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SUCCESSFUL FACTORS IN STATISTICS LEARNING FOR NON-STEM COURSES STUDENTS: A PLS-PM APPROACH

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Abstract *The paper focuses on factors affecting students' Statistics performance in non-STEM (Science, Technology, Engineering, and Mathematics) degree courses. Specifically, this study examines the effect of students' math knowledge, amotivation, self-efficacy, attitude toward Statistics and statistical anxiety on performance in higher education. Data were collected from 201 Italian psychology students enrolled in an undergraduate introductory Statistics course. The partial least squares path modelling (PLS-PM) was used to test our hypothesis. Overall, our findings show the potential role of math knowledge, self-efficacy and attitude toward Statistics as predictors of Statistics performance. Instead, statistical anxiety is not significantly related to students' performance. Finally, directions for future research and practical implications of the findings are also discussed.*

Keywords: *Statistics performance Statistical anxiety Statistics education research Structural equation modelling PLS-PM.*

1. INTRODUCTION

Statistics is widely used and contributes to various fields, and most graduate students are required to enrol in Statistics courses. Although the number of statistical courses depends on the undergraduate programs, the latter have at least one introduction course to the basic concepts of descriptive and inferential Statistics. Knowledge of Statistics aims to help students analyse and interpret real-life data (Ben-Zvi and Makar, 2016). Specifically, learning Statistics allows students to grasp and answer research questions, analyse the data using appropriate statistical techniques, and interpret data and results (Bechrakis et al., 2011).

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However, many students find several difficulties in dealing with this discipline with consequences on their performance. Students of non-mathematics courses often feel discomfort and angst when approaching Statistics. This evidence seems especially true for students attending psychology, social, and educational degrees, non STEM[2] degrees more generally (Davino et al., 2022). Several studies about statistical anxiety showed its effect on students' performance (Macher et al., 2012; Onwuegbuzie, 2004; Onwuegbuzie and Wilson, 2003) and academic achievement (Ghani et al., 2018). However, other studies found no or only a low significant correlation between statistical anxiety and performance (Macher et al., 2015). Instead, literature agrees with the relationship between attitudes toward Statistics and performance in a Statistics course (Chiesi and Primi, 2010; Coetzee and Merwe, 2010; Emmioğlu and Capa-Aydin, 2012), and some of these highlights the role of students' mathematics background may have on students' attitudes towards Statistics (Chiesi and Primi, 2010; Nasser, 2004).

The current study is concerned with modelling the statistical performance of students. As detailed below, previous studies have addressed this topic. However, to our knowledge, these studies have considered only one or a few factors that may affect statistical performance. The present work would fill this gap by proposing a multivariate model that covers the possible factors affecting Statistics performance. Specifically, this study aims to strengthen the existing research literature on performance in Statistics in an introductory Statistics course understanding the role of mathematics skills, attitudes toward Statistics, academic motivation, self-efficacy, and statistical anxiety using a partial least square path modelling (PLS-PM) approach.

2. THE STATE OF THE ART

2.1. MATH BACKGROUND

The importance of math background to student performance is widely recognised as a key skill that helps students to cope in learning Statistics in introductory and advanced courses (Johnson and Kuennen, 2006). In particular, it is crucial in those disciplines founded on a quantitative approach, such as economics (Johnson and Kuennen, 2004) and finance (Ely and Hittle, 1990). In the last years, the interest in studying mathematics skills as a determinant variable of student performance in Statistics has been spreading (Cui et al., 2019; Luttenberger et al., 2018; Rabin et al., 2018, 2021). Some students reported that the lack of mathematical com-

[2] STEM: Science, Technology, Engineering, and Mathematics

petency seems like a roadblock to the successful completion of Statistics courses (Rabin et al., 2018). For example, Bourne (2014) investigated mathematical ability related to Statistics performance in a year-long undergraduate Statistics course. Results showed higher scores on mathematical procedures and interpretation predicted significantly higher course grades, while semantics was not a significant predictor of performance.

Several studies showed that insufficient previous math experience and the perception of low skills could feed the feeling of anxiety (Baloğlu, 2003; Hong and Karstensson, 2002), that in turn could affect performance. Specifically, literature suggested that basic mathematics skills, Statistics prior knowledge, number of prior mathematics courses completed were relevant to statistical anxiety (Roberts and Saxe, 1982; Tomazic and Katz, 1988).

2.2. STATISTICAL ANXIETY

According to the literature, learning Statistics is associated with statistical anxiety, namely *"an anxiety that comes to the fore when a student encounters Statistics in any form and at any level"* (Onwuegbuzie and Wilson, 2003). Zeidner (1990) defined statistical anxiety more specifically as *"a performance characterised by extensive worry, intrusive thoughts, mental disorganisation, tension, and physiological arousal [...] when exposed to Statistics content, problems, instructional situations, or evaluative contexts, and is commonly claimed to debilitate performance in a wide variety of academic situations by interfering with the manipulation of Statistics data and solutions of Statistics problems"*.

Although statistical anxiety and mathematics anxiety are closely related to psychological traits, the most accredited theories make a sharp and clear distinction between them. Mathematics anxiety has been defined as physiological reactivity (Dew et al., 1984), negative cognition (Ashcraft and Kirk, 2001), and avoidance behaviours (Hopko et al., 2003) in a situation that deals with mathematics. According to some studies, mathematics anxiety and statistical anxiety share the same nature (Birenbaum and Eylath, 1994; Zeidner, 1991). However, other studies considered the different nature of statistical anxiety (Paechter et al., 2017) highlighting that statistical task is most linked to cognitive operations that include thinking about probabilities, effects and understanding social phenomena. According to Paechter et al. (2017), it is not clear whether statistical anxiety is only an after-effect of mathematics anxiety. For example, statistical anxiety might replace mathematics anxiety when a student no longer has to take courses in mathematics but encounters Statistics tasks that seem to look like mathematics tasks.

Overall, it is important to remark that math anxiety and statistical anxiety is different, particularly in understanding their applications and not having the same etiologies.

Antecedents of statistical anxiety are categorised around three major factors: *environmental*, *situational* and *dispositional*. Environmental factors are antecedents that have affected the students prior to attending Statistics courses (*e.g.*, socio-demographic characteristics such as gender and age). Situational antecedents refer to the immediate factors resulting from Statistics courses. They refer to the external environment and are mostly related to the class environment, curriculum format and teaching style. Some studies focused on the instructional situations that could affect statistical anxiety, for example, heavy pedagogical style (Lesser and Reyes III, 2015), the teachers' verbal expressions (Williams, 2013), lack of real-life example (Neumann et al., 2013). Finally, dispositional antecedents are mostly related to psychological and emotional factors. Several dispositional antecedents have been shown in the statistical anxiety field of studies, such as attitude toward Statistics (Harvey et al., 1985; Zanakis and Valenzi, 1997) and self-efficacy (Perepiczka et al., 2011). In this study, we focused specifically on situational and dispositional antecedents in predicting statistical anxiety.

2.3. ATTITUDE TOWARD STATISTICS

Along with statistical anxiety, the attitudes toward Statistics represent non-cognitive factors related to students' performance in Statistics. However related, they represent distinct constructs. Attitude toward Statistics is a disposition to respond to Statistics learning favourably or unfavourably (Gal et al., 1997). It is a multidimensional concept composed by affect in terms of positive or negative feelings about Statistics; cognitive competence; value assigned to Statistics in personal and professional life; the difficulty of Statistics as a subject (Schau et al., 1995).

Literature showed a strong link between attitude towards Statistics and statistical anxiety (Baloğlu, 2003; Chiesi and Primi, 2010; Harvey et al., 1985; Khavenson et al., 2012; Zanakis and Valenzi, 1997). According to Judi et al. (2011), students with positive attitudes toward Statistics should use statistical knowledge to real-life problems and desire to participate in more advanced statistical courses in the future, while students with negative attitudes towards Statistics feel anxiety about attending statistical courses.

2.4. ACADEMIC MOTIVATION

In a learning process, motivation has a driving force. Indeed, it can be defined as an internal state that arouses, directs and maintains behaviour. According to the self-determination theory (Deci and Ryan, 1985), individuals have an innate desire for learning from birth. The more specific construct of academic motivation refers to the general cognitive view of motivation (McKeachie et al., 1985) and consists of students' value beliefs for their skills to succeed in a course and their anxiety about tests in a course. Academic motivation has a key role in predicting academic performance (Cokley et al., 2001).

Three components make up the motivation: intrinsic motivation, extrinsic motivation and a-motivation (Lavigne and Vallerand, 2010). Intrinsic motivation refers to a driving power of an individual toward performing a specific homework spontaneously, while extrinsic motivation is mostly related to a performing activity beyond the pleasure itself (Lee et al., 2010). Finally, amotivation is a state of motivational apathy in which students do not use any effort in the learning process. According to the self-determination theory (Deci and Ryan, 1985), the students' amotivation is related to the difficulty of autonomy and competence that generates frustration and negative affect. Therefore, amotivation leads to a lack of control, and it is also defined as "learned helplessness" (Lavasani et al., 2014).

2.5. SELF-EFFICACY

According to the self-regulated learning theories (Zimmerman, 1990), self-efficacy is assumed to be an important determinant of learning and hence academic performance. In this view, self-efficacy means learning appropriate cognitions and motivations and confidence that a task can be performed. The extant literature provides support for the relationship between self-efficacy, as academic self-efficacy, and students performance (Honicke and Broadbent, 2016; Richardson et al., 2012).

Perepiczka et al. (2011) highlighted the importance of students' belief in their competence to face learning Statistics' challenges, reporting a significant relationship between self-efficacy and statistical anxiety. Several studies showed the relationship between academic motivation and anxiety during the process of Statistics learning and maladaptive coping with failures (Lavasani et al., 2014).

3. CURRENT STUDY

Over the years, research interest for statistical anxiety has increased mainly due to its effect on students' performance and academic achievement (Keeley et al., 2008). Statistical anxiety is negatively related to various academic outcomes, such as failing a Statistics course, drop-out and lower academic grades (Siew et al., 2019). Moreover, statistical anxiety influences performance also during the preparation phase of an examination in which worry and rumination and reduction of cognitive resources could arise (Eysenck et al., 2007), impairing academic performance (Macher et al., 2013).

Despite in the literature there was a consensus on the inverse correlation between statistical anxiety and performance in Statistics classes (Macher et al., 2012; Onwuegbuzie and Seaman, 1995), most recent studies that directly investigated this link are less univocal. Some studies have reported a small significant negative correlation between statistical anxiety and performance (Macher et al., 2015). However, other studies have not found significant correlations (Lester, 2016; Paechter et al., 2017).

Macher et al. (2015) reviewed 11 studies that explained statistical anxiety's direct and indirect effects. First of all, Macher et al. (2015) describe that other predictors explain better the performance than statistical anxiety, such as the basic mathematical abilities (Chiesi and Primi, 2010), reasoning and high school mathematics grade (Birenbaum and Eylath, 1994), self-concept and interest of Statistics (Macher et al., 2013). Moreover, Keeley et al. (2008) suggested that the relationship between anxiety and performance may be moderated by the situational and dispositional factors of statistical anxiety. Related to the dispositional factors, the literature showed that students with low academic motivation have lower grade-point averages (Cokley et al., 2001; Vallerand and Blssonnette, 1992). Moreover, the performance on Statistics assessments is also clearly related to students' attitudes toward Statistics (Rosli and Maat, 2017).

According to the literature, it may be that previous experiences in maths and Statistics might lead to the formation of attitudes toward Statistics (Carmona et al., 2005), which in turn will affect assessment outcomes. Studies of performance have used the longitudinal design to understand the role of attitude toward Statistics. Specifically, Lalonde and Gardner (1993) have measured attitude toward Statistics in the first part and the middle of the course. Wisenbaker et al. (2000) assessed attitudes at the beginning and end of the course. Results revealed that attitudes toward Statistics measured at the end of the course, but not at the beginning, were good predictors of students' achievement.

Overall, previous research indicates that prior math skills and students' attitudes toward Statistics are important predictors of statistical anxiety and performance in Statistics in undergraduate class. The present research has clarified further the nature of these relationships. Considering the evidence of the literature mentioned above, the present study reports on an attempt to model performance in Statistics inside a structural equation model (SEM) approach. Specifically, this study aims to assess the effect of math knowledge, amotivation, self-efficacy, attitude toward Statistics and statistical anxiety on students' performance. Moreover, we considered the changes in attitudes toward Statistics during the course. The attitude toward Statistics was measured twice, at the beginning (pre-course) and during the course (post-course). Consistent with Chiesi and Primi (2010), the course may impact views about Statistics and their ability relating to the Statistics.

From a methodological point of view, the paper proposes a covariance-based SEM approach to studying the antecedents of students' performance in Statistics. As deeper described in the section 5, covariance-based SEMs could be advantageous in addressing issues that often emerge in psychological studies. Furthermore, these models allow considering also constructs as formative, which often better suits the nature of the considered variables, for example, in the case of capabilities or performance (herein math ability and Statistics performance).

Following is the list of hypotheses:

- H1: Math Knowledge has a positive impact on performance, pre-course attitude toward Statistics and self-efficacy, and a negative effect on statistical anxiety
- H2: Academic amotivation has a negative effect on pre-course attitude toward Statistics and students' performance
- H3: Self-efficacy has a positive impact on pre-course attitude toward Statistics and a negative effect on statistical anxiety
- H4: Pre-course attitude toward Statistics has a positive impact on post-course attitude toward Statistics and a negative effect on statistical anxiety
- H5: Statistical anxiety has a negative impact on post-course attitude toward Statistics and performance

4. METHODS

4.1. PARTICIPANTS AND PROCEDURE

Our study involved 201 psychology students enrolled in an undergraduate introductory Statistics course at the University of Naples Federico II in Italy. Due to the Covid-19 issue, the course was arranged online. Participants' age ranged from 18 to 43 with a mean age of 19.7 years (SD = 2.77), and most of the participants were women (84%). 23.28% of students came from scientific high schools, 12.40% from classical high schools, 46.53% from other high schools (mainly from the socio-psycho-pedagogical one), and 17.79% from other schools. Students were requested to fill out all the questionnaires at the beginning of the Statistics course through the MOODLE platform. After the descriptive Statistics module was completed (a month and a half from the beginning of the course), we asked students to take a test about descriptive Statistics and complete the attitude towards Statistics scale again. Only students volunteering to take part were involved in the research.

4.2. MEASURES

Statistics performance

Students' performance in Statistics was evaluated in a multidimensional way according to the Dublin descriptors (Gudeva et al., 2012), which are widely used as assessment criteria in higher education. In particular, we considered three ability dimensions: Knowledge, Application, and Judgement. Knowledge refers to the students' knowledge and understanding of the topics. Application refers to the students' ability to apply knowledge to solve problems. Judgement refers to the students' critical skill, namely the ability to evaluate information to exercise appropriate judgement.

For each dimension, five multiple-choice questions were considered to assess students' performance in descriptive Statistics topics. Table 1 provides an example of the questions developed for each of the three considered Dublin descriptors. Correct answers receive one mark, whereas wrong and missing answers receive no credits. We considered students' scores in the three Dublin descriptors domains as components defining students' performance.

Math knowledge

Students' math knowledge was assessed using the *Mathematical Prerequisites for Psychometrics* (PMP; Galli et al., 2008). The scale consists in 30 multiple choice questions (with one correct answer), allowing to evaluate the basic mathematics abilities for an introductory Statistics course in psychology degree programme. The scale included 6 domains: Fractions, Operations, Set theory, Equations, Relations, and Probability. Some item examples are: "Knowing that $xy = 3$ which of the following is true? (i) $y = 3/x$; (ii) $y = 3 - x$; (iii) $y = 3x$; and (iv) $xy/3$" (Equations); "If set A is composed by the letters A M A and set B by the letters A M A R E, which of the following relations is true? (i) A and B are coincident; (ii) B is included in A; (iii) A is included in B; (iv) A and B share elements" (Set theory).

Table 1: Question example for each of the considered Dublin descriptors

Knowledge	**Question** If all values in a dataset are equal to a constant, the arithmetic mean will be: **Answerlist** a) equal to the constant b) equal to the constant divided by the size of the dataset c) equal to 0 d) equal to 1
Application	**Question** A group of 48 students were asked how many hours they usually sleep each night. The results are shown in the following frequency table: *Hours* 5 6 7 8 9 10 *Frequency* 4 5 7 12 15 5 Which of the following statement most accurately describes the first quartile of reported hours of sleep per night? **Answerlist** a) It is equal to 7 b) It is smaller than 9 c) It is equal to 2 d) It is equal to 5
Judgement	**Question** Suppose the manager of a clothing store is asked which is the most commonly sold hat size. Which statistical measure best describes the manager's answer? **Answerlist** a) The mode b) The median c) The arithmetic mean d) Any measure of central tendency

Correct answers receive one mark, whereas wrong and missing answers receive no credits. Students' scores in the different six domains define the components of their math knowledge.

Statistical anxiety
Statistical Anxiety Scale (SAS; Vigil-Colet et al., 2008; Chiesi et al., 2011) was used to assess students' statistical anxiety. The measure consists of 24-item on a 5-point Likert scale ranging from 1 (= no anxiety) to 5 (= very much anxiety). The instrument includes 3 subscales related to different aspects of statistic anxiety: Examination Anxiety (8 items) refers to anxiety experienced by students while attending a Statistics class or taking a Statistics test (e.g., Walking into the classroom to take a Statistics test); Interpretation Anxiety (8 items) refers to anxiety experienced by students when they have to interpret or make a decision about statistical data (e.g., Trying to understand the statistical analyses described in a journal article); Fear for Asking for Help (8 items) refers to anxiety experienced while requesting the help of a peer, a tutor, or a professor in understanding specific contents (e.g., Going to the teacher's office to ask questions).

Attitudes toward Statistics
Attitude toward Statistics was assessed using the *Survey of Attitudes toward Statistics* (SATS; Schau et al., 1995; Chiesi and Primi, 2009). The instrument contains 28 items aiming at providing a multidimensional measure of attitude toward Statistics. The instrument consists of the following components: Affect (6 items) measures positive and negative feelings concerning Statistics (e.g. "I will feel insecure when I have to do Statistics problems" or "I like Statistics"); Cognitive Competence (6 items) measures students' attitudes about their intellectual knowledge and skills when applied to Statistics (e.g. "I can learn Statistics" or "I make a lot of math errors in Statistics"); Value (9 items) measures attitudes about the usefulness, relevance, and worth of Statistics in personal and professional life (e.g. "Statistics is worthless or Statistical skills will make me more employable"); and Difficulty (7 items) measures students' attitudes about the difficulty of Statistics as a subject (e.g. "Statistics formulas are easy to understand" or "Statistics is a complicated subject"). Responses were on a 7-point Likert scale from 1 (= strongly disagree) to 7 (= strongly agree).

Self-efficacy
Self-efficacy was assessed using the *The Motivated Strategies for Learning Questionnaire* (MSLQ; de Groot et al., 1990; Bonanomi et al., 2018). The Self-efficacy

scale consists of 9 items (e.g., “Compared with other students in this class I expect to do well”) and includes expectancy for success, the judgement of ability to complete the task, and self-confidence (Duncan and McKeachie, 2005). Students were asked to indicate their agreement on a 5-point Likert scale ranging from 1 (= not at all true for me) to 5 (= very true for me).

Academic amotivation
Academic amotivation was evaluated using *The Academic Motivation Scale* (AMS; Vallerand and Blssonnette, 1992; Vallerand et al., 1993). Amotivation consists of 4 items and assesses if students do not perceive contingencies between outcome and their actions (Vallerand and Blssonnette, 1992). Participants responded to each item on a 7-point Likert scale from 1 (= does not correspond at all) to 7 (= corresponds exactly), which corresponds to possible responses to the question “Why do you go to university?” (e.g., “Honestly, I don’t know”; “I really feel that I am wasting my time in school”).

5. STATISTICAL ANALYSIS

To test our hypotheses, we exploited structural equation modelling (SEM), a widely used method in social sciences and psychology for investigating the relationship between theoretical constructs (Karimi and Meyer, 2014; MacCallum and Austin, 2000). SEM theory distinguishes between two conceptually distinct parts of models, a measurement and a structural part, combining the principles of factorial analysis and path analysis.

In particular, the measurement or outer model specifies the relationship between each construct (unobservable variable) to the corresponding set of (observed) indicators. In SEM, constructs can be conceived as latent or emerged variables. The first are typically used for psychological variables like attitudes, emotions, and personality traits, whereas the latter describes phenomena like capabilities, satisfaction, strategies, and performance (Henseler, 2020).

More in depth, latent variables represent common factors underlying observed variables that are assumed to be a manifestation of the corresponding latent variable plus a unique random error. Thus, given a vector of observed variables $\mathbf{y}$ measuring a latent variable η, we have:

$$\mathbf{y} = \lambda\eta + \varepsilon \tag{1}$$

where λ is a vector of loadings and ε is a vector of measurement errors.

Emergent variables, instead, result from a linear combination of indicators (composite):

$$\eta = \sum_{k=1}^{K} w_k \cdot y_k \tag{2}$$

where, in this case, η is an emergent variable, $y_1, \ldots, y_K$ represent its components, and $w_1, \ldots, w_K$ are the component weights that express the strength of the relationship between the emergent variable and its indicators. Note that concepts described as latent variables are also called reflective constructs, whereas emergent variables are also referred to as formative constructs.

The second part of models considered in SEM framework is the structural or inner model that specifies the relationships between the constructs according to theoretical hypotheses. In this part of the model, constructs are defined endogenous if other constructs explain them in the inner model, whereas the exogenous constructs only assume the role of predictors. The relationships between variables are supposed to be linear; thus, endogenous variables are estimated through simple or multiple linear regression considering the causal relations with the other variables. More formally, the inner model equation for a generic endogenous construct η_j can be expressed as follows:

$$\eta_j = \sum_{h=1}^{j-1} \beta_{jh}\eta_h + \zeta_j \tag{3}$$

where β_{jh} denoted the path coefficients, $\eta_1, \ldots, \eta_{j-1}$ refers to all the exogenous or preceding endogenous variables that are supposed to predict η_j, and ζ_j is the residuals error.

5.1. COVARIANCE-BASED OR COMPONENT-BASED SEM?

Two main statistical modelling approaches have been proposed in the SEM literature: covariance-based SEM (Jöreskog, 1978) and component-based SEM (Wold, 1982). The first commonly exploit the maximum likelihood method (Bollen, 1989) to estimate the model parameters by minimising the discrepancy between the empirical and the theoretical covariance matrix. The second, instead, is based on an iterative parameter estimation that alternates the outer and the inner estimation step, optimising the construct scores as linear combinations of the corresponding indicators and maximising the explained variance of the endogenous variables in the structural model jointly.

Given the different estimation procedures, some study characteristics should be considered to drive the choice between covariance-based SEM and component-based SEM approaches. Firstly, covariance-based SEM is more appropriate in studies pursuing a theory testing and confirmation goal. In contrast, component-based SEM is mainly used when the research aim is prediction and theory development (Hair et al., 2011). The second feature regards the nature of the constructs involved in the model: covariance-based SEM should be preferred when only latent variables are considered, component-based SEM when the model includes both latent and emergent variables (Benitez et al., 2020). Moreover, component-based SEM is considered a more flexible approach, allowing to address a broader range of problems than covariance-based SEM. Indeed, the classical SEM approach assumes the multivariate normal distribution of the data and requires many indicators per construct and a large sample size (Iacobucci, 2010). Conversely, component-based SEM represents a soft modelling approach not relying on strong assumptions about data distribution, number of indicators, and sample size. For this reason, it should be preferred when dealing with some research challenges such as the violation of distributional assumption, small samples, and model complexity (Hair et al., 2011).

According to the above, we followed a component-based approach in the present study. Indeed, both latent and emergent variables were included in the model, where psychological constructs (e.g., anxiety, attitude) were conceived as reflective, whereas capabilities (i.e., math knowledge and performance in Statistics) were devised as formative. Furthermore, the complex structure of the model and the small sample size also support the use of the greater flexible approach supplied by the component-based SEM. In particular, we employed the partial least squares path modelling (PLS-PM; Tenenhaus et al., 2005), which is the most developed estimation method for the component-based approach. For more details about the PLS-PM algorithm see Henseler (2010). It is worth underling that the PLS-PM estimates composites and not common factors in principle; thus, latent variable scores contain measurement errors. To address this issue, a consistent PLS-PM (PLSc) has been proposed (Dijkstra and Henseler, 2015) allowing to obtain consistent estimates for reflective measurement models. Because the theoretical model we proposed in the present study includes mostly latent variables, we exploited the consistent PLS-PM approach to test our hypotheses. All the analyses were performed using the package `cSEM` (Rademaker and Schuberth, 2020) of R version 4.1.1.

5.2. PLS-PM MODEL ASSESSMENT

The PLS-PM model assessment follows a sequential approach: once the measurement model's goodness of fit is established, it is possible to consider the structural model. This kind of assessment is defined as "local" because it considers the model part by part.

With respect to the measurement model, the assessment phase differs for latent and emergent variables (see Henseler (2020) for more details). When latent variables are considered, the evaluation focuses on the indicators' reliability and validity. More in depth, *internal consistency reliability* quantifies the amount of random measurement error contained in the construct scores. The indicator ρ_a represents a valid measure for this evaluation with values greater than 0.707 indicating a good construct scores reliability. *Indicator reliability*, instead, measures the amount of variance presented in a latent variable in terms of the contribution of each indicator and can be assessed through loadings (Hair et al., 2006). In particular, loadings values higher than 0.707 indicate that the latent variable explains more than 50% of the indicator variance (Fabbricatore et al., 2021a). It is worth noting that slightly lower values are still accepted, especially when construct reliability is ensured. *Convergent validity* evaluates the amount of the indicators' variance explained by the underlying latent variable. The average variance extracted (AVE) is considered the assessment criteria for which values equal to 0.5 or higher are considered good. The threshold of 0.4 is still acceptable when internal consistency reliability is satisfactory (Hair et al., 2016). Finally, *discriminant validity* provides evidence of the differentiation between the different concepts measured by latent variables. In this case, the heterotrait-monotrait ratio of correlation (HTMT) criterion can be used (Henseler et al., 2015): if the HTMT value is less than 0.85, the discriminant validity is good. Regarding the emergent variables, the only aspects to be considered for the measurement model assessment are the sign, size, and significance of the weights. In addition, the possible multicollinearity among the indicators must be checked.

With respect to the structural model, the sign and size of the coefficients are evaluated, and the 95% bootstrap confidence intervals are used to test their significance. Moreover, the R^2 statistic can be computed for each endogenous variable to measure the percentage of variance explained by the predictors. Finally, the standardized root mean squared residual (SRMR) is considered for the global model assessment, where a value smaller than 0.080 indicates an acceptable model fit (Henseler et al., 2015).

6. RESULTS

The hypothesised model aims to investigate the effect of math knowledge, amotivation, self-efficacy, statistical anxiety, and attitude toward Statistics on students' performance in Statistics inside a structural equation model (SEM) approach.

The results related to the measurement model assessment are first presented. For multidimensional constructs, namely statistical anxiety and attitude toward Statistics, a factor analysis was carried out as the first step. Then, factor scores corresponding to the dimension-specific subscales are included in the PLS-PM model as observed variables of the most general latent variable. Figure 1 depicts indicators' factor loadings. As can be seen, many indicators present good reliability, reporting loading values greater or close to 0.707. It is worth noting that indicators under the minimum threshold of 0.50 (i.e., MSLQ2, MSLQ16, MSLQ18, Help) were eliminated. Therefore, all the results presented below refer to the model estimated after removing those low reliable indicators.

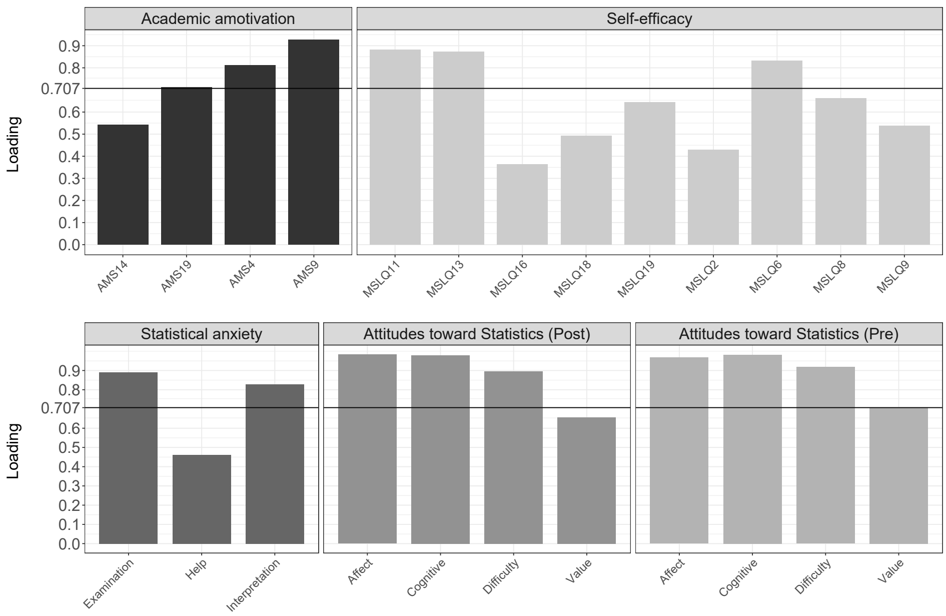


Figure 1: Indicators' factor loadings for the considered latent variables. The horizontal line indicates the threshold for a good indicator reliability

Table 2 reports the reliability and validity measures for the latent variables. The Dijkstra-Henselers's ρ_a values were all higher than 0.707, pointing at good internal reliability for all constructs. Furthermore, the average variance extracted (AVE) indicated a good convergent validity, assuming values higher than 0.50 for the considered constructs. Finally, all the heterotrait-monotrait ratio of correlations (HTMT) values were less than 0.85, pointing to a good discriminant validity (see Table 3).

Table 2: Measurement model assessment for latent variables

Construct	ρ_a	AVE
Academic motivation	0.86	0.58
Self-efficacy	0.89	0.54
Attitude toward Statistics (Pre)	0.95	0.81
Attitude toward Statistics (Post)	0.95	0.79
Statistical Anxiety	0.79	0.66

Table 3: Discriminant validity assessment

	1	*2*	*3*	*4*
1. Academic motivation	1			
2. Self-efficacy	0.16	1		
3. Attitude toward Statistic (pre)	0.23	0.72	1	
4. Attitude toward Statistic (post)	0.15	0.64	0.79	1
5. Statistical anxiety	0.09	0.52	0.75	0.63

Regarding emergent variables, the weight variance inflation factors ranged from 1.06 to 1.80, thus below the threshold of 5 (Hair et al., 2011), indicating that multicollinearity is not an issue. Moreover, the three estimated weights for the performance construct were all sizeable, whereas only the weights corresponding to fraction and set theory abilities proved to be significant for math knowledge. Despite some indicators of math knowledge reporting non-significant weights, we still decided to keep them in the model to be consistent with the construct's theoretical definition proposed by Galli et al. (2008). Indeed, as Hair Jr et al. (2021) pointed out, removing formative indicators may compromise the content validity of the construct. For more details about the measurement assessment of the emergent variables, see Table 4.

Moving to the structural model, results about the direct paths are depicted in Figure 2. Results showed that academic amotivation did not affect students' attitude toward Statistics at the beginning of the course and their performance. In contrast, amotivated students reported a lower level of self-efficacy ($\beta = -0.15$, 95% CI = -0.30 to -0.02). On the other hand, math knowledge positively influenced students' self-efficacy ($\beta = 0.32$, 95% CI = 0.22 to 0.49) and pre-course

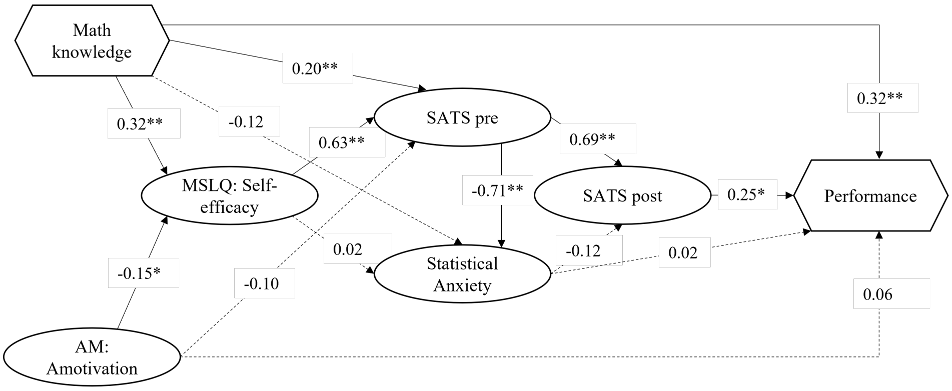
Table 4: Measurement model assessment for emergent variables

Weight	Estimate	Std. error	t-value	95% CI	VIF
Math knowledge					
Operations	0.01	0.14	0.06	[-0.29; 0.28]	1.43
Fractions	0.63	0.12	5.18	[0.38; 0.85]	1.52
SetTheory	0.37	0.14	2.65	[0.05; 0.59]	1.41
Equations	0.10	0.16	0.64	[-0.20; 0.41]	1.72
Relations	0.11	0.17	0.68	[-0.19; 0.45]	1.80
Probability	0.09	0.13	0.68	[-0.16; 0.34]	1.31
Performance					
Knowledge	0.53	0.14	3.70	[0.22; 0.79]	1.23
Application	0.48	0.15	3.21	[0.15; 0.72]	1.23
Judgement	0.36	0.15	2.34	[0.04; 0.64]	1.06

attitude toward Statistics ($\beta = 0.20$, 95% CI = 0.07 to 0.33), whereas it only had an indirect negative effect on anxiety via pre-course attitude toward Statistics ($\beta = -0.28$, 95% CI = -0.39 to -0.18). Indeed, the pre-course attitude toward Statistics affected statistical anxiety ($\beta = -0.71$, 95% CI = -0.89 to -0.48) and post-course attitude toward Statistics ($\beta = 0.69$, 95% CI = 0.55 to 0.85) in a negative and positive way, respectively. However, contrary to our hypothesis, statistical anxiety is not significantly related to post-course attitude toward Statistics and students' performance. The latter, instead, is influenced directly and positively by post-course attitude toward Statistics ($\beta = 0.25$, 95% CI = 0.05 to 0.45) and math knowledge ($\beta = 0.32$, 95% CI = 0.18 to 0.48). The estimated total effects of the considered predictors on students' performance are depicted in Figure 3. Overall, math knowledge turned out to be the most influential factor, followed by attitude toward Statistics and self-efficacy. Conversely, amotivation and statistical anxiety did not significantly impact the performance.

The R^2 values for the endogenous variables indicated a good proportion of explained variance for all variables: $R^2 = 0.13$ for self-efficacy, $R^2 = 0.55$ for pre course attitude toward Statistics, $R^2 = 0.61$ for post course attitude toward Statistics, $R^2 = 0.57$ for statistical anxiety, and $R^2 = 0.22$ for performance.

Finally, the SRMR value for the estimated model is equal to 0.06, thus below the suggested threshold of 0.080, indicating a good global model fit.



Note: dashed lines indicate no significant paths. *p<0.05; **p<0.01

Figure 2: Structural model with standardised regression coefficients. Ellipses represent latent variables whereas hexagons depict emergent variables

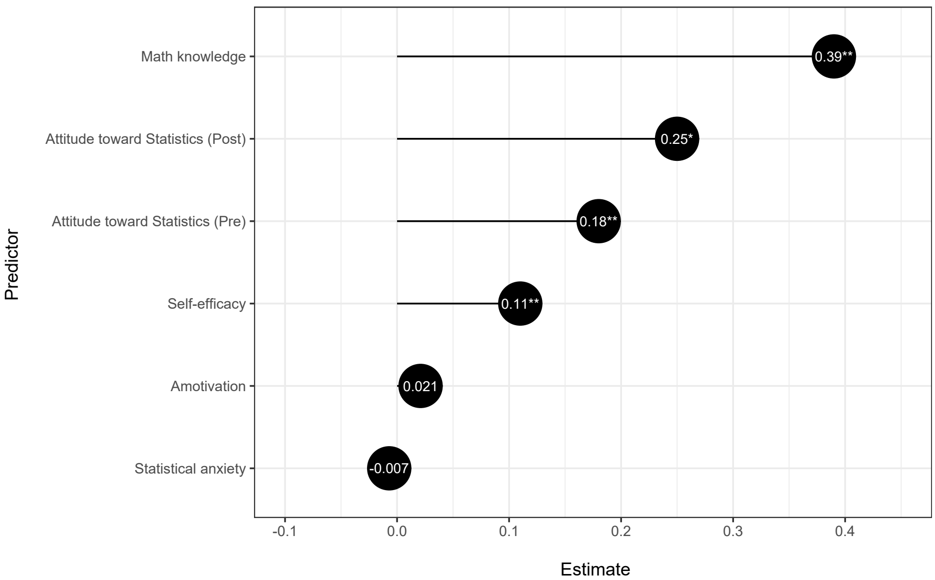


Figure 3: Estimated total effects of the considered predictors on students' performance. *p<0.05; **p<0.01

7. DISCUSSION

Learning Statistics in many social science degrees is associated with high levels of statistical anxiety and performance and academic achievement problems. The present study aimed to examine psychology students' performance in an introductory Statistics course to ascertain the impact of some antecedents of statistical anxiety, such as math knowledge, amotivation, self-efficacy and attitudes toward Statistics on students' performance.

Related to the H1, as expected, the basic mathematical knowledge of students directly affected performance. This finding is in line with the previous literature that showed the strong relationship between the mathematical skills acquired during high school and performance in Statistics during university courses (Chiesi and Primi, 2010; Lavidas et al., 2020; Tremblay et al., 2000). Furthermore, mathematics knowledge appears to be related to more positive attitudes toward Statistics assessed in the first part of the course, and in turn, these pre-course attitudes affected attitudes at the end of the course (H4) that, in turn, influenced the performance. This evidence is in line with previous studies (Chiesi and Primi, 2010; Sorge and Schau, 2002; Wisenbaker et al., 2000). Contrary to our assumption, math knowledge does not significantly directly affect statistical anxiety but only indirectly through pre-course attitudes towards Statistics. Despite the lack of direct effect in our study, which is not in line with the literature (Sesé Abad et al., 2015), some studies showed the effect of numerical abilities on anxiety through attitudes towards Statistics (Williams, 2013). In our study, math knowledge contributes to their attitudes toward Statistics, which in turn contributes to feelings of Statistics anxiety.

Moreover, in line with the literature and as expected, math knowledge has a direct positive effect on self-efficacy; while, not in line with the literature, in our study, no direct effect emerged between self-efficacy and statistical anxiety (Baloğlu et al., 2017; de Vink, 2017; Stella and Glory, 2018). Instead, as hypothesised (H3), self-efficacy directly affects the pre-course attitude toward Statistics, which in turn affects statistical anxiety. Students with higher academic self-efficacy tend to display more active attitudes towards Statistics and, therefore, experience lower levels of statistical anxiety. Contrary to our hypotheses (H2), academic amotivation did not affect attitude toward Statistics and students' performance.

Finally, the controversial discussion between statistical anxiety and performance must be addressed. The hypothesised path between statistical anxiety and performance (H5) was not observed, consistent with Chiesi and Primi (2010); Lalonde and Gardner (1993); Lester (2016); Nasser (2004) and Paechter et al. (2017), but in contrast to Onwuegbuzie and Wilson (2003) and Tremblay et al.

(2000). Moreover, also the indirect effect was not significant.

Our study suggested the key role of attitude toward Statistics. Instead of statistical anxiety, the attitudes towards discipline, self-efficacy and math background explain the performance in Statistics. Moreover, the math knowledge acquired previously seems to be effective in improving attitudes toward Statistics.

This study has some limitations that need to be considered in future research. First, the number of participants resulted in a small sample for the analysis. Future studies should need a more representative sample to test the model. Second, the sample is not gender-balanced, but the highest percentage of females than males reflects the gender distribution of the population of psychology students in Italy. We would need further studies with balanced samples to determine the role of gender in the study of Statistics performance. Third, the study did not consider other situational antecedents of statistical anxiety, such as the learning environments, pedagogical style and the teacher language. Specifically, the data was collected through the MOODLE platform, and the course was arranged online. This is an aspect of the study that we may consider when interpreting the findings. Moreover, the small proportion of performance's explained variance highlighted the need to consider also other predictors, such as students' engagement, in order to attain a more comprehensive understanding of factors that affect students' performance in Statistics. The lack of relationship between statistical anxiety and performance should be more explored. It could be interesting to study the personality traits as antecedents of statistical anxiety, which in recent studies seem to assume an important role in explaining statistical anxiety (Levpušček and Cukon, 2022). Future research should investigate the presence of moderators in the relationship between statistical anxiety and performance to mitigate this effect. Moreover, it might be interesting to carry out multigroup analysis to explore the difference between different subgroups of students, for example gender and school degree provenience (classic, technique and scientific).

Despite these limitations, the current findings have important conceptual and practical implications. First of all, our findings suggested that it would be useful to plan interventions aimed at increasing both basic mathematics knowledge and attitudes toward Statistics in order to help students in increasing their performance in Statistics (Chiesi and Primi, 2010). Students may become familiar with some basic mathematical techniques (e.g., arranging a short series of lessons and learning to apply basic computational procedures) aimed at mastering the basic mathematical skills necessary to solve the tasks. Moreover, it would be helpful to let students exercise to provide feedback about their results and allow them to monitor their progress. Students' confidence in learning Statistics should be improved by increasing how useful they think developing statistical knowledge and skills is for attaining their future goals and explaining the importance of Statistics in different domains. Previous theory and research suggested that clarifying statistical terminology and concepts using examples to experience mastery of the statistical topics, and providing students with purposes and reasons for engaging in academic tasks can help them to give more value to statistical tasks (Brophy, 1999; Hofer, 2002; Latham et al., 1988; Chiesi and Primi, 2010). According to Chiesi and Primi (2010) perspective, once problems with basic mathematics are reduced, all students should benefit from these intervention strategies. In recent years, also several instructional methods have been employed to support students in learning Statistics. Among them, intelligent tutoring systems deserve particular interest, personalising learning activities according to individual characteristics (Fabbricatore et al., 2021b; Pacella et al., 2022).

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