastery and performance goals, which were established by [38] and later refined by [41]. Briefly, mastery goal orientation places more emphasis on personal development and learning than performance goal orientation does on relative competence and peer comparison. The valences of "approach" and "avoidance" were added to the mastery versus performance goal paradigm, extending it beyond the dichotomic conceptualization [42, 43]. This more recent two-by-two matrix of goal orientation states that whereas learners with performance-avoidance goals do not want to be perceived as incompetent, learners with performance-approach goals want to show their skill and competence in relation to others. Comparably, students with mastery-approach objectives concentrate on acquisition of the material, whereas those with mastery-avoidance goals worry about not learning it [44]. Therefore, the self-concept from the expectancy component of the social cognitive model was expanded to include both affective and cognitive elements, which are reflected by the achievement goal theory.

4 LITERATURE REVIEW

Academic motivation, referred to as the intangible generator driving students' quest for knowledge, is a key predictor of academic achievement, sparking intellectual curiosity and tenacity that inspire students toward their educational aspirations. Among the factors associated with motivation for success, which in turn directly impact academic achievement, are self-concept, interest, and future ambitions; these factors are widely instrumental [35]. Academic self-concept was originally defined as an evaluative perception of one's academic competence [45]. Following the self-enhancement model, academic self-concept is a key predictor of academic achievement [46–50]. Nevertheless, it was demonstrated that academic motivation mediates the association between academic self-concept and academic achievement; a positive self-concept may contribute to academic achievement, and motivation is essential in determining how self-concept translates into actual performance [51]. The academic achievement of students in statistics was found to be substantially influenced by students' self-concept in statistics [52]. Despite self-concept being repeatedly reported as the central motivational construct [53–57], the majority of college students suffer from extremely low levels of statistics self-concept [58] owing to insufficient knowledge [59] and negative attitudes toward mathematical courses [60]. To remediate these attitudes and anxiety toward statistics, [61] a study was conducted using descriptive (comparison of one's performance with classmates) and predictive (comparison of one's performance with previous performances) dashboards to provide ongoing feedback for students' performance in a statistics course, so as to assess their impact on motivation levels, anxiety, and attitudes. The study demonstrated that whereas the predictive dashboard enhanced motivation for highly motivated students, it demotivated others, questioning the notion that self-referenced feedback is typically beneficial [62]. This highlights the importance of analyzing self-concept in specific domains such as statistics and data science to develop targeted strategies for enhancing student motivation [63, 64].

Besides self-concept, interest stands as a crucial catalyst for academic motivation among college students, fueling their engagement and persistence in the pursuit of scholarly excellence [65–69]. Accordingly, several studies attempted to boost the interest of students by employing different, enjoyable pedagogical strategies and tested their impact on students' interest and ultimately academic motivation for success. A significant relationship was observed between students' interest in the contents of statistics courses and students' statistical achievement [52]. It was

found that making the learning process more enjoyable improves student attitudes and reduces student anxiety in statistics and mathematics courses [68–70]. Despite their proven effectiveness, fun activities are not widely used in college mathematics classrooms as a study demonstrated that while female students lacked the skills to implement these activities, male students were concerned about the time required, leading to hesitation in the incorporation of such strategies [71–72]. It is suggested that the implementation of healthy and interesting learning activities by instructors in online courses of statistics improves students' enjoyment of the learning process and promotes students' creative ideas in statistics [73]. The findings of [74] suggest that the use of mobile applications in calculus learning enhanced the positive perception of students in terms of motivation, attractiveness, relevance, and effectiveness.

Similarly, how students envision their futures seems to affect their motivation to succeed and, consequently, their academic success. The expectancy-value theory of motivation states that students are more inclined to perform tasks they value and relate to their objectives. Students lose the desire to succeed in a course when they do not perceive how it relates to their personal or professional goals [75]. As students mature, they place more emphasis on future planning and creating goals [76], and many college students already have a clear idea of prospective career routes, which greatly improves their drive to accomplish such objectives. The correlation between increased motivation and academic achievement has been substantiated by recent research [77–79]. However, if students view statistics or data science as unrelated to their future job goals, their motivation may diminish, highlighting the importance of students recognizing the significance of their coursework in relation to their envisioned professions [60, 80]. To demonstrate, a study conducted by [81] stated that interventions focused on the enhancement of the perceived significance of course material result in enhanced student motivation and performance by amplifying their interest as well as academic motivation. Moreover, it is reported that achievement motivation functions as a mediator to students in the course of introductory statistics, as it was found that expectancy is substantially correlated with performance in statistics [82]. Similarly, [83] highlighted three different approaches to enhancing the perceived course value for students by (a) establishing connections between new content and students' preexisting knowledge and future objectives, (b) facilitating students' understanding of how the course content aligns with a wider framework, and (c) illustrating the practical relevance of course materials to real-life scenarios and professional aspirations.

In light of the conducted literature review, it can be concluded that factors such as interest, importance recognition, self-concept, and enjoyment have an instrumental effect on academic motivation and academic performance. Accordingly, this study aimed to evaluate the relative importance of many key achievement motivation constructs in predicting the motivation of college students in statistics and data science courses. The expansion of this study upon previous research in this area is achieved by considering (1) diverse motivational constructs, (2) two facets of self-concept (affective and cognitive), and (3) multiple models of motivational constructs that can represent students' academic motivation for success.

5 RESEARCH METHODOLOGY

A 55-item survey questionnaire was designed using a quantitative research approach to collect the dataset for the present study. The sample population of this study consisted of students enrolled in undergraduate statistics and data science courses in various engineering programs, as they were the optimal target to gather the related information to the main objective of this paper. Four colleges and

universities in United Arab Emirates (UAE) were reached out to engage with students majoring in engineering programs such as computer, chemical, civil, mechanical, electrical, and cybersecurity engineering. Higher-education institutions agreed to participate and granted the required ethical approval for the study to be conducted on their students. The study population consisted of all engineering students registered in statistics and data science courses at the four colleges and universities in the UAE. The professors of statistics and data science courses were approached and informed consent was attained from the students. It was explained to the students that their participation was completely optional and that they might opt out at any time. Employing a simple random sampling methodology, students from the four colleges and institutions were selected and were requested to complete the survey form. The use of simple random sampling methodology provided each student with an equal and independent chance of being selected. The study sample consisted of 245 engineering students enrolled in statistics and data science courses. In this group, there were 101 male and 144 female students. Furthermore, 103 students were 18–20 years old, 89 were 21–24 years old, 34 were 25–29 years old, 14 were 30 to 34 years old, 4 were 35 to 39 years old, and 1 was 40 years or older. The students were provided with the opportunity to answer all the 55 items using a 5-point Likert scale, where the choices ranged from strongly disagree (1) to strongly agree (5). The use of a 5-point Likert scale was deemed appropriate owing to its simplicity and clarity, i.e., this scale made the questions easy to understand and answer which ultimately enhanced students' response rates and the reliability of the collected data for this study. The answers of the students were handled with the highest confidentiality and used exclusively for the purpose of this study. The quantitative analysis was conducted using the SPSS 26.0 software, which included the factor and regression analyses. The use of factor analysis enhanced the reliability and validity of the collected data. The rationale behind the use of regression analysis was to determine how the independent variables influence the main dependent variable of the study.

The self-attribution [84], self-determination [85], and self-concept [86] theories were employed to gauge students' evaluations of their own self-concept, enjoyment, satisfaction, value recognition, and expectations of future careers and incomes in relation to statistics and data sciences courses. These theories provide important comprehension of the student's motivation in the courses indicated; particularly, how they see their own abilities and comprehension of the subject matter, how fulfilled they feel after completing the course, and how important the course is to them now and in the future for their jobs and earnings. The components of the questionnaire were tailored using several validated tools, together with additional questions specifically generated to fulfill the primary objective of the study. The intrinsic motivation inventory, a multidimensional tool, was used to examine the students' subjective experience related to a specific task, i.e., statistics and data science courses in this study, which facilitated the identification of students' subjective experience associated with the courses' enjoyment, perceived competence, importance, and tension [87]. Other tools such as the motivated strategies for learning questionnaire [88], attitude toward mathematics inventory [89], and self-description questionnaire [90–92] were used to gauge students' attitudes toward statistics and data science courses.

6 FACTOR ANALYSIS

This section examined the correlation between the items of the survey questionnaire by conducting a principal axis factor analysis using a Promax (oblique) rotation to evaluate the extent to which the items weigh into the factors. Chiefly, the

Kaiser-Meyer-Olkin (KMO) values and *P*-values from Bartlett's test of sphericity were calculated to evaluate the feasibility of factor analysis for the dataset used in this study (refer to Table 1). All the subscales have KMO values exceeding 0.7, and the *P*-values of the Bartlett's test of sphericity were below 0.01, indicating that factor analysis is adequate for investigating the study's variables associated with the constructs of the main variables listed in Table 1. A reliability test was employed to examine the cohesion and homogeneity among the items within each subscale. The objective of this test was to evaluate the reliability of each subscale by examining the consistency and unity among the items within each subscale. To determine the reliability coefficients of mathematical self-concept and mathematical motivation in statistics and data science courses, Cronbach's alpha reliability coefficients were computed. Table 1 shows that all scales have alpha reliability coefficients greater than 0.8, indicating strong internal validity and reliability.

Table 1. KMO, Bartlett's test, and reliability analysis

Variables' Scales	KMO Values	Bartlett's Test of Sphericity *P*-Values	Cronbach's Alpha Coefficient
Students' motivation	.887	.000	.923
Importance	.835	.000	.845
Students' enjoyment	.926	.000	.880
Students' expectation of future careers and incomes	.781	.000	.834
Students' self-concept	.899	.000	.906

7 REGRESSION ANALYSIS AND MATHEMATICAL MODELING

The main objective of this study was to analyze the factors that improve engineering students' motivation for success in statistics and data science courses in higher education. As a result, several hypotheses have been formulated in four mathematical models using a deductive approach to investigate the ways in which different predictive factors impact and mold students' motivation for success in statistics and data science courses. This section pivots around elaborating on each of the four models designed and demonstrating how effectively they describe this study's target variable, students' motivation for success in data science and statistics courses. It also provides a suitable basis for potential future research of parallel aims. Regression analysis is deemed the most statistically appropriate choice to analyze the relationship between students' motivation for success in statistics and data science courses as well as other predictive factors within each model. Accordingly, various regression tests have been employed to evaluate the effectiveness of every model. Essentially, the dependent variable considered by all four models is students' motivation for success in statistics and data science. The performance of each model has been examined by conducting several regression analysis tests.

Furthermore, a global regression test has been conducted for each model to measure how effectively the assessed independent variables (X) explain the variations in the targeted dependent variable (Y'). This is accomplished primarily using the R^2 coefficient of determination, which typically measures the model's capability to forecast real values, thus serving as an evaluation tool to the model's accuracy. In other words, R^2 quantifies the proportion of the total variability in the dependent variable that can be accounted for by the variation in the independent variables. In addition, the regression coefficients (β) supplement the validation loop by attributing the indicated variations observed in R^2 to chance or the variation in the dependent variable.

7.1 Model I

Model I analyzes the effect of engineering students' value recognition of statistics and data science courses (independent variable) as well as their motivation for success in the associated courses (dependent variable). According to the expectancy-value theory, the success of an individual in a certain task depends on two factors: one's belief of how well they can perform and the subjective value of the task. The latter is the pivot of this model and constitutes intrinsic value (i.e., interest), attainment value (i.e., self-identity confirmation), utility value (i.e., usefulness), and cost (i.e., effort). Therefore, the theory suggests that an interplay between these factors determines the motivation of a person to accomplish the assigned task, which corresponds to the motivation for success in data science and statistics courses in the scope of this study. This approach was employed by [93] to predict students' performance in science, technology, engineering, and mathematics subjects. The results indicated that both expectancy and value significantly influenced students' academic achievement in the courses, with value element playing a slightly more dominant role. Accordingly, it is likely that perception of the importance of statistics and data science courses impacts the motivation for success, and that is the base of the formulation of our first null hypothesis as follows:

Ho_1: There is no relationship between the importance of statistics and data science courses and students' motivation for success in these courses ($b_1 = 0$).

Table 2. Model I summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
I	.845[a]	.714	.712	10.54837

Note: [a]Predictors: (Constant), Importance of statistics and data science.

Table 3. Model I ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
I	Regression	52987.233	1	52987.233	476.212	.000[b]
	Residual	21252.197	191	111.268		
	Total	74239.430	192			

Notes: [a]Dependent Variable: Students' motivation for success in statistics and data science, [b]Predictors: (Constant), Importance of statistics and data science.

Table 4. Model I coefficients[a]

Model		Unstandardized Coefficients		Std. Coefficients	t	Sig.
		B	Std. Error	Beta		
I	(Constant)	34.986	4.134		8.464	.000
	Importance of statistics and data science	2.401	.110	.845	21.822	.000

Note: [a]Dependent Variable: Students' motivation for success in statistics and data science.

Tables 2, 3, and 4 present statistical data on the relationship between students' view of the significance and requirement of statistics and data science courses, and their motivation for achieving success. This is accomplished by evaluating the model using several

goodness-of-fit metrics to confirm its validity. Table 2 demonstrates that the coefficient of determination is 0.714, which implies that 71.4% of the variance in students' motivation for academic success in statistics and data science courses can be explained by their view of the value and need of the subject. The adjusted coefficient of determination, denoted as $R^2_{adj} = 0.712$, exhibits a strong affinity with the unadjusted coefficient, indicating reliable and well-supported findings. Therefore, it may be inferred that the data exhibits a high degree of conformity to the model. The solidity of the model is further supported by the comparatively tiny value of the standard estimate of error. In addition, Table 3 presents a strong correspondence to the data with a significant F value of 476.2 and a *P*-value of zero. The null hypothesis is rejected based on the *P*-value being less than 0.01, indicating a statistically significant association between engineering students' opinion of the importance of statistics and data science courses and their motivation for success in these courses. As can be seen from Table 4, the unstandardized coefficient has a value of 2.401, whereas the standardized coefficient has a value of 0.845.

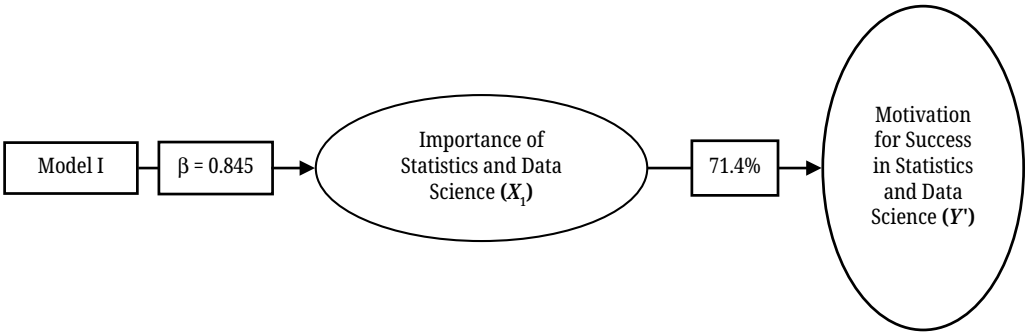

Fig. 1. Graph-based visualization of model I

Figure 1 presents a graphical illustration of model I. It demonstrates that the perception of the importance of statistics and data science courses with a coefficient (β) of 0.845 explains 71.4% of the increase in students' motivation to succeed in their respective courses.

A mathematical linear model is formulated using regression analysis as follows:

$$Y' = a + bX_1 + u,$$

$$Y' = 34.986 + 2.401X_1 + u \quad (1)$$

where Y' denotes the response variable (motivation for success in statistics and data science courses); a, the intercept; b, the coefficient illustrating the extent of dependency of the response variable on the explanatory one; X_1, the independent variable (perception of the importance of statistics and data science courses); and u, the stochastic error showing the significance of other potential explanatory variables.

7.2 Model II

Model II evaluates the effect of engineering students' enjoyment of the learning process on the academic motivation for success in statistics and data science courses. Fundamentally, academic enjoyment corresponds to the pleasure and fulfillment that students derive from participating in a collaborative and engaging learning experience. It fosters intrinsic motivation, hereby resulting in higher levels of engagement

and attention. Moreover, the extent to which the lecture is enjoyable determines the persistence levels of students against challenging concepts and setbacks as they become more inclined to invest more effort when they find the process rewarding. A study conducted by [94] found that there exists a favorable correlation between enjoyment and both intrinsic and extrinsic motivational drives. In other words, students who derived satisfaction from their lessons were more likely to actively participate and excel in examinations. Contrarily, negative feelings such as boredom were associated with less motivation and inferior academic achievements. Similar findings were reported by multiple literature sources [95, 96]. Thus, it is probable that the level of satisfaction and enjoyment derived from statistics and data science courses influences one's drive for achievement. This forms the foundation for our second hypothesis, which is stated as follows:

Ho_1: There is no relationship between students' enjoyment of statistics and data science courses and students' motivation for success in these courses ($b_1 = 0$).

Table 5. Model II summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
II	.869[a]	.755	.753	9.76730

Note: [a]Predictors: (Constant), Enjoyment of statistics and data science.

Table 6. Model II ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
II	Regression	56018.016	1	56018.016	587.191	.000[b]
	Residual	18221.414	191	95.400		
	Total	74239.430	192			

Notes: [a]Dependent Variable: Students' motivation for success in statistics and data science, [b]Predictors: (Constant), Enjoyment of statistics and data science.

Table 7. Model II coefficients[a]

Model		Unstandardized Coefficients		Std. Coefficients	t	Sig.
		B	Std. Error	Beta		
II	(Constant)	52.800	3.007		17.556	.000
	Enjoyment of statistics and data science	1.999	.083	.869	24.232	.000

Note: [a]Dependent Variable: Students' motivation for success in statistics and data science.

Tables 5, 6, and 7 show statistical insights about the correlation between the level of enjoyment and fulfillment of learning practices in statistics and data science courses and the drive to succeed in these courses. This is achieved by assessing the model's validity through the evaluation of several goodness-of-fit measures. As can be seen from Table 5, the coefficient of determination is 0.755. This means that 75.5% of the variation in students' motivation for academic achievement in statistics and data science courses can be explained by the level of enjoyment they experience throughout the class. The adjusted coefficient of determination, denoted by $R^2_{adj} = 0.753$, shows a significant correlation with the unadjusted coefficient, indicating dependable and well-substantiated results. Thus, it can be deduced that the data demonstrates a

significant level of adherence to the model. The model's robustness is reinforced by the relatively small value of the standard error estimate. Furthermore, Table 6 demonstrates a robust correlation with the data, as evidenced by a substantial F value of 587.191 and a *P*-value of zero. The null hypothesis is rejected as the *P*-value is less than 0.01, demonstrating a statistically significant correlation between the pleasure of statistics and data science courses and the drive for success in such courses. Table 7 shows that the unstandardized beta coefficient is 1.999, whereas the standardized beta coefficient is 0.869. According to the results of models I and II, it can be anticipated that the enjoyment ($R^2 = 0.755$) of students in the data science and statistics courses loads slightly more into their motivation for success compared with the value recognition of these courses ($R^2 = 0.714$). The findings of model II agree with the previous literature as it was reported that students' enjoyment strongly and positively boosts the intrinsic motivation of students, which ultimately promotes students' achievement [96].

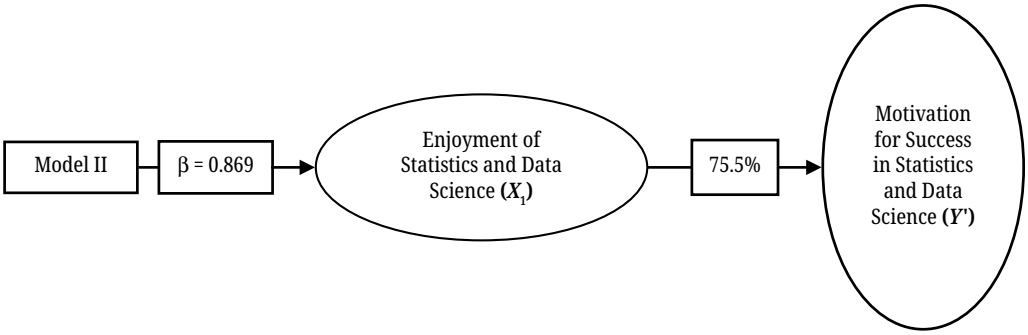

Fig. 2. Graph-based visualization of model II

Figure 2 presents a depiction of the findings of model II. It shows that the variation of enjoyment and fulfillment of statistics and data science courses with a coefficient (β) of 0.869 is responsible for 75.5% of the increase in students' motivation to succeed in their respective courses.

A mathematical linear model is formulated using the regression analysis as follows:

$$Y' = a + bX_1 + u,$$

$$Y' = 52.800 + 1.999X_1 + u \quad (2)$$

where Y' denotes the response variable (motivation for success in statistics and data science courses); a, the intercept; b, the coefficient illustrating the extent of dependency of the response variable on the explanatory one; X_1, the independent variable (enjoyment in statistics and data science courses); and u, the stochastic error showcasing the significance of other unconsidered explanatory variables.

7.3 Model III

Model III measures the dependability of motivation for success in statistics and data science courses on engineering students' self-concept as a single unit of motivational construct, in such courses. Self-concept is a widely studied aspect in the academic research field as it has been repeatedly proven to have a strong and direct correlation with academic achievement [97]. As self-concept is a latent construct that cannot

be directly observed, rigorous scrutiny is essential to demonstrate its validity. A recent study demonstrated that self-concept is considered to be a product of personal, social, and contextual factors [98]. First, personal factors involve past academic experiences, self-efficacy, and personal traits. To elaborate, while repeated successes can bolster self-efficacy and in turn self-concept, sequential failures undermine it. Similarly, the perception of students' academic abilities is considerably dependent on their persona, e.g., a student who is naturally resilient, persistent, and focused tends to experience less failures, which reflects a higher degree of self-concept. Second, social factors, such as parental, peer, and teacher influences, also play a pivotal role in determining the self-concept of students. For example, a recent study by [99] demonstrated empirical evidence on the positive effects of positive parental contributions, such as autonomy encouragement, academic involvement, and emotional support on students' self-concept and academic achievement. Lastly, contextual factors correlated with the pedagogical strategies implemented in the classroom, academic environment, etc. are associated with the level of students' self-concept. Notably, the design of curriculum and assessments that can cater to diverse learning styles can aid in enhancing students' self-concept [100]. Accordingly, studies that expose levels of domain-specific self-concept greatly contribute to the formulation of tailored curricula and pedagogy. Specifically, in a mathematics-related course such as statistics, in which students typically suffer from low self-concepts [101], positioning the level of students' self-concept is instrumental in this essence. Therefore, to evaluate self-concept in statistics and data science on engineering students' motivation to succeed, the third null hypothesis was formulated as follows:

Ho_1: There is no relationship between students' self-concept in statistics and data science courses and students' motivation for success in these courses ($b_1 = 0$).

Table 8. Model III summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
III	.764[a]	.583	.581	12.72720

Note: [a]Predictors: (Constant), Students' self-concept in statistics and data science.

Table 9. Model III ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
III	Regression	39679.945	1	39679.945	244.966	.000[b]
	Residual	28346.801	175	161.982		
	Total	68026.746	176			

Notes: [a]Dependent Variable: Students' motivation for success in statistics and data science, [b]Predictors: (Constant), Students' self-concept in statistics and data science.

Table 10. Model III coefficients[a]

Model		Unstandardized Coefficients		Std. Coefficients	t	Sig.
		B	Std. Error	Beta		
III	(Constant)	39.574	5.424		7.296	.000
	Students' self-concept in statistics and data science	1.206	.077	.764	15.651	.000

Note: [a]Dependent Variable: Students' motivation for success in statistics and data science.

The statistical outcomes of the association between engineering students' self-concept in statistics and data sciences and their motivation for success in these courses are presented in Tables 8, 9, and 10. The validity of the model was mainly tested using the coefficient of determination value, which was found to be 0.583, as shown in Table 8. To elaborate on this result, 58.3% of the variations in the motivation for academic success in the courses specified were directly attributed to the variations in the self-concept of students in statistics and data science courses. Similar to the past models, a further indication to the validity of the model can be indicated by the affinity between R^2 and R^2_{adj}($R^2_{ad} = 0.581$) and the minor standard error estimate value, which suggests a reliable model. Accordingly, it can be deduced that the model quite precisely describes the variables. The null hypothesis is rejected as a result of a zero *P*-value (< 0.01); therefore, there is a statistically significant correlation between the domain-specific self-concept and the motivation for success in the associated courses (refer to Table 9). The standardized and unstandardized beta values of the statistical analysis are 0.764 and 1.206, respectively, as shown in Table 10.

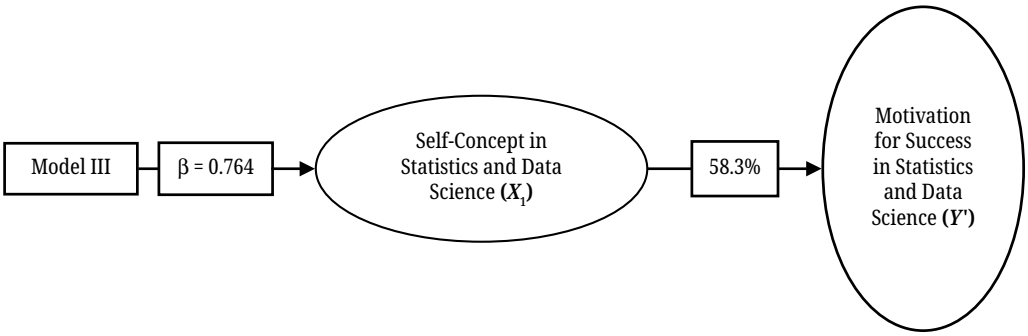

Fig. 3. Graph-based visualization of Model III

For clarity and simplicity purposes, Figure 3 represents a depiction of the general findings of models III. It shows that the variation of self-concept in statistics and data science courses with a coefficient (β) of 0.764 is responsible for 58.3% of the increase in students' motivation to succeed in their respective courses.

A mathematical linear model is formulated using the regression analysis as follows:

$$Y' = a + bX_1 + u,$$

$$Y' = 39.574 + 1.206X_1 + u \quad (3)$$

where Y' denotes the response variable (motivation for success in statistics and data science courses); a, the intercept; b, the coefficient illustrating the extent of dependency of the response variable on the explanatory one; X_1, the independent variable (self-concept in statistics and data science courses); and u, the stochastic error.

7.4 Model IV

Unlike previous models, model IV is comprehensive as it regresses the collective impacts of several factors on motivation for academic success in statistics and data science courses. Some of the factors were elaborated on earlier in the preceding

models, such as value recognition, fulfillment and enjoyment, as well as self-concept. Nevertheless, in this model the multidimensionality of the global self-concept term is addressed. Essentially, self-concept can be broadly categorized into cognitive and affective. As regards the scenario of this study, the former is descriptive in nature as it refers to a subjective estimation of competence in learning and employs concepts related to statistics and data science, whereas the latter is inherently evaluative and corresponds to one's emotional and motivational responses to one's worth and abilities [102, 103]. For example, cognitive self-concept is developed from previous academic achievements in the courses, which reflects one's belief that they have the capability to perform well in future assessments [104]. From another perspective, [104] showed that self-efficacy, defined as the conviction that one can successfully execute the behavior required to produce the desired outcomes, provides a single and substantial ingredient to cognitive self-concept. To demonstrate, [105] conducted a study on college students to establish a correlation between self-efficacy, student engagement, and academic achievement. The findings indicated a strong relationship between self-efficacy and academic achievement among college students, while being mediated with student engagement. Another study complemented these findings by reporting that autonomous motivation of success mediates the association between self-efficacy and engagement [106]. Therefore, it is of great importance to evaluate students' self-efficacy, within the framework of cognitive self-concept, to determine their levels of motivation for success. Meanwhile, affective self-concept is merely based on personal feelings rather than objective measures. A student, therefore, may feel proud and confident or anxious and inadequate about their academic abilities regardless of their actual academic performances [107]. Although students' learning experiences are influenced by both positive affect and effort, the former has a greater impact on long-term motivation and engagement than the latter. Stated differently, students who have robust emotional self-perception are more inclined to invest time in and focus on a specific academic subject that they find interesting, which can eventually lead to greater success [108]. However, the present study has not definitively determined the distinct associations between the two aspects of self-concept and different education and professional outcomes, such as career intention, educational goals, and resilience. Therefore, this study specifically addresses their impact as motivational constructs on the motivation for success in statistics and data science courses. Moreover, education and career ambitions are powerful motivators that direct an individual's efforts toward achieving goals, which in turn can impact performance [109]. Conventionally, when individuals first dedicate themselves to future objectives that hold personal importance, they have the ability to intentionally create a logical structure or system of proximal subgoals to direct their actions toward achieving those future goals. The proximal subgoals function as target goals, which are precise behaviors and performance criteria that direct action, thereby, improving motivation. As the system of subgoals becomes more evident and specific subgoals are achieved, the level of dedication to the future goals intensifies [110]. On the basis of the limited empirical evidence so far, it is possible to speculate that future aspirations are positively correlated with motivational components. The following five hypotheses have been developed to forecast students' motivation for success in statistics and data science. The five hypotheses were examined in light of the performance of model IV.

Ho_1: There is no relationship between the importance of statistics and data science courses and students' motivation for success in these courses ($b_1 = 0$).

Ho_2: There is no relationship between students' enjoyment of statistics and data science courses and students' motivation for success in these courses ($b_2 = 0$).

Ho_3: There is no relationship between students' expectations of future careers and income and students' motivation for success in statistics and data science courses ($b_3 = 0$).

Ho_4: There is no relationship between students' cognitive self-concept in statistics and data science courses and students' motivation for success in these courses ($b_4 = 0$).

Ho_5: There is no relationship between students' affective self-concept in statistics and data science courses and students' motivation for success in these courses ($b_5 = 0$).

Table 11. Model IV summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
IV	.972[a]	.944	.943	4.68609

Note: [a]Predictors: (Constant), Importance of statistics and data science, Enjoyment of statistics and data science, Expectations of future careers and income, Cognitive self-concept in statistics and data science, Affective self-concept in statistics and data science.

Table 12. Model IV ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
IV	Regression	64493.055	5	12898.611	587.382	.000[b]
	Residual	3798.990	173	21.959		
	Total	68292.045	178			

Notes: [a]Dependent Variable: Motivation for success in statistics and data science, [b]Predictors: (Constant), Importance of statistics and data science, Enjoyment of statistics and data science, Expectations of future careers and income, Cognitive self-concept in statistics and data science, Affective self-concept in statistics and data science.

Table 13. Model I coefficients[a]

Model		Unstandardized Coefficients		Std. Coefficients	t	Sig.
		B	Std. Error	Beta		
IV	(Constant)	21.192	2.382		8.898	.000
	Importance of statistics and data science	1.390	.065	.489	21.316	.000
	Enjoyment of statistics and data science	1.114	.073	.492	15.158	.000
	Expectations of future careers and income	.897	.126	.163	7.106	.000
	Cognitive self-concept in statistics and data science	–.038	.072	–.017	–.529	.597
	Affective self-concept in statistics and data science	.107	.163	.020	.660	.510

Note: [a]Dependent Variable: Students' motivation for success in statistics and data science.

Tables 11, 12, and 13 provide statistical insights into the relative effects of the aforementioned factors on motivation for success in statistics and data science courses. As shown in Table 11, the coefficient of determination of the model, taken as a measure of model validity, is relatively higher than those of all the previous

models, with a value of 0.944. In other words, 94.4% of the variations in the motivation for success in data science and statistics courses can be explained by the variations in the factors enlisted. Indeed, this model is relatively proven to be complete of all the potential, major motivational constructs. Similarly, the adjusted value of coefficient of determination only differs by approximately 0.001 from the unadjusted one, indicating strong model reliability and dependability. Moreover, the standardized error value was found to be the smallest relative to all the other models examined in this study, further supporting to the goodness-of-fit and precision of model IV. As shown in Table 12, the *P*-value of the model indicates the rejection of the null hypothesis and a statistically significant correlation between motivation for success and all the studied constructs. Essentially, Table 13 provides the beta coefficients of all the factors that facilitate the comparison of their loadings into the motivation aspect of students. The standardized beta coefficients of importance recognition, enjoyment, expectations of future career and income, as well as affective and cognitive self-concepts are 0.489, 0.492, 0.163, 0.02, and –0.017 respectively. This proves that the variable magnitudes of their effects peak with the enjoyment of statistics and data science courses and reaches a minimum with cognitive self-concept. These conclusions also agree with the unstandardized values (refer to Table 13).

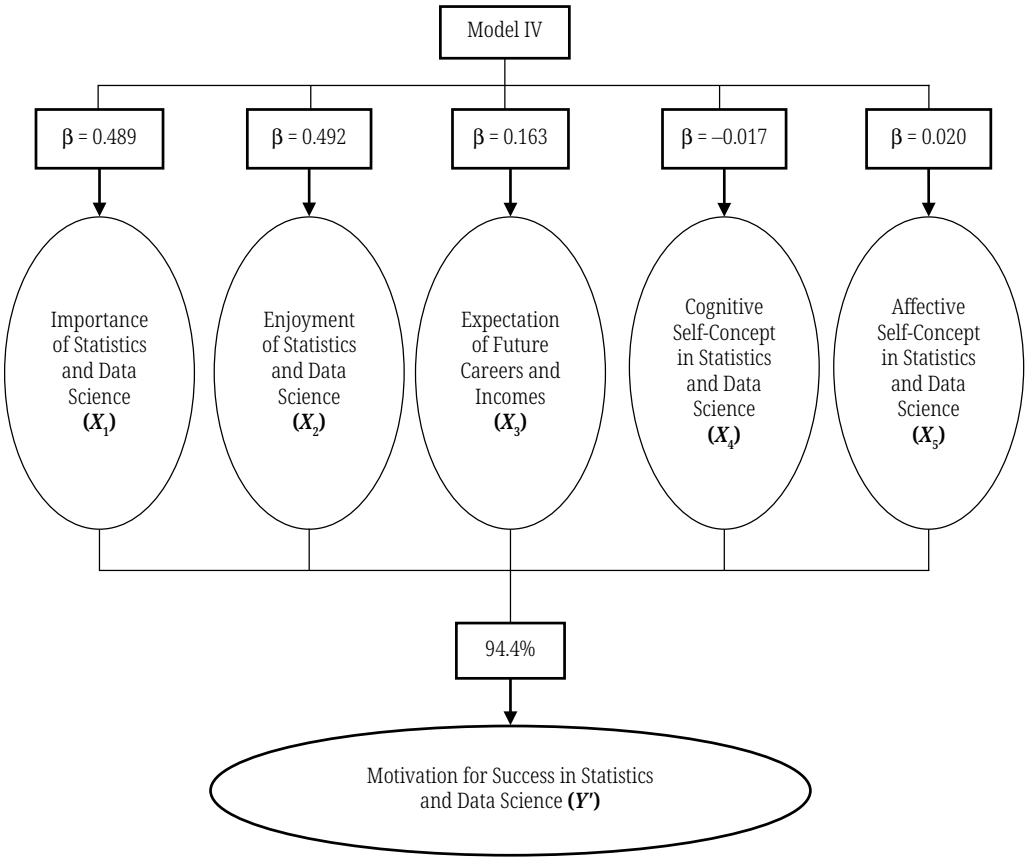

Fig. 4. Graph-based visualization of model IV

Figure 4 presents the findings of model IV. It shows that the variation of importance recognition, enjoyment and fulfillment, expectations of future careers and incomes, cognitive self-concept, and affective self-concept of statistics and data science courses with coefficients (β) of 0.489, 0.492, 0.163, –0.017, and 0.020, respectively,

are responsible for 94.4% of the variance in engineering students' motivation to succeed in statistics and data science courses. A mathematical linear model was formulated via regression analysis as follows:

$$Y' = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + u,$$

$$Y' = 21.192 + 1.390X_1 + 1.114X_2 + 0.897X_3 - 0.038X_4 + 0.107X_5 + u, \quad (4)$$

where Y' denotes the response variable (motivation for success in statistics and data science courses); a, the intercept; b, the coefficient illustrating the extent of dependency of the response variable on the explanatory one; X_1, the independent variable (importance of statistics and data science), X_2 (enjoyment of statistics and data science), X_3 (expectations of future careers and income), X_4 (cognitive self-concept in statistics and data science), and X_5 (affective self-concept in statistics and data science); and u, the stochastic error.

8 COMPARATIVE ANALYSIS

In this section, the results provided by the students were analyzed based on gender. Figures 5–10 present box-and-whisker plots with scales based on the responses provided by the students for the items designed to measure a certain variable among those studied, motivation for success, importance recognition, enjoyment, future income expectations, affective, and cognitive self-concept. As can be seen from Figure 5, motivation for success in statistics and data science courses has the maximum cumulative responses from engineering students; ranging from 85 to 175. The distributions of responses between male and female students were more or less similar in terms of mean and interquartile ranges. Nevertheless, female students alone had four outliers in their distributions. Therefore, there were insignificantly small percentage of students (females) suffering from very low motivational levels (0.8% of the total population). Figure 6 shows the same measure but for importance of statistics and data science courses variable. The cumulative response values ranged from 25 to 50 with a similar distribution among genders to that of motivation. However, the range of the importance variable was substantially smaller than that of motivation, reflecting the small variation of importance recognition among engineering students. There was a total of three outliers, one belonging to male students and the rest belonging to female students. Accordingly, it could be speculated that no student overestimated the value of statistics and data science courses, whereas some (minority) underestimated it.

Furthermore, enjoyment of statistics and data science (see Figure 7) responses lie in approximately the same range of importance recognition of the courses, but lacks any outlier, showing no extremities of boredom or entertainment among engineering students of both genders. The approximately balanced distribution of the responses also demonstrated a reasonable resemblance to that of the importance variable. Expectations of future careers and income, as shown in Figure 8, fell far below the cumulative responses of importance and enjoyment variables, with values ranging from 4 to 20. Elaborating on the distribution, it is clear that the female students' responses were spread over smaller ranges around the mean and had a higher minimum than those of male students, indicating that they

aspire for more career opportunities and income than male students. However, female students had two low outliers that fell within the range of male students' responses.

Figures 9 and 10 present gender differences in terms of two self-concept dimensions, cognitive and affective, respectively. In general, the cognitive component by far outweighs the affective component in the responses for both male and female students, as can be interpreted from the cumulative responses of both aspects. In addition, female students were found to have more proximate responses for cognitive self-concept and are generally lower than males. There were few outliers in both distributions, suggesting that few female and male students had very low levels of cognitive self-concept in statistics and data science. Contrarily, female students exhibited a higher affective self-concept than male students, with a single outlier, and that too higher than the minimum male response.

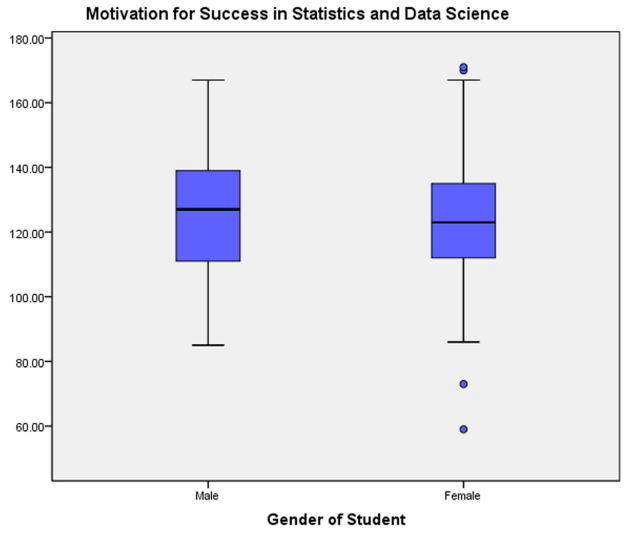

Fig. 5

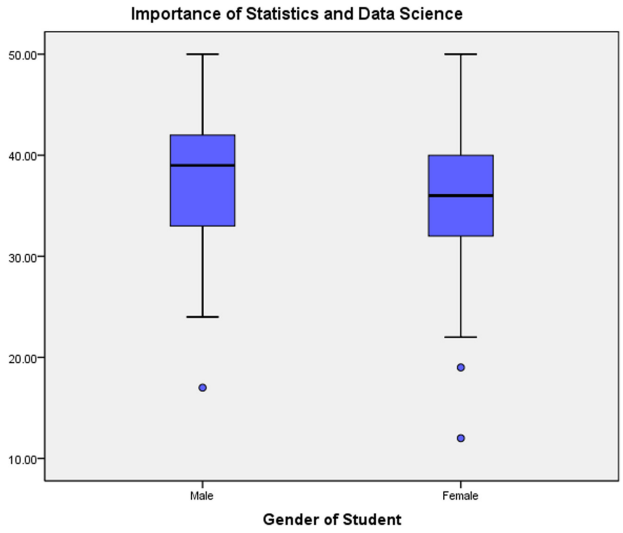

Fig. 6

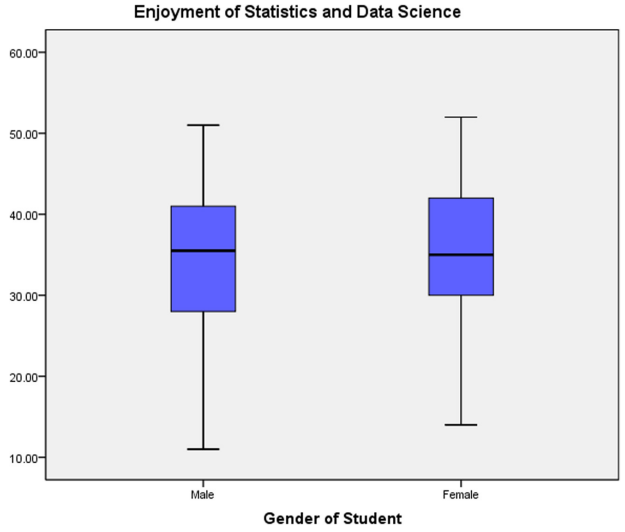

Fig. 7

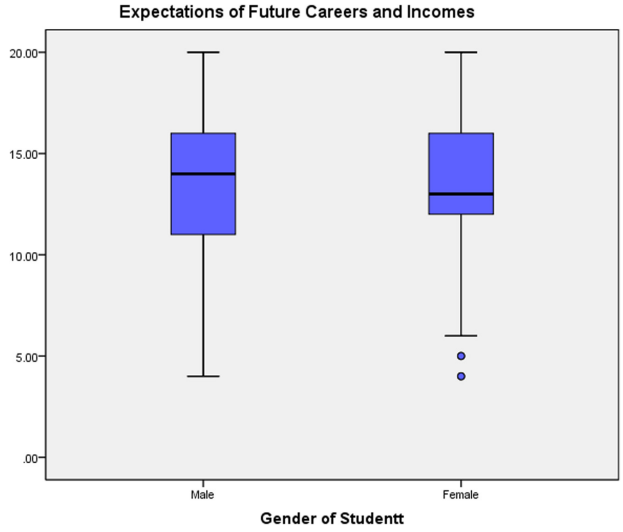

Fig. 8

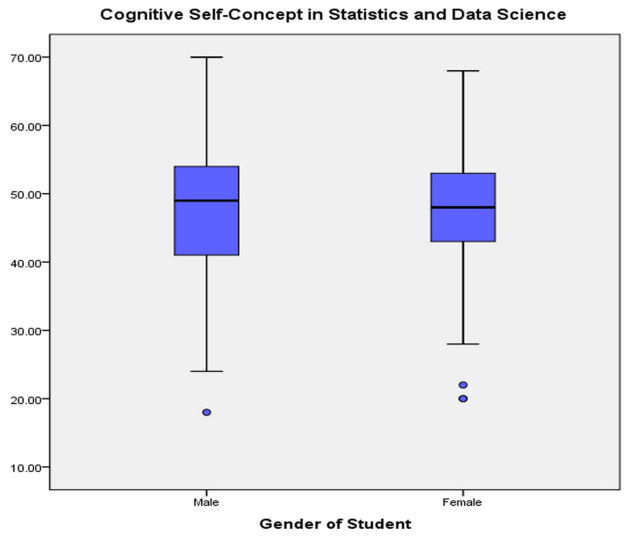

Fig. 9

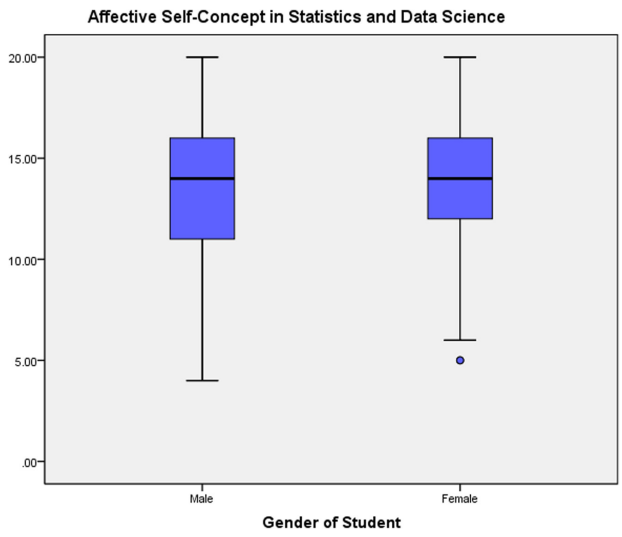

Fig. 10

9 DISCUSSION

This study formulated four mathematical models to investigate the effect of course importance recognition, enjoyment, future career and income expectations, and two dimensions of self-concept, namely, affective and cognitive, on the motivation for success in statistics and data science courses. The results of this study contribute to the current body of literature by forming a solid, reliable foundation of the motivational constructs for the success of engineering students studying statistics and data science courses. This study has four fundamental findings, which are clearly postulated in the graph-based visualization of the four models (see Figure 11). The results of the analysis of variance (ANOVA) indicated that models IV, II, I, and III, had the strongest to weakest impacts, in the specified order. Specifically, models I, II, and III study single independent variables of importance, enjoyment, and global self-concept, and are investigated to explain 71.4%, 75.5%, and 58.3%, respectively, of the motivation of engineering students for success in the courses mentioned.

In other words, enjoyment (model II) ranks as the strongest motivational construct, followed by importance recognition (model I) and then global self-concept (model III). Indeed, the results of model II agree with those of previous literature, as enjoyment had been widely reported to be strongly and positively correlated with motivation and academic achievement [96, 111]. In particular, the level of interest in mathematics courses frequently aligns with the level of enjoyment, as students who are really interested tend to be more engaged and driven. Engaging with the content may enhance comprehension, increase enjoyment, and promote future investigation. This finding is consistent with that of previous research, highlighting a widespread negative perception and attitude toward mathematics courses, usually driven by the lack of engagement in teaching approaches that could spark greater student interest in the subject [60, 71]. Similarly, students' important recognition of statistics and data science courses explain nearly three-quarters of the variation in their motivation for success. In the same vein, the findings are consistent with those of studies reporting that recognizing the value of courses and acknowledging

their importance in relation to other courses highly impact students' motivation and, consequently, their academic performance in the course [112]. Despite its core relevance to motivation, self-concept is proven to be the weakest indicator of motivation among engineering students. This observation is in coherence with previously reported studies that denoted a positive slight to moderate correlation between global self-concept and the motivational component of students [113]. In many cases, the weakness of this correlation is attributed to student-centered learning environments, which support students' sense of competence and help reduce reliance on academic self-concept for motivation by making students feel more capable and engaged, encouraging them to learn for the joy of the experience rather than for how they academically perceive themselves [114]. Furthermore, model IV best describes the study variables. It comprises all the independent variables discussed, i.e., importance, enjoyment, cognitive, and affective self-concept, along with future expectations of career and income; it also explains 94.4% of the variance in the overall motivation of engineering students' success. Besides integrating single variables, the addition of expectations of future career and income enhanced the explanatory power of the model, in comparison with the others, highlighting its pivotal role in determining the motivation levels of students, consistent with previous studies [76, 115].

Overall, the findings of this study suggest a holistic approach to enhancing the motivation of engineering students in academic settings. Considering that enjoyment is the most potent motivating element, educators need to provide captivating and pleasurable learning experiences, particularly in statistics and data science courses, to cultivate a favorable learning environment that stimulates students' interest. This need for engagement is associated with the finding that cognitive self-concept has a stronger impact on motivation than affective self-concept, suggesting that enhancing students' understanding and cognitive skills can reciprocate to more meaningful and enjoyable learning experiences.

The distribution of responses among female and male students was analyzed to distinguish the motivational drives of each gender (see Figures 5–10). Essentially, motivation for success in statistics and data science courses exhibited the maximum cumulative responses of students ranging from 85 to 175. Female students' responses for future career expectations and income factors were spread over smaller ranges around the mean and had a higher minimum than that of male students, indicating that they aspire for more career opportunities and income than male students. This conclusion was previously reported by several literatures [116] and peculiarly explained by [117], who stated that female students often exhibit noticeably larger levels of social, artistic, and conventional interests, whereas male students generally display significantly higher realistic and investigative interests, regardless of their age.

Contrarily, other studies demonstrated the exact opposite results. For example, [118] reported that women contemplate less about the future than men in many contexts. In addition, it has been observed that the cognitive component outweighs the affective component in the responses for both male and female students, as can be interpreted from the cumulative responses of both aspects (see Figures 9 and 10). This difference was attributed to cognitive self-concept having a more robust and consistent relationship with academic motivation and achievement; college students tend to prioritize their cognitive assessments over their emotional judgments in academic situations [119]. Nonetheless, the balance between emotions and cognitive self-concept was reported to be tuned by several factors, such as domain and age [120].

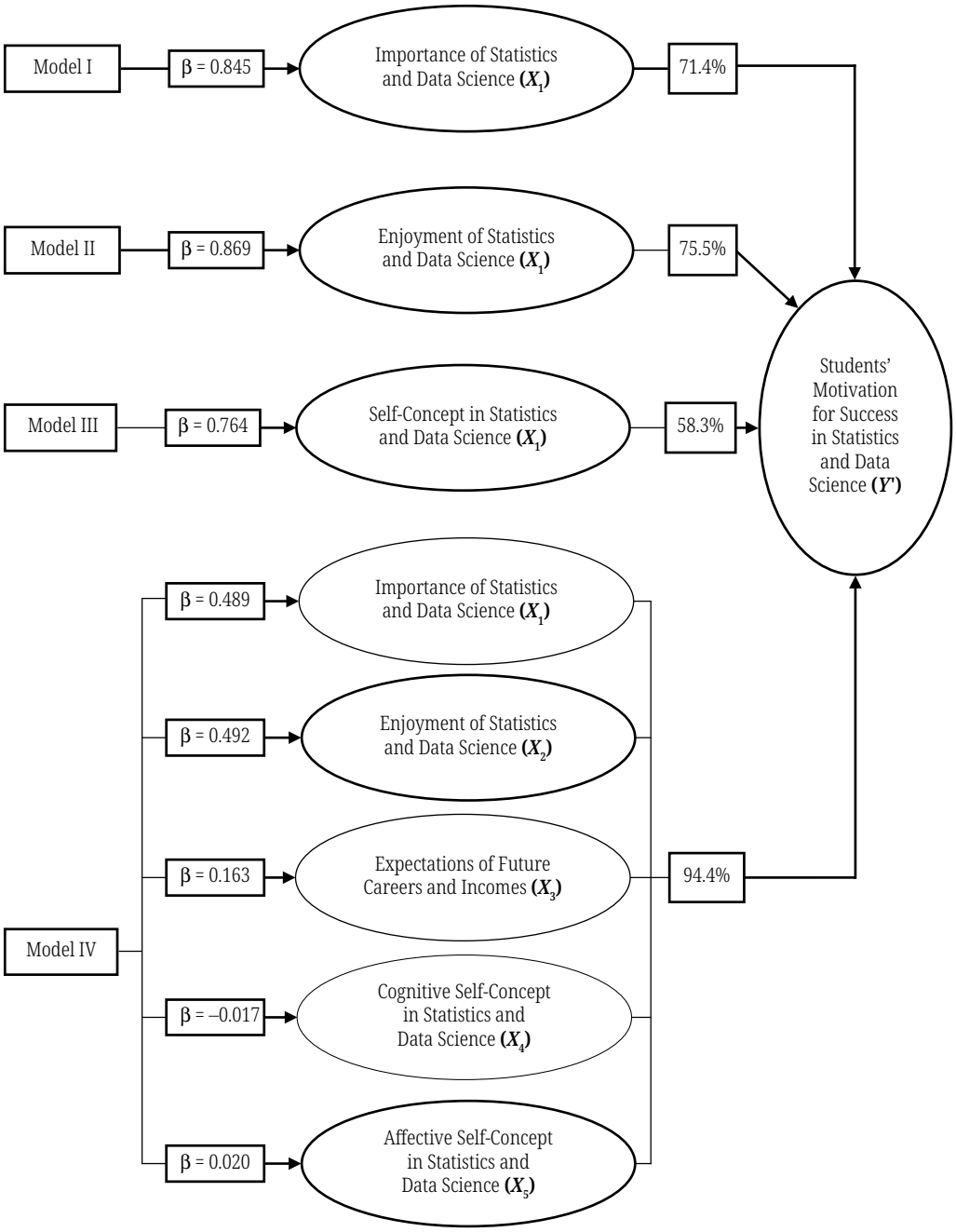

Fig. 11. Visualization of four integrated models

10 CONCLUSION

Within the realm of educational research in statistics and data science, the investigation of variables that impact students' academic motivation has received considerable empirical scrutiny owing to its potential to uncover novel approaches for enhancement in pedagogical strategies in higher-education institutions. Specifically, this study aimed to assess the effect of enjoyment, importance recognition, future expectations of career and income, and two self-concept dimensions, i.e., cognitive and affective on engineering students' motivation for success in statistics and

data science courses offered at universities in the UAE. For this purpose, surveys were distributed, and responses collected from engineering students enrolled in statistics and data science courses were used to develop four graph-based visualizations; consequently, their respective explanatory powers of motivation for success in the mentioned courses were statistically analyzed via ANOVA to determine the mathematical relationships between the study factors and the response variable, i.e., motivation.

In decreasing order of importance, the most important models for improving students' motivation for success in statistics and data science courses are the models IV, II, I, and III. Model IV explained 94.4% of the variations in the motivation for achieving success in statistics and data science courses, whereas models II and I explained 75.5% and 71.4%, respectively. The findings indicated that model IV, which included the importance, enjoyment, future ambitions, and self-concept dimensions, exhibited the highest explanatory power of motivation to academic success in statistics and data science courses. Nevertheless, model III, which investigated the effect of global self-concept, had the least impact on students' motivational drive. Enjoyment and fulfillment of the learning process of the course had the highest impact on students' motivation, with enjoyment levels explaining almost 75.5% of the variance in academic motivation for success. In light of these results, instructors, educators, policymakers, and higher-education institutions are recommended to apply the following to improve students' learning experience:

1. Provide regular feedback on students' academic progress in statistics and data science courses to improve cognitive self-concept while simultaneously fostering a classroom atmosphere that prioritizes emotional welfare.
2. Integrate a diverse range of teaching methodologies in statistics and data science courses that accommodate various learning preferences, including practical experiments or projects, collaborative conversations, and imaginative tasks, which enable students to investigate subjects in personally engaging manners.
3. Implement active learning activities in the teaching and learning of statistics and data science courses, as it is expected to enhance students' engagement, enjoyment, and ultimately achievement, provided that such activities are properly implemented.
4. Highlight the significance and pertinence of statistics and data science courses' contents to students' future objectives and practical applications.
5. Employ the study's constructed models and input data of discussed factors to evaluate students' motivation for success in statistics and data science at the start and end of the course period to evaluate the effectiveness of the pedagogical style used.

This study had limitations that need to be acknowledged. First, the findings are contingent on the unique educational environment or cultural framework in which the study was conducted and may not be applied in general. Second, the selected environment might not support generalization, as all the participants had cultural features that were similarly associated with gender differences. Third, most of the students shared common characteristics in terms of language, culture, tradition, and other factors within the higher education system in the UAE, with minor differences. Fourth, the rules were common among all the accredited higher-education institutions in the UAE in terms of the language of teaching and quality of education. Hence, it is recommended to use the proposed models for this study in statistics and data science courses offered by universities on different continents. This might greatly enhance the generalizability of the results and strengthen their practicality and could be valuable for scholars within the field.

Author contributions: Conceptualization, M.M.H. and S.G.; methodology, M.M.H. and S.G.; software, M.M.H.; statistical analyses, M.M.H., S.G., and Y.A.; writing-original draft preparation, M.M.H., S.G., and Y.A.; writing-review and editing, M.M.H., S.G., and Y.A. All authors have sufficiently contributed to the study and agreed with the results and conclusions.

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Institution review board statement: Authors stated that the study was approved by the Research Ethics Committee at one university. The other three universities didn't have specific protocols. The approvals were given by the research directors either in person or via email.

Informed consent statement: The instructors of statistics and data science courses were contacted, and students gave their informed consent after being told that their participation was completely voluntary and they could withdraw at any time. The responses provided by students were treated with the strictest confidentiality and were used for research purposes only.

Data Availability statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

Conflict of interest: No conflict of interest is declared by authors.

11 REFERENCES

[1] P. J. Diggle, "Statistics: A data science for the 21st century," *Journal of the Royal Statistical Society Series A: Statistics in Society*, vol. 178, no. 4, pp. 793–813, 2015. https://doi.org/10.1111/rssa.12132

[2] P. Galeano and D. Peña, "Data science, big data and statistics," *Test*, vol. 28, pp. 289–329, 2019. https://doi.org/10.1007/s11749-019-00651-9

[3] D. C. Montgomery and G. C. Runger, *Applied Statistics and Probability for Engineers*. Hoboken, NJ: John wiley & sons, 2020.

[4] S. J. Walters, M. J. Campbell, and D. Machin, *Medical Statistics: A Textbook for the Health Sciences*. Chichester: John Wiley & Sons, 2021.

[5] K. Black, *Business Statistics: For Contemporary Decision Making*. Danvers, MA: John Wiley & Sons, 2023.

[6] P. Maravelakis, "The use of statistics in social sciences," *Journal of Humanities and Applied Social Sciences*, vol. 1, no. 2, pp. 87–97, 2019. https://doi.org/10.1108/JHASS-08-2019-0038

[7] T. A. Severini, *Analytic Methods in Sports: Using Mathematics and Statistics to Understand Data from Baseball, Football, Basketball, and Other Sports*. New York, NY: Chapman and Hall/CRC, 2020. https://doi.org/10.1201/9780367252090

[8] S. Ceri, "On the role of statistics in the era of big data: A computer science perspective," *Statistics & Probability Letters*, vol. 136, pp. 68–72, 2018. https://doi.org/10.1016/j.spl.2018.02.019

[9] I. Carmichael and J. S. Marron, "Data science vs. statistics: Two cultures?" *Japanese Journal of Statistics and Data Science*, vol. 1, pp. 117–138, 2018. https://doi.org/10.1007/s42081-018-0009-3

[10] M. M. Hammoudi and S. Grira, "Optimization of the motivation for success in mathematics at higher education: Evidence from novel graph-based visualization of three models," *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 19, no. 11, 2023. https://doi.org/10.29333/ejmste/13808

[11] M. Paechter, D. Macher, K. Martskvishvili, S. Wimmer, and I. Papousek, "Mathematics anxiety and statistics anxiety. Shared but also unshared components and antagonistic contributions to performance in statistics," *Frontiers in Psychology*, vol. 8, p. 1196, 2017. https://doi.org/10.3389/fpsyg.2017.01196

[12] J. H. Lumbantoruan, "The impact of student engagement and motivation in the statistics learning process," *REDIMAT-Journal of Research in Mathematics Education*, vol. 13, no. 1, pp. 1–22, 2024. https://doi.org/10.17583/redimat.12884

[13] S. M. Hasim, R. Rosli, and L. Halim, "A quantitative case study of secondary school students' level of statistical thinking," *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 20, no. 4, 2024. https://doi.org/10.29333/ejmste/14358

[14] M. Credé, S. G. Roch, and U. M. Kieszczynka, "Class attendance in college," *Review of Educational Research*, vol. 80, no. 2, pp. 272–295, 2010. https://doi.org/10.3102/0034654310362998

[15] R. Garg, "Predicting student performance of different regions of Punjab using classification techniques," *International Journal of Advanced Research in Computer Science*, vol. 9, no. 1, 2018. https://doi.org/10.26483/ijarcs.v9i1.5234

[16] Y. Cao *et al.*, "Orderliness predicts academic performance: Behavioural analysis on campus lifestyle," *Journal of the Royal Society Interface*, vol. 15, p. 20180210, 2018. https://doi.org/10.1098/rsif.2018.0210

[17] V. Kassarnig, E. Mones, A. Bjerre-Nielsen, P. Sapiezynski, D. Dreyer Lassen, and S. Lehmann, "Academic performance and behavioral patterns," *EPJ Data Science*, vol. 7, 2018. https://doi.org/10.1140/epjds/s13688-018-0138-8

[18] D. Gašević, A. Zouaq, and R. Janzen, "Choose your classmates, your GPA is at stake!" *American Behavioral Scientist*, vol. 57, no. 10, pp. 1460–1479, 2013. https://doi.org/10.1177/0002764213479362

[19] A. Lepp, J. E. Barkley, and A. C. Karpinski, "The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students," *Computers in Human Behavior*, vol. 31, pp. 343–350, 2014. https://doi.org/10.1016/j.chb.2013.10.049

[20] H. P. H. Chow, "Life satisfaction among university students in a Canadian Prairie city: A multivariate analysis," *Social Indicators Research*, vol. 70, no. 2, pp. 139–150, 2005. https://doi.org/10.1007/s11205-004-7526-0

[21] B. Nur Guler, S. Sajadi, A. Alenezi, and D. Bairaktarova, "From doubt to drive: How instructional modality and self-efficacy shape motivation in remedial spatial visualization courses," *International Journal of Engineering Pedagogy (iJEP)*, vol. 14, no. 5, pp. 37–50, 2024. https://doi.org/10.3991/ijep.v14i5.46097

[22] K. Lavidas *et al.*, "Determinants of humanities and social sciences students' intentions to use artificial intelligence applications for academic purposes," *Information*, vol. 15, no. 6, p. 314, 2024. https://doi.org/10.3390/info15060314

[23] N.-Z. Legaki, N. Xi, J. Hamari, K. Karpouzis, and V. Assimakopoulos, "The effect of challenge-based gamification on learning: An experiment in the context of statistics education," *International Journal of Human-Computer Studies*, vol. 144, p. 102496, 2020. https://doi.org/10.1016/j.ijhcs.2020.102496

[24] M. A. Rostami and H. M. Bücker, "Redesigning interactive educational modules for combinatorial scientific computing," in *Computational Science – ICCS 2019.* ICCS 2019, vol. 11540, 2019, pp. 363–373. https://doi.org/10.1007/978-3-030-22750-0_29

[25] Y.-A. Bachiri, H. Mouncif, and B. Bouikhalene, "Artificial intelligence empowers gamification: Optimizing student engagement and learning outcomes in e-learning and MOOCs," *International Journal of Engineering Pedagogy (iJEP)*, vol. 13, no. 8, pp. 4–19, 2023. https://doi.org/10.3991/ijep.v13i8.40853

[26] J. H. Parra-Fica, M. del Mar López-Martín, and D. Díaz-Levicoy, "Measures of central tendency in primary education textbooks in Chile," *EURASIA Journal of Mathematics, Science and Technology Education*, vol. 20, no. 6, 2024. https://doi.org/10.29333/ejmste/14592

[27] S. Aravantinos, K. Lavidas, I. Voulgari, S. Papadakis, T. Karalis, and V. Komis, "Educational approaches with AI in primary school settings: A systematic review of the literature available in Scopus," *Education Sciences*, vol. 14, no. 7, p. 744, 2024. https://doi.org/10.3390/educsci14070744

[28] W. J. AlKasasbeh and A. T. Amawi, "The effectiveness of using mobile learning application on undergraduates' intrinsic motivation and their general nutrition knowledge," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 17, pp. 19–37, 2023. https://doi.org/10.3991/ijim.v17i17.40959

[29] N. Asmianto, M. Hafiizh, D. Rahmadani, K. Pusawidjayanti, and S. Wahyuningsih, "Developing android-based interactive e-modules on trigonometry to enhance the learning motivation of students," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 2, pp. 159–170, 2022. https://doi.org/10.3991/ijim.v16i02.27503

[30] J. Bonnell, M. Ogihara, and Y. Yesha, "Challenges and issues in data science Education," *Computer*, vol. 55, no. 2, pp. 63–66. https://doi.org/10.1109/MC.2021.3128734

[31] L. Cao, "Data science," *ACM Computing Surveys*, vol. 50, no. 3, pp. 1–42, 2018. https://doi.org/10.1145/3076253

[32] R. M. Abdelrahman, "Metacognitive awareness and academic motivation and their impact on academic achievement of Ajman University students," *Heliyon*, vol. 6, no. 9, p. e04192, 2020. https://doi.org/10.1016/j.heliyon.2020.e04192

[33] T. Feraco, D. Resnati, D. Fregonese, A. Spoto, and C. Meneghetti, "An integrated model of school students' academic achievement and life satisfaction. Linking soft skills, extracurricular activities, self-regulated learning, motivation, and emotions," *European Journal of Psychology of Education*, vol. 38, pp. 109–130, 2023. https://doi.org/10.1007/s10212-022-00601-4

[34] I. Musabirov, S. Pozdniakov, and K. Tenisheva, "Predictors of academic achievement in blended learning: The case of data science minor," *International Journal of Emerging Technologies in Learning (IJET)*, vol. 14, no. 5, pp. 64–74, 2019. https://doi.org/10.3991/ijet.v14i05.9512

[35] R. Steinmayr, A. F. Weidinger, M. Schwinger, and B. Spinath, "The importance of students' motivation for their academic achievement – replicating and extending previous findings," *Frontiers in Psychology*, vol. 10, 2019. https://doi.org/10.3389/fpsyg.2019.01730

[36] A. J. Elliot and M. A. Church, "A hierarchical model of approach and avoidance achievement motivation," *Journal of Personality and Social Psychology*, vol. 72, no. 1, pp. 218–232, 1997. https://doi.org/10.1037/0022-3514.72.1.218

[37] P. R. Pintrich, R. W. Marx, and R. A. Boyle, "Beyond cold conceptual change: The role of motivational beliefs and classroom contextual factors in the process of conceptual change," *Review of Educational Research*, vol. 63, no. 2, pp. 167–199, 1993. https://doi.org/10.3102/00346543063002167

[38] E. S. Elliott and C. S. Dweck, "Goals: An approach to motivation and achievement," *Journal of Personality and Social Psychology*, vol. 54, no. 1, pp. 5–12, 1988. https://doi.org/10.1037/0022-3514.54.1.5

[39] A. Wigfield and J. Cambria, "Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes," *Developmental Review*, vol. 30, no. 1, pp. 1–35, 2010. https://doi.org/10.1016/j.dr.2009.12.001

[40] A. Wigfield and J. S. Eccles, "Expectancy–value theory of achievement motivation," *Contemporary Educational Psychology*, vol. 25, no. 1, pp. 68–81, 2000. https://doi.org/10.1006/ceps.1999.1015

[41] C. Ames, "Classrooms: Goals, structures, and student motivation," *Journal of Educational Psychology*, vol. 84, no. 3, pp. 261–271, 1992. https://doi.org/10.1037/0022-0663.84.3.261
[42] A. J. Elliot and J. M. Harackiewicz, "Approach and avoidance achievement goals and intrinsic motivation: A mediational analysis," *Journal of Personality and Social Psychology*, vol. 70, no. 3, pp. 461–475, 1996. https://doi.org/10.1037/0022-3514.70.3.461
[43] A. J. Elliot and H. A. McGregor, "Test anxiety and the hierarchical model of approach and avoidance achievement motivation," *Journal of Personality and Social Psychology*, vol. 76, no. 4, pp. 628–644, 1999. https://doi.org/10.1037/0022-3514.76.4.628
[44] P. R. Pintrich, "The role of goal orientation in self-regulated learning," in *Handbook of Self-Regulation*, 2000, pp. 451–502. https://doi.org/10.1016/B978-012109890-2/50043-3
[45] S. Harter and R. L. Leahy, "The construction of the self: A developmental perspective," *Journal of Cognitive Psychotherapy*, vol. 15, no. 4, pp. 383–384, 2001. https://doi.org/10.1891/0889-8391.15.4.383
[46] R. J. Calsyn and D. A. Kenny, "Self-concept of ability and perceived evaluation of others: Cause or effect of academic achievement?" *Journal of Educational Psychology*, vol. 69, no. 2, pp. 136–145, 1977. https://doi.org/10.1037/0022-0663.69.2.136
[47] S. Dulay, "The effect of self-concept on student achievement," in *The Factors Effecting Student Achievement*, 2017, pp. 117–132. https://doi.org/10.1007/978-3-319-56083-0_7
[48] Z. Şen Akçay and N. Senemoğlu, "Prediction of physics lesson learning level by students' characteristics and teaching-learning process," *International Journal of Education in Mathematics, Science and Technology*, vol. 9, no. 4, pp. 625–654, 2021. https://doi.org/10.46328/ijemst.1754
[49] D. Sewasew and U. Schroeders, "The developmental interplay of academic self-concept and achievement within and across domains among primary school students," *Contemporary Educational Psychology*, vol. 58, pp. 204–212, 2019. https://doi.org/10.1016/j.cedpsych.2019.03.009
[50] M. I. Susperreguy, P. E. Davis-Kean, K. Duckworth, and M. Chen, "Self-concept predicts academic achievement across levels of the achievement distribution: Domain specificity for math and reading," *Child Development*, vol. 89, no. 6, pp. 2196–2214, 2018. https://doi.org/10.1111/cdev.12924
[51] F. Guay, C. F. Ratelle, A. Roy, and D. Litalien, "Academic self-concept, autonomous academic motivation, and academic achievement: Mediating and additive effects," *Learning and Individual Differences*, vol. 20, no. 6, pp. 644–653, 2010. https://doi.org/10.1016/j.lindif.2010.08.001
[52] M. Hazaimeh, A. M. Al-Ansi, J. Al-Hrinat, G. Adwan, and A. Hendi, "Analyzing impact of effort, interest and cognitive-competence on statistics achievement through meditation of self-concept statistics," *Acadlore Trans. Appl Math. Stat*, vol. 2, no. 2, pp. 81–93, 2024. https://doi.org/10.56578/atams020203
[53] H. M. Alkhateeb, E. F. Abushihab, B. H. Alkhateeb, and R. H. Alkhateeb, "Academic self-concept and its relationship to academic achievement among university students," *International Journal on Social and Education Sciences*, vol. 4, no. 4, pp. 517–528, 2022. https://doi.org/10.46328/ijonses.342
[54] G. Basarkod and H. W. Marsh, "Academic self-concept: A central motivational construct," in *Motivation Science: Controversies and Insights*, 2023, pp. 59–64. https://doi.org/10.1093/oso/9780197662359.003.0010
[55] M. M. Hammoudi, "Measurement of students' mathematics motivation and self-concept at institutions of higher education: Evidence of reliability and validity," *International Journal of Mathematical Education in Science and Technology*, vol. 51, no. 1, pp. 63–86, 2020. https://doi.org/10.1080/0020739X.2019.1670369
[56] H. W. Marsh, "Self-concept theory, measurement and research into practice: The role of self-concept in educational psychology," *British Psychological Society*, vol. 25, 2006.

[57] D. Paumier and J. Chanal, "The differentiated mediation effect of academic autonomous and controlled motivation in the relation between self-concept and achievement," *Learning and Motivation*, vol. 83, p. 101918, 2023. https://doi.org/10.1016/j.lmot.2023.101918

[58] M. Filiz, E. Early, A. Thurston, and S. Miller, "Measuring and improving university students' statistics self-concept: A systematic review," *International Journal of Educational Research Open*, vol. 1, p. 100020, 2020. https://doi.org/10.1016/j.ijedro.2020.100020

[59] L. S. Hirsch and A. M. O'Donnell, "Representativeness in statistical reasoning: Identifying and assessing misconceptions," *Journal of Statistics Education*, vol. 9, no. 2, 2001. https://doi.org/10.1080/10691898.2001.11910655

[60] I. Gal and L. Ginsburg, "The role of beliefs and attitudes in learning statistics: Towards an assessment framework," *Journal of Statistics Education*, vol. 2, no. 2, 1994. https://doi.org/10.1080/10691898.1994.11910471

[61] N. Valle *et al.*, "Predict or describe? How learning analytics dashboard design influences motivation and statistics anxiety in an online statistics course," *Educational Technology Research and Development*, vol. 69, pp. 1405–1431, 2021. https://doi.org/10.1007/s11423-021-09998-z

[62] A. J. Martin and A. J. Elliot, "The role of personal best (PB) goal setting in students' academic achievement gains," *Learning and Individual Differences*, vol. 45, pp. 222–227, 2016. https://doi.org/10.1016/j.lindif.2015.12.014

[63] A. K. Arens, M. Jansen, F. Preckel, I. Schmidt, and M. Brunner, "The structure of academic self-concept: A methodological review and empirical illustration of central models," *Review of Educational Research*, vol. 91, no. 1, pp. 34–72, 2021. https://doi.org/10.3102/0034654320972186

[64] U. Trautwein, O. Lüdtke, O. Köller, and J. Baumert, "Self-esteem, academic self-concept, and achievement: How the learning environment moderates the dynamics of self-concept," *Journal of Personality and Social Psychology*, vol. 90, no. 2, pp. 334–349, 2006. https://doi.org/10.1037/0022-3514.90.2.334

[65] A. A. Al-Saggaf, "Enhancing student motivation and engagement in business statistics via instructional technology," in *Proceedings of the HCT International General Education Conference (HCI-IGEC 2023)*, 2023, pp. 4–13. https://doi.org/10.2991/978-94-6463-286-6_2

[66] J. M. Harackiewicz, J. L. Smith, and S. J. Priniski, "Interest matters: The importance of promoting interest in education," *Policy Insights from the Behavioral and Brain Sciences*, vol. 3, no. 2, pp. 220–227, 2016. https://doi.org/10.1177/2372732216655542

[67] F. H. Muller and J. Louw, "Learning environment, motivation and interest: Perspectives on self-determination theory," *South African Journal of Psychology*, vol. 34, no. 2, pp. 169–190, 2004. https://hdl.handle.net/10520/EJC98276

[68] K. Gogol, M. Brunner, F. Preckel, T. Goetz, and R. Martin, "Developmental dynamics of general and school-subject-specific components of academic self-concept, academic interest, and academic anxiety," *Frontiers in Psychology*, vol. 7, 2016. https://doi.org/10.3389/fpsyg.2016.00356

[69] M. M. Hammoudi and S. Grira, "Improving students' motivation in calculus courses at institutions of higher education: Evidence from graph-based visualization of two models," *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 19, no. 1, 2023. https://doi.org/10.29333/ejmste/12771

[70] L. van der Westhuizen, C. Niepel, S. Greiff, A. Fischbach, and A. K. Arens, "The big-fish-little-pond effect on academic self-concept and interest in first- and third-grade students," *Learning and Instruction*, vol. 87, p. 101802, 2023. https://doi.org/10.1016/j.learninstruc.2023.101802

[71] L. M. Lesser *et al.*, "Using fun in the statistics classroom: An exploratory study of college instructors' hesitations and motivations," *Journal of Statistics Education*, vol. 21, no. 1, 2013. https://doi.org/10.1080/10691898.2013.11889659

[72] T. Chao, J. Chen, J. R. Star, and C. Dede, "Using digital resources for motivation and engagement in learning mathematics: Reflections from teachers and students," *Digital Experiences in Mathematics Education*, vol. 2, pp. 253–277, 2016. https://doi.org/10.1007/s40751-016-0024-6

[73] L. F. Casinillo, "Modeling creativity and enjoyment in learning statistics online in the new normal," *Philippine Social Science Journal*, vol. 5, no. 4, pp. 100–108, 2022. https://doi.org/10.52006/main.v5i4.601

[74] A. M. Ahmad, M. B. Md. Aziz, and M. S. B. Shahrudin, "Students' perception of mobile applications in calculus learning," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 21, pp. 25–33, 2023. https://doi.org/10.3991/ijim.v17i21.44761

[75] D. M. Roberts and J. E. Saxe, "Validity of a statistics attitude survey: A follow-up study," *Educational and Psychological Measurement*, vol. 42, no. 3, pp. 907–912, 1982. https://doi.org/10.1177/001316448204200326

[76] J. E. Nurmi, "How do adolescents see their future? A review of the development of future orientation and planning," *Developmental Review*, vol. 11, no. 1, pp. 1–59, 1991. https://doi.org/10.1016/0273-2297(91)90002-6

[77] L. Andre, T. T. D. Peetsma, A. E. M. Van Vianen, J. J. I. De Wal, D. S. Petrović, and T. Bunjevac, "Motivated by future and challenges: A cross-cultural study on adolescents' investment in learning and career planning," *Journal of Vocational Behavior*, vol. 110, pp. 168–185, 2019. https://doi.org/10.1016/j.jvb.2018.11.015

[78] M. M. Hammoudi, "Predictive factors of students' motivation to succeed in introductory mathematics courses: Evidence from higher education in the UAE," *International Journal of Mathematical Education in Science and Technology*, vol. 50, no. 5, pp. 647–664, 2019. https://doi.org/10.1080/0020739X.2018.1529339

[79] T. Peetsma and I. van der Veen, "Relations between the development of future time perspective in three life domains, investment in learning, and academic achievement," *Learning and Instruction*, vol. 21, no. 3, pp. 481–494, 2011. https://doi.org/10.1016/j.learninstruc.2010.08.001

[80] J. S. Eccles and A. Wigfield, "From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation," *Contemporary Educational Psychology*, vol. 61, p. 101859, 2020. https://doi.org/10.1016/j.cedpsych.2020.101859

[81] C. S. Hulleman, O. Godes, B. L. Hendricks, and J. M. Harackiewicz, "Enhancing interest and performance with a utility value intervention," *Journal of Educational Psychology*, vol. 102, no. 4, pp. 880–895, 2010. https://doi.org/10.1037/a0019506

[82] C. C. Sutter, K. B. Givvin, and C. S. Hulleman, "Concerns and challenges in introductory statistics and correlates with motivation and interest," *The Journal of Experimental Education*, vol. 92, no. 4, pp. 662–691, 2023. https://doi.org/10.1080/00220973.2023.2229777

[83] S. A. Ambrose, M. M. W., D., Bridges, M. C. Lovett, and M. K. Norman, "How learning works: Seven research-based principles for smart teaching," J. Ward and E. Daniel, Eds., Jossey-Bass, 2010. https://doi.org/10.1002/9781119208242

[84] T. J. Sullivan and B. Weiner, "Achievement motivation and attribution theory," *Contemporary Sociology*, vol. 4, no. 4, p. 425, 1975. https://doi.org/10.2307/2062395

[85] E. L. Deci and R. M. Ryan, *Intrinsic Motivation and Self-Determination in Human Behavior*. New York, NY: Springer, 1985. https://doi.org/10.1007/978-1-4899-2271-7

[86] H. Marsh and J. Hattie, *Theoretical Perspectives on the Structure of Self-Concept*. New York, NY: Wiley, 1966.

[87] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," *American Psychologist*, vol. 55, no. 1, pp. 68–78, 2000. https://doi.org/10.1037/0003-066X.55.1.68

[88] P. R. Pintrich, "A manual for the use of the motivated strategies for learning questionnaire (MSLQ)," *APA PsycTests*, 1991. https://doi.org/10.1037/t09161-000

[89] C. Primi, A. Bacherini, C. Beccari, and M. A. Donati, "Assessing math attitude through the attitude toward mathematics inventory – Short form in introductory statistics course students," *Studies in Educational Evaluation*, vol. 64, p. 100838, 2020. https://doi.org/10.1016/j.stueduc.2020.100838

[90] E. Y. Leng, W. Z. B. W. Ali, R. Baki, and R. Mahmud, "Stability of the intrinsic motivation inventory (IMI) for the use of Malaysian form one students in ICT literacy class," *EURASIA Journal of Mathematics, Science and Technology Education*, vol. 6, no. 3, pp. 215–226, 2010. https://doi.org/10.12973/ejmste/75241

[91] K. S. Ostrow and N. T. Heffernan, "Testing the validity and reliability of intrinsic motivation inventory subscales within assistments," in *Artificial Intelligence in Education*, 2018, pp. 381–394. https://doi.org/10.1007/978-3-319-93843-1_28

[92] A. K. Arens, A. S. Yeung, R. G. Craven, and M. Hasselhorn, "A short German version of the self-description questionnaire I: Theoretical and empirical comparability," *International Journal of Research & Method in Education*, vol. 36, no. 4, pp. 415–438, 2013. https://doi.org/10.1080/1743727X.2012.710503

[93] M.-T. Wang and J. L. Degol, "Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions," *Educational Psychology Review*, vol. 29, pp. 119–140, 2017. https://doi.org/10.1007/s10648-015-9355-x

[94] R. Pekrun, S. Lichtenfeld, H. W. Marsh, K. Murayama, and T. Goetz, "Achievement emotions and academic performance: Longitudinal models of reciprocal effects," *Child Development*, vol. 88, no. 5, pp. 1653–1670, 2017. https://doi.org/10.1111/cdev.12704

[95] E. Acosta-Gonzaga and A. Ramirez-Arellano, "The influence of motivation, emotions, cognition, and metacognition on students' learning performance: A comparative study in higher education in blended and traditional contexts," *SAGE Open*, vol. 11, no. 2, 2021. https://doi.org/10.1177/21582440211027561

[96] M. L. Kelly, J. Nieuwoudt, R. Willis, and M. F. Lee, "Belonging, enjoyment, motivation, and retention: University students' sense of belonging before and during the COVID-19 pandemic," *Journal of College Student Retention: Research, Theory & Practice*, 2024. https://doi.org/10.1177/15210251241231242

[97] H. Wu, Y. Guo, Y. Yang, L. Zhao, and C. Guo, "A meta-analysis of the longitudinal relationship between academic self-concept and academic achievement," *Educational Psychology Review*, vol. 33, pp. 1749–1778, 2021. https://doi.org/10.1007/s10648-021-09600-1

[98] Y. Wei, Y. Shi, J. MacLeod, and H. H. Yang, "Exploring the factors that influence college students' academic self-efficacy in blended learning: A study from the personal, interpersonal, and environmental perspectives," *SAGE Open*, vol. 12, no. 2, 2022. https://doi.org/10.1177/21582440221104815

[99] J. Holzer, S. Korlat, E. Pelikan, B. Schober, C. Spiel, and M. Lüftenegger, "The role of parental self-efficacy regarding parental support for early adolescents' coping, self-regulated learning, learning self-efficacy and positive emotions," *The Journal of Early Adolescence*, vol. 44, no. 2, pp. 171–197, 2024. https://doi.org/10.1177/02724316231162306

[100] A. Geske, K. Kampmane, and A. Ozola, "The influence of school factors on students' self-concept: Findings from PIRLS 2016," *Human, Technologies and Quality of Education*, pp. 227–241, 2021. https://doi.org/10.22364/htqe.2021.16

[101] K. S. Rothrock and A. S. Gay, "What college freshmen believe about themselves: An investigation of mathematical mindset, identity, self-efficacy, and use of self-regulated learning strategies in mathematics," *International Journal of Research in Undergraduate Mathematics Education*, 2023. https://doi.org/10.1007/s40753-023-00229-9

[102] A. K. Arens, A. S. Yeung, R. G. Craven, and M. Hasselhorn, "The twofold multidimensionality of academic self-concept: Domain specificity and separation between competence and affect components," *Journal of Educational Psychology*, vol. 103, no. 4, pp. 970–981, 2011. https://doi.org/10.1037/a0025047

[103] H. Marsh, R. W. Craven, and R. Debus, "Separation of competency and affect components of multiple dimensions of academic self-concept: A developmental perspective," *Merrill-Palmer Quarterly*, vol. 45, no. 4, pp. 567–601, 1999.

[104] M. Bong and R. E. Clark, "Comparison between self-concept and self-efficacy in academic motivation research," *Educational Psychologist*, vol. 34, no. 3, pp. 139–153, 1999. https://doi.org/10.1207/s15326985ep3403_1

[105] Q. Luo, L. Chen, D. Yu, and K. Zhang, "The mediating role of learning engagement between self-efficacy and academic achievement among Chinese college students," *Psychology Research and Behavior Management*, vol. 16, pp. 1533–1543, 2023. https://doi.org/10.2147/PRBM.S401145

[106] E. M. Azila-Gbettor, C. Mensah, M. K. Abiemo, and M. Bokor, "Predicting student engagement from self-efficacy and autonomous motivation: A cross-sectional study," *Cogent Education*, vol. 8, no. 1, 2021. https://doi.org/10.1080/2331186X.2021.1942638

[107] S. Black and J. D. Allen, "Part 4: Academic self-concept and emotions," *The Reference Librarian*, vol. 59, no. 1, pp. 42–55, 2018. https://doi.org/10.1080/02763877.2017.1349022

[108] M. Jansen, O. Lüdtke, and U. Schroeders, "Evidence for a positive relation between interest and achievement: Examining between-person and within-person variation in five domains," *Contemporary Educational Psychology*, vol. 46, pp. 116–127, 2016. https://doi.org/10.1016/j.cedpsych.2016.05.004

[109] A. Widlund, H. Tuominen, A. Tapola, and J. Korhonen, "Gendered pathways from academic performance, motivational beliefs, and school burnout to adolescents' educational and occupational aspirations," *Learning and Instruction*, vol. 66, p. 101299, 2020. https://doi.org/10.1016/j.learninstruc.2019.101299

[110] J. Nuttin, R. P. Lorion, and J. E. Dumas, *Motivation, Planning, and Action: A Relational Theory of Behavior Dynamics.* Leuven, Belgium: Leuven University Press, 1984.

[111] C. B. Hodges and C. Kim, "Improving college students' attitudes toward mathematics," *TechTrends*, vol. 57, pp. 59–66, 2013. https://doi.org/10.1007/s11528-013-0679-4

[112] A. S. Salifu and A. Bakari, "Exploring the relationship between students' perception, interest and mathematics achievement," *Mediterranean Journal of Social & Behavioral Research*, vol. 6, no. 1, pp. 13–20, 2022. https://doi.org/10.30935/mjosbr/11491

[113] I. García-Martínez, J. M. Augusto-Landa, R. Quijano-López, and S. P. León, "Self-concept as a mediator of the relation between university students' resilience and academic achievement," *Frontiers in Psychology*, vol. 12, 2022. https://doi.org/10.3389/fpsyg.2021.747168

[114] M. M. Hammoudi, S. Grira, and Y. Alseksek, "Mathematics motivation success optimization in higher education: Novel graph-based visualization of three models," in *Proceedings of the 2023 7th International Conference on Education and E-Learning*, 2023, pp. 138–142. https://doi.org/10.1145/3637989.3637997

[115] K. Burger and J. T. Mortimer, "Socioeconomic origin, future expectations, and educational achievement: A longitudinal three-generation study of the persistence of family advantage," *Developmental Psychology*, vol. 57, no. 9, pp. 1540–1558, 2021. https://doi.org/10.1037/dev0001238

[116] Ms. D. Rani, "Adolescents career aspirations, gender and socio-economic status," *Journal of Advances and Scholarly Researches in Allied Education*, vol. 15, no. 8, pp. 37–46, 2018. https://doi.org/10.29070/15/57865

[117] R. Su, J. Rounds, and P. I. Armstrong, "Men and things, women and people: A meta-analysis of sex differences in interests," *Psychological Bulletin*, vol. 135, no. 6, pp. 859–884, 2009. https://doi.org/10.1037/a0017364

[118] S. Van Der Sluis, A. A. E. Vinkhuyzen, D. I. Boomsma, and D. Posthuma, "Sex differences in adults' motivation to achieve," *Intelligence*, vol. 38, no. 4, pp. 433–446, 2010. https://doi.org/10.1016/j.intell.2010.04.004

[119] H. Peiffer, T. Ellwart, and F. Preckel, "Ability self-concept and self-efficacy in higher education: An empirical differentiation based on their factorial structure," *PLoS ONE*, vol. 15, no. 7, p. e0234604, 2020. https://doi.org/10.1371/journal.pone.0234604

[120] T. Goetz, H. Cronjaeger, A. C. Frenzel, O. Lüdtke, and N. C. Hall, "Academic self-concept and emotion relations: Domain specificity and age effects," *Contemporary Educational Psychology*, vol. 35, no. 1, pp. 44–58, 2010. https://doi.org/10.1016/j.cedpsych.2009.10.001

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