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Salient and Mythical Sources of Secondary School Students' Difficulties in Learning Mathematics in Cameroon

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Abstract

Several studies have identified sources of students' difficulties in learning mathematics. In most of these studies however, mainly qualitative methodology has been the leading inquiry strategy. Making a distinction between valid and mythical sources of learning difficulties have not been given much attention in studies, especially within the context of Africa. The present study approached, the antecedents of students' difficulties in learning mathematics from two directions and attempted to identify through interviews, validate through confirmatory factor analysis, and classify through regression analyses, salient and mythical sources of students' difficulties in learning mathematics. The study utilised an exploratory sequential research design and sampled 500 first and second cycle secondary school students from all school types. Nine sub-themes emerged from the thematic analyses of interview data. Six separate confirmatory factor analysis models consisting of a univariate, multivariate, 4-factor 1st order, 5-factor 1st order, 1-factor hierarchical, and 4-factor hierarchical models were tested at separate stages. The results revealed the 4-factor 1st order model to be the most parsimonious for salient sources of difficulties [CMIN/DF=1.755, RMSEA=0.039, CFI=0.971, SRMR=0.0323], while the 5-factor 1st order model appeared to be the most parsimonious for mythical sources of difficulties [CMIN/DF=1.770, RMSEA=0.039, CFI=0.954, SRMR=0.0381]. Salient sources were classified in order of their regression weights as follows; perceived prior mathematics achievement, personal interest, mathematics anxiety, and presecondary school myths, while mythical sources of students' difficulties in learning mathematics classify as follows; knowledge of mathematical concepts, peer pressure, classroom/home environment, teaching strategies, and teaching methods.

Keywords: Sources, Mathematics Learning Difficulty, Mathematical Myths, Mathematics Performance, Factor Model, Confirmatory Factor Analysis

Introduction

Secondary school students often view mathematics as a difficult subject and given the subject's ever 'all-important' content, obscure vocabulary, strict algorithmic syntax, unfamiliar notations, and systematic language; students inexhaustibly often tend to believe that mathematics qualifies for one of the most, if not the most 'difficult' subject in the secondary school curriculum. Consequently, for most students in secondary school, mathematics appears to be the least liked subject (Bojanivić, 2021; Gafoor & Kurukkan, 2015) [12, 24]. The difficulties students face in learning mathematics which ensue from cognitive failure, gaps in learning, and low information processing abilities (Abdulsahid, 2021, p. 2322); often cumulate over time and eventually open students up to certain behavioural patterns and a myriad of negative beliefs about the subject which harm students' ability to progress in the discipline. From believing that; classroom mathematics is all about looking for "x and y" to that mathematics is least applied in most jobs among others (The United States National Research Council, 2001) [43], harm students' career goals, and the list goes on ad infinitum. Though most of these beliefs are unfounded, they however have found a foothold among many learners of mathematics irrespective of the fact that a manifold of evidences exists to counter beliefs about mathematics being a difficult subject. In addition, several studies have found sufficient evidence pointing to the fact that interventions targeting changing mindsets have improved students' performance in academic disciplines, and they exist neuroscientific empirical evidences linking the development of new connections in the brain to students' active learning and practice (Robin *et al.*, 2018) [50]. Unfortunately, students' beliefs about mathematics being a difficult subject exist and are endemic in the Cameroon secondary school environment. Nevertheless, every student irrespective of their level of intelligence and learning styles face difficulties in learning mathematics (Dewi *et al*., 2021) [16]. Regardless of this, some of the reasons which students have often faulted for the difficulties they face in learning the subject needs to be assessed for their authenticity.

Historically, sources of students' difficulties in learning mathematics have been associated with dyscalculia, attention-deficit/hyperactivity disorder (ADHD), and dyslexia which are learning disorders triggered by students' low memory capacity, low reasoning and low visuo-spatial ability (Faulkenberry & Geye, 2014; Karagiannakis *et al*., 2014, p. 2) [20, 33]. On the other hand, beliefs about mathematics being a difficult subject to learn are manifold and have been around since the early age of salient discoveries in the discipline, but have only recently attracted the attention of African researchers. Conceptually, they exist both valid and mythical sources of difficulties in learning mathematics for secondary school students and in different forms and about different aspects of mathematics including in the subject and in specific situations within the discipline in which students learn mathematics. Clements and Sarama (2018) [14] reaffirm that even though these beliefs about mathematics being a difficult subject for students to learn have a grain of truth in them they are largely just myth. They further remarked that these myths about mathematics could develop early in children even before pre-school. Myths have been categorised differently, including first of all societal myths, which Rubin (1952) [52] argues are inexpungible, and secondly educational myths which are believed to have been around for as 'eternal' as the field of education itself (Bob, 1999; Joan *et al*., 2008) [11, 29].

Within the African context, studies that have attempted to explore the sources of students' difficulties in learning mathematics (SOSDILM) have mostly been focused on projecting the prevalence of myths and in designing interventions (Frank, 1990; Mensah & Quan-Baffour, 2015) [23, 40] in an attempt to enable students, overcome myths. From both the African and the Western contexts nonetheless, factors which contribute in the development of mathematical myths especially myths about math being a difficult subject to learn have not been given much attention and sufficiently explored. In particular, the factorial structures believed to constitute salient and mythical SOSDILM have not been confirmed, given that mathematics performance continues to drop in secondary schools in Cameroon (Akuro & Ngozi, 2014) [6]. Also, mathematics avoidance continues to grow and students are ending up in careers that do not require the exclusive applications of mathematics (Carmo *et al*., 2019) [13]. Studies have identified a number of possible SOSDILM (Archarya, 2017; Jega *et al*., 2019 [28]; Karagiannakis *et al*., 2014 [33]; Rajkumar & Hema, 2017) [47]. General antecedents identified include; environmental, personal and cognitive, while specific sources include; poor teaching strategies, mathematics anxiety, negative attitudes, socio-economic factors, parent's educational background, poor school management and lack of infrastructure. However, studies that have utilized exploratory and confirmatory factor analyses techniques in identifying sources of students' frustration in learning mathematics are completely lacking in the context of Cameroon. The present study approached sources of students' difficulties in learning mathematics from two directions; salient and mythical sources, and attempted to identify SOSDILM, through qualitative methodology and classified through quantitative methodology, salient factors that foster them.

The specific objectives of the study therefore were to;

1. Identify sources of students' difficulties in learning mathematics among secondary schools in Cameroon.
2. Confirm a valid factorial structure for sources of students' difficulties in learning mathematics among secondary schools in Cameroon.
3. Classify salient and mythical sources of secondary school students' difficulties in learning mathematics in Cameroon.

Operationally, in the context of this study, sources of students' learning difficulties in mathematics refer to the series of events and experiences, personal or environmental which students encounter during the process of learning mathematics which act together to frustrate learning in the subject. According to William (1980) [62], though the definition of the word 'myth' is complex and problematic, mathematical myths are categorised as widely held but false beliefs or ideas about mathematics or mathematical concepts. In the context of this study, mathematics myths refer to students' beliefs that the subject of mathematics presents insurmountable challenges during specific situations in which mathematics is learnt compared to other subjects, driven exclusively by a range of curricular (environmental) and non-curricular (psychological) antecedents.

Literature Review

Mathematics Learning Difficulties

It has been shown that most students face difficulties in learning mathematics compared to other academic subjects (Dowker *et al*., 2016; Punaro & Reeve, 2012) [17, 46]. Students who view mathematics as difficult often tend to show great dislike towards the discipline (Aguilar, 2021 [5]; Anigbo, 2016; Azmidar *et al*., 2017 [8]). Consequently, these students are less likely to persevere in learning the concepts, become easily bored, display unnoticeable interest and possess less self-efficacy beliefs in the subject. Mathematics learning difficulties are driven partly by mathematics learning disorders, and emotions surrounding mathematics achievement. Mathematics learning difficulties are compounded and include both mathematics achievement and the difficulty involve in learning mathematics (mathematics skill deficit) also known as mathematics learning difficulty (Gafoor & Kurukkan, 2015 [24]; Sepeng & Madzorera, 2014) [56]. According to Karagiannakis *et al*. (2014) [33] mathematics skills deficit subtypes include difficulties in acquiring arithmetic strategies, difficulties retrieving information from long term memory, and issues with spatial representation of numbers. Mathematics learning difficulties are exacerbated by the fact that students are often require to possess a number of different abilities (from foundational to problem solving abilities), possess a mathematics learning profile void of gaps (since topics are sequenced such that previous learning informs current learning), and effective mastery of content in a challenging time-based curricular environment.

Sources of Mathematics Learning Difficulties and Myths

Abdul and Abidha (2015) [1] summarised the SOSDILM into three main themes; cognitive, affective and psychomotor factors. Specific sub-sources, include; student variables, instructional design options, gender, teaching methods, teacher attitudes, personal variables including arithmetic ability and motivation, peer influence and contextual antecedents. Among these, personal or individual factors including cognitive (intellectual abilities), along with motivational variables (such as perceived utility, intrinsic motivation and causal attributions for success and failure) and emotional variables (math anxiety) have been determined to be the best predictors of mathematics achievement (Amanda *et al*., 2020) [7]. In summary, the SOSDILM emerge from issues surrounding the translation of mathematics curriculum documents (Kesiki & Nekang, 2022) [35].

The mythical SOSDILM are student and teacher-based. While the former can diminish students' self-confidence, and increase mathematics difficulty, the later can limit a teacher's vision of the breadth of best instructional strategies necessary for students' learning, and therefore can lead to bias on how a teacher teaches, assesses and relates with students (Clements & Sarama, 2018; Eleanor *et al*., 2018; Martha, 1990) [14, 18, 38]. In general, teaching strategies adopted by teachers can do two things. They can be educative or mis-educative and can contribute in either enhancing or distorting students' further progress and experience. When poor teaching strategies are adopted, students' capacity to belief in mathematical myths are stretched (Linda, 2016) [37], thereby providing conditions necessary for the formation of new SOSDILM. In addition, the learning environment is a much bigger source of difficulties in learning mathematics, given that it is largely influenced by culture and language. This is due to the fact that differences exist in culture and language among those that have pioneered major discoveries in mathematics, so this influences how mathematics is conceptualized (Kantner, 2008) [32]. This makes the learning of mathematics prone to so many myths particularly in contexts such as Cameroon, which have not served as incubators of mathematical ideas but have had to learn basic 'foreign' mathematics instructed in a 'foreign' language and represented using the same 'foreign' symbols. The new foothold for myths in today's mathematics curriculum among all stakeholders from students who learn the disciple, to teachers who teach it, to experts who plan and design the curriculum, to parents who pay for students' learning tools; is in part largely due to failure by all involve in recognizing that learning with understanding involves connecting and organizing knowledge, that learning builds on what children already know, and that formal school instruction needs to take advantage of children's informal everyday knowledge of mathematics (The National Research Council, 2001) [43].

Guiding Theories

From a theoretical perspective, social representation of mathematics plays a significant contributing role in the dissemination of myths surrounding the difficulty in mathematics and in students' ability to belief and sustain myths. Under social representation, students copy behaviour, beliefs, ideas and practices from their home environment and culture which tend to influence how they imagine, think, learn and talk about mathematics (Abreu & Cline, 1998) [3]. In that diverse learning environment, be it the personal environment where emotional reactions towards mathematics (mathematics anxiety) prevail, or in the classroom and in the school where myths rub off onto students and teachers or the home background where parents' and society's myths about mathematics prevail, students' craft to belief myths about mathematics being a difficult academic subject are perfected. In addition, to students' social construction of mathematics, negative expectations of learning outcomes and the value students attach to the knowledge gained are potential SOSDILM (Wigfield, 1994, p. 49) [61].

Methodology

The study utilised a mixed research design as the study's inquiry strategy. The specific mixed research design that was employed in the study, was the exploratory sequential design. To this inquiry strategy the quantitative phase of data collection is preceded by a qualitative phase of data collection and analysis (Creswell, 2014, p. 247) [15]. In the context of the present study, the goal of the mixed research design in particular, was to first capture the experiences of secondary school students through qualitative techniques, on the antecedents of difficulties in learning mathematics and to later utilise the findings from the qualitative study to inform and build a survey which would facilitate the construction and validation of salient and mythical factorial structures for the SOSDILM and their further classification by determining their individual impacts on mathematics performance.

The population of the study included all secondary school students from the Fako Division of the South West Region of Cameroon. Fako was the geographical area of choice for the study because of the cosmopolitan, diverse (have students from all 10 regions of the country studying in secondary schools in Fako) and bilingual make-up of the Division. The target population of the study consisted of first and second cycle students of secondary school from the Fako Division. The accessible population was made up of form 5, lower, and upper sixth students from all school types in the Fako Division of the South West Region of Cameroon. The sample consisted of 500, form 5, lower, and upper sixth students, who were selected from six secondary schools through a stratified proportionate random sampling technique. Specifically, 419 students were selected from the first cycle while 81 students were selected from the second cycle. The condition for inclusion in the sample was that a student ought to have spent at least five years in secondary school. The students who had spent less than five years in the first cycle of secondary school were not included in the sample. The rationale for which students from both levels of secondary school (first and second cycle) were selected for the study revolved around variability and fairness in responses to questionnaire measures. According to Kozey and Feeley (2009) [36], "current students are more likely to use dispositional cues whereas former students would most likely use more situational cues (e.g., course difficulty) when rating course and instructor quality". while second cycle students were more likely to rate teachers and subject content, less positively and exhibit greater variability in responses to study factors, current students were most likely going to attribute the cause of behaviour to some internal personal characteristics rather than on external influences. In addition, second cycle students were considered to have amassed much experience following their five-to-seven years of study in secondary school and therefore had the advantage of hindsight with regard to individual and collective mathematics learning experiences and fairness of responses to interview questions and questionnaire items compared to current form five students who were still studying through the first cycle of secondary school. The schools were stratified into, public, denominational and lay private. Two schools were selected from each of the three school types. Concerning school type demographics, 218 students were selected from public schools, 157 from denominational and 125 from lay private schools.

In total, forty-five (45) semi-structured interviews were conducted with the students. As a confirmatory step and to ensure that data collection had become redundant, ten more interviews were conducted to ensure that data saturation for the interviews had been reached (Hennink & Kaiser, 2022) [27]. From the 46th to the 56th interviews, categories began to repeat and no new categories emerged. For the survey, the sub-themes that emerged from the thematic analysis of interview data were then used to develop a questionnaire to measure students' sources of difficulties in learning mathematics. Two hundred and ninety-nine (299) girls and two hundred and one (201) boys were selected. To control for bias in the measurement process, more girls than boys were selected on the basis that male students' mathematics performance have been shown to be better on average than that of female students in secondary school (Felson & Trudeau, 1991; OECD, 2011) [21, 45] though the gap has recently been growing significantly nigher (Kane & Mertz, 2012) [31]. Secondly, the variance ratio for most respondents' opinions on constructs in the questionnaire and in performance related to mathematics, were mostly less than 1. The variance ratio, expresses the variance of males in relation to that of females and, a value greater than 1 signifies that male respondents tend to perform better or capture the problem better than female respondents (Baye & Monseur, 2016) [9]. The variance ratio, for the present study was 0.98, implying that on average, female students' variances were 2% higher than male students' variances on responses to questionnaire items. In other words, female students captured the problem better than male students and explained on average 2% more of the variance in the dataset. The students ages ranged between 15 and 30 years old. The mean age of respondents was 17.01 years. The age variance and standard deviations were 8.33 and 2.9 respectively.

Data was collected through three instruments; Firstly, data for the qualitative study was collected through an interview guide which was structured in the form of an open-ended questionnaire. Students were required to reflect on their secondary school experiences and provide perceived sources of frustrations in mathematics. Secondly, data for the quantitative study on the SOSDILM were collected through a questionnaire which was abbreviated as Q-SOSDILM (questionnaire on sources of secondary school students' difficulties in learning mathematics). While second cycle students answered the Q-SOSDILM (see appendix), first cycle students answered an equivalent version of the Q-SOSDILM, and the instruments only differed in terms of the tenses used in describing the various items. A configural test of invariance was carried out to ensure that the same constructs were being measured across the two groups of first and second cycle respondents. The test revealed that the interpretation of the items in the instruments were the same for both groups. The response intensity for each item on the Q- SOSDILM was selected on a 4-point Likert scale. The mathematics anxiety rating scale (MARS) developed by Richardson and Suinn (1972) [49] was adopted for measuring mathematics anxiety in the study, due to the fact that, the MARS scale utilises a bidimensional perspective and follows the modern measurement theoretical approach to measuring mathematics anxiety (Cavanaugh & Sparrow, 2010). In all, sixty-two (62) items were formulated and grouped under various sub-themes (factors) identified through the thematic analysis of interview data and also from empirical literature. Students were requested to respond to each item in the Q-SOSDILM by placing a tick (√) against the most relevant of four response categories (Strongly Disagree, Disagree, Agree, Strongly Agree) for items under the various sub-themes. This process improved the reliability of students' responses. This was done in order to effectively identify prominent and mythical factors which reinforced beliefs about mathematics being a difficult subject in the population of secondary school students by making sure that even if students forgot outlining a reason during the interview, they could still make up for such omissions in the questionnaire with ordinal measures.

The Q-SOSDILM yielded content validity indices (referring here to the ratio of experts who declared an item valid to the total number of experts who examined the questionnaire) ranging between 0.79 and 0.93. To determine the quality of measurement for the study, three different estimates were calculated. The cronbach reliability, composite reliability (C.R), and average variance extracted (AVE). For the measurement quality values of each factor in the study, see Table 5. The instrument was first tested for reliability following a pilot study with 20 respondents. The overall cronbach reliability coefficient for the pilot study was 0.80. After a period of 7 months the instrument was retested for 20 more respondents and a new cronbach reliability coefficient of 0.89 was obtained. The new value demonstrated the stability of the Q-SOSDILM as a reliable instrument for the study. This proved that the Q-SOSDILM was stable and therefore trustworthy for use in collecting data for the study. The final reliability coefficient for the study was 0.96 for the total sample of 500 respondents. To determine the best possible way of scoring the Q-SOSDILM, an ancillary bifactor analysis of the instrument revealed a unidimensional internal structure for the Q-SOSDILM. The explained common (ECV)=0.751, and the percentage of uncontaminated correlations (PUC)=0.909 which according to Rodriguez *et al*. (2016) [51] signifies that the instrument is a reliable scale for measuring the overall construct (in this case sources of difficulties in learning mathematics for any group of secondary school students).

Finally, to measure mathematics performance, the researchers did a documentary analysis of form five students' mathematics achievement in the South West regional mock examinations for a 3-year period beginning from 2020 to 2022. Students' mathematics raw scores were obtained from school documents of six secondary schools for the three-year period, which included scores from public, denominational, and lay private school documents. The scores were randomly and disproportionately selected from school documents for the three different years. Approximately 167 scores were selected at random from each school type, irrespective of the proportion of candidates in that particular stratum. In total, 500 students' raw scores were selected to represent the dataset for mathematics performance for the study. The Regional mock examination is directly associable with the General Certificate of Education (GCE) examination and therefore provides evidence of predictive criterion validity given that it is a standardized examination.

Data from interviews was analysed through thematic analysis. Various categories were identified from interview transcripts, sub-themes were developed and interpreted. Data from the questionnaire items were analysed descriptively, and inferentially in three stages;

1. Confirmatory factor analysis
2. Regression analysis
3. Confirmatory factor analysis

During the first stage of the quantitative data analysis, *confirmatory factor analysis (CFA)* was utilised to initially test four hypothesized models; consisting of, a *1-factor or univariate model*, an n-*factor or multivariate model, a 1-factor hierarchical*, and an *m-factor hierarchical* or *hierarchical model (m<n, m,nεℕ)*. This was done in order to confirm the most fitting of the different models (Pletzer *et al*., 2016) for the sources of secondary school students' difficulties in learning mathematics (SOSDILM) structure. The aim here was to identify the most fitting of the four factorial models of valid/mythical sources of difficulties in learning mathematics.

During the second stage of quantitative data analysis, a *stepwise regression analysis* was first performed to identify the most useful sets of predictors among the n factors identified as sources of students' difficulties in learning mathematics. The test removed unwanted variables (weakly corelated with mathematics performance) from the group of n predictor variables that did not significantly contribute in the model. In addition, the stepwise regression identified the amount of variance in the response variable significantly explained by each predictor variable. Following this, a simple multivariate regression model consisting of the 'useful' set of predictors was then performed to determine the most salient SOSDILM on the one hand and the mythical SOSDILM on the other hand, through a simple comparism of the models' regression weights. The final stage of the analyses involved the construction of two new CFA models; the salient model consisting of factors established as the valid SOSDILM, and a mythical model consisting of factors established as the invalid SOSDILM.

Findings

The findings of the study were presented in three sections, according to the specific research questions of the study. The first section consists of a table presentation of the findings of the qualitative study, organised under three columns consisting of sub-themes, categories, and their respective sample quotations of respondents, which were uplifted word verbatim from interview transcripts on students' perceived sources of difficulties in learning mathematics. In the second section, analyses and results for the confirmatory factor analyses of the first four hypothesized factorial structures were presented. Finally, in the third section, a multivariate regression analysis and two new confirmatory factor analyses models were performed to confirm the classification of the SOSDILM into salient and mythical antecedents.

Research Question One: Which factors are perceived by secondary school students in Cameroon to be credible sources of difficulties in learning mathematics?

The interview guide given to students was a semi-structured open-ended questionnaire. Students were requested to list specific reasons or causes of the difficulties they encountered in secondary school mathematics classrooms. Students' sample responses were transcribed, categorised and later developed into sub-themes. These were listed in Table 1 below. Respondents were identified by letter 'P', and numbered from 1 to 45 (P#n, where, 1 ≤ n ≥ 45). Some sample quotations were given by more than one respondent.

Table 1: Students' Perceived Sources of Difficulties in Learning Mathematics

Sample Quotations of Participants	Categories	Sub-Themes
"It was just the mentality that I developed that maths is difficult"………………….P#25	Mindset	Pre-secondary school myths
"Mathematics was not for me"……..P#2 *"The teacher that handled the subject was a woman who could not really manage the students like a male teacher"*…..P#10	Mathematical stereotypes	
"My mentality was made up that it was very tough"…..P#38	Sustained myths	
"From the way the teacher taught I could hardly understand"…..P#2 *"Our teacher only had eyes for fast learners"*…..P#31	Poor lesson planning	Teaching strategies
"The teacher always give cheap exercises and difficult assignments"…..P#7	Poor assessment strategies	
"Sometimes the approach used by certain teachers to teach" *"I believed it was difficult because of the teaching technique that the teacher was using"*….. P#12	Teacher's personal teaching theory	
"teacher was not teaching well"…..P#35	Teacher-centered teaching	
"The teacher was very strict".…..P#40	Teacher failed as a facilitator	
"The maths teacher used to punish when a mistake is made"…..P#17 *"The teacher was harsh to students"*…..P#27 *"Because of the behaviour of my teacher"*…..P#13	Absent recitation	Teaching methods
"The teacher was not encouraging, he taught mostly the bright students"…..P#20	Pure lecture	
"I hated math because of the teacher that taught it"….. P#18 *"Very boring and toxic teacher"*…..P#15	Absent demonstration	
"The teacher that taught me mathematics made me belief that math was difficult" …..P#1, P#6	Teacher-induced perception of math	
"Because I did not understand it"…..P#15	Non giftedness	Personal Interest
"I did not like calculations"…..P#16 *"I lost interest in the subject for a while"*….P#22 *"Lack of concentration"*…..P#33	Lack of interest	

"Math was so boring".....P#44		
"I did not make any efforts in improving".....P#36 *"I used to abandone it at the slightest difficulty"*.....P#9	Lack of efforts	
"The influences from my friends"……P#8 *"My friends made me believe it was difficult so I never made more efforts to study it"*..... P#29	Peer influence	Peer Pressure
"Because of what senior students said".....P#23	Peer math scare	
"I was always staying away from math classes" .....P#8	Lesson boycott	
"Family members discouraged me from maths" .....P#3 *"my elder siblings"*.....P#11	Home environment	Classroom and home environment
"Rumours also contributed" ………P#16 *"Someone told me maths was difficult"*.....P#30 *"Because of the way people were talking about it"*.....P#39	Social environment	
"I never had someone who will teach me and motivate me".....P#4	Lack of a teaching assistance	
"When the teacher was teaching and others were making noise it was difficult to learn maths".....P#37	Classroom aversions	
"Maths was difficult for me because I never had the opportunity to have a textbook for better understanding".....P#41	Lack of study materials	
"I was scared of the figures especially when calculating numbers detailly".....P#37	Number anxiety	Mathematics anxiety
"I never liked the subject" ..... P#5 *"Maths use to make me fail asleep"*.....P#42	Subject anxiety	
"It was because don't like calculations".....P#39	Calculation anxiety	
"I hated the way the teacher treats us after w fail his evaluation".....P#21	Test anxiety	
"It was difficult for me to understand".....P#45 *"I was not quick at grabbing math lessons"*.....P#2	Poor knowledge mastery	Knowledge of mathematical concepts
"Difficult to understand new concept given that previous concepts were not understood".....P#10	Gaps in learning	
"Some topics discouraged completely".....P#31	Challenging topics	
"Because math deals with figures and letters"....P#40 *"The x matter"*....P#16 *"The several unknowns the x and y that we were always asked to look for"*....P#21	Issues with variables	
"It's complexity, method of solving"…..P#28	Algorithm issues	
"Formula was my main problem"....P#41 *"My inability to retain and apply formulas correctly"*....P#6	Complexity of mathematical formulas	
"Sometimes the concepts felt very abstract to me"....P#22 *"Took me more time and effort to understand"*....P#45 *"It involves so many unfamiliar concepts"*....P#17	Abstract concepts	
"The usage of signs as plus and minus"....P#12	Issues with operation signs	
"Maths was tough because of the solving"....P#33 *"Solving over and over again made it difficult"*....P#43	Failure to practice regularly	
"Questions were always difficult to interpret"....P#24	Problems of question interpretation	
"Inability to comprehend examples"....P#26 *"I was not a quick thinker in math"*....P#30	Difficulty to follow up	
"No matter how hard I tried to understand I never understood maths"...P#34 *"Everything was difficult"*....P#9	Stalled performances	Perceived prior mathematics achievement
"Tried but it still wasn't going"....P#32 *"Poor results from test"*…….P#14 *"My answers were always wrong and different from the teachers own"*……..P#1	Persistent failure	
"Failed in all calculations especially those involving x"……..P#37	Constant failure	
"Most people could not succeed in mathematics"...P#3	Mass failure	
"I did not understand no matter how well the teacher explains"...P#25	Mastery difficulty	
"I never believe it will be a great help t me in the future".....P#19	No knowledge on importance of math	

P#=Participant number

There were nine sub-themes in total which emerged from the thematic analyses of interview data. The sub-themes were collectively grouped under forty-four categories which were identified from coding respondents' sample quotations from interview transcripts. A sub-theme named *'presecondary school myths'* comprised of three categories which included, *mindset, stereotypes, and sustained myths*. These categories emerged from respondents (P#25, P#2, P#10, P#38) sample quotations listed in the table above. A second sub-theme named *'teaching strategies'* comprised of five categories, namely; *poor lesson planning, poor assessment strategies, teacher's personal teaching theory, teacher-centered teaching, and teacher failed as a facilitator*. These categories emerged from respondents (P#2, P#31, P#7, P#12, P#35, P#40) sample quotations listed in the table above. In addition, a sub-theme named *'teaching methods'*, comprising of four categories, namely; *absent recitation, pure lecture, absent demonstration, and teacher-induced perception of math* also emerged from respondents (P#13, P#27, P#17, P#20, P#18, P#1, P#6) sample quotations. Another sub-theme named *'personal interest'* and comprising of three categories also emerged. These categories included; *non-giftedness, lack of interest, and lack of efforts* and were coded from the following examples of respondents (P#15, P#16, P#22, P#33, P#44, P#36, P#9) sample quotations as listed in the table. Moreover, one other sub-theme named '*peer pressure'* also emerged (P#8, P#29, P#23, P#8) and comprised of three categories*; peer influence, peer math scare, and lesson boycott.* Another sub-theme named '*classroom and home environment'* emerged from five categories which were coded from respondents (P#3, P#11, P#16, P#16, P#30, P#39, P#37, P#41) sample quotations from the interview guides. These categories included; *home environment*, *social environment*, *lack of a learning assistance*, *noisy classroom*, and *lack of study materials*.

A sub-theme named as *'mathematics anxiety'* emerged from four categories. These categories were respectively coded as; *number anxiety, subject anxiety, calculation anxiety, and test anxiety* from respondents (P#37, P#5, P#42, P#39, P#21) sample quotations from interview transcripts. Furthermore, a sub-theme named *'knowledge of mathematical concepts'* was developed from eleven categories which were coded as follows; *poor knowledge mastery, gaps in learning, challenging topics, issues with variables, algorithm issues, complexity of mathematical formulas, abstract concepts, issues with operation signs, failure to practice regularly, problems of question interpretation, and difficulty to follow up,* were derived from respondents (P#45, P#2, P#10, P#31, P#40, P#16, P#21, P#28, P#41, P#6, P#22, P#45,17, P#12, P#33, P#43, P#24, P#26, P#30) sample quotations. Finally, the last sub-theme for the study, named, '*perceived prior mathematics achievement'* was developed from six categories. These included; *stalled performances, persistent failure, constant failure, mass failure, mastery difficulty, and no knowledge on importance of math.* These categories emerged from respondents (P#34, P#9, P#32, P#14, P#37, P#3, P#25, P#19, P#25, P#2, P#10, P#38) sample quotations listed in the table above.

Analyses

To establish a valid factorial structure for the SOSDILM, four different models were initially tested. The researchers tested for each of the theoretical models in the study, the null hypothesis (H_0), that the covariances implied in a specific theoretical model ($\Sigma(\Theta)$) equals to the population covariance matrix for that specific model (Σ). A non-significant chi-square (χ^2), that is a p-value greater than 0.05 indicates that data fits the particular theoretical model (Goretzko *et al*., 2023) [25]. According to Goretzko and colleagues, in case the p-value for the chi-square is not greater than 0.05 for a large sample of data (that is the number of cases outnumber the variables in the study by between 5:1 and 10:1), then fit indices shall be considered ($\frac{x^2}{df} < 3,$ GFI>0.9, AGFI>0.9, NFI/NNFI/TLI>0.95, CFI>0.95, RMSEA<0.08 or <0.05, RMR/SRMR<0.08, RFI close to 1, PNFI>0.5) for model fitness. However, even though evaluating model fit using a strict null hypothesis "$\Sigma=\Sigma(\Theta)$" for a large sample size has a higher statistical power, it is unrealistic in real-world settings (is affected by a large number of latent factors) and for this reason researchers tend to rely on fit indices for model fitness. In this study, the sample size of 500, was within the 401-1,000 range, and the item-to-factor ratio was between the 5:1 and 10:1 range for all latent factors, which Goretzko *et al*. (2023) [25] found to be associated with the best CFA models. To classify the antecedents of the SOSDILM, four separate confirmatory factor analysis models were first performed as mentioned earlier. These included; *a univariate, a multivariate, 1-factor hierarchical, and a 4-factor hierarchical models*. Different theoretical models utilised in the study were an attempt to find the most data fitting structure of the four hypothesized structures of the SOSDILM.

The univariate model (1-factor) assumed that the covariances (correlations) among the 62-items in the Q-SOSDILM were due to a single common factor. The univariate model loaded all 62 items of the Q-SOSDILM into a single factorial structure. The multivariate or correlated model (9-factor 1st order) assumed that the correlations among all 62-items in the Q-SOSDILM were accounted for by nine first order factors. The number of items initially loaded unto individual factors in the new structure ranged from a minimum of 5 items per factor to a maximum of 7 items per factor. The factors included, presecondary school myths consisting of 6-items, teaching strategies consisting of 7 items, teaching methods consisting of 7 items, personal interest consisting of 6 items, peer pressure consisting of 7 items, classroom/home environment consisting of 7 items, mathematics anxiety consisting of 9 items, knowledge of mathematical concepts consisting 6 items, and perceived prior mathematics achievement consisting of 7 items. The 1-factor hierarchical model (1-factor 2nd order) assumed that the correlations among the set of nine factors were accounted for by one second order factor. The 4-factor hierarchical model (4-factor 2nd order) assumed that the correlations among the set of nine latent factors were accounted for by four second-order factors (main themes). The criteria for arranging and pairing factors in the 4-factor hierarchical model was guided by two major considerations. Firstly, the factors were paired only if their arrangement was conceptually sensible, and secondly if their correlations were high (0.8 or above). Following these criteria, three separate second order factors, with three pairs of two first order factors and one other second order factor consisting of three first order latent factors were formed (see Table 5 for correlations). The second order factor consisting of a set of three first order factors included a factor named presecondary school myths which did not meet one out of two criteria (correlations with other latent factors were less than 0.8), and was therefore initially not paired with any other latent factor. Initially, that factor was left as a special second order latent factor without an association with any first order or pair of first order factors. That arrangement however did not work because it resulted in negative error variances in that hierarchy and was therefore dropped. The arrangement of hierarchies were therefore restructured as follows (see Fig 3); curricular factors or teacher-based factors (teaching strategy and teaching methods), affective factors (personal interest, mathematics anxiety), environmental factors (peer pressure and classroom/home-environment), and cognitive factors (perceived prior mathematics achievement, knowledge of mathematical concepts, and presecondary school myths).

During the analyses phase, in line with Savalei (2020) [55] guidelines, on improving fit indices, items with standardized factor loadings less than 0.4, for the univariate model, and items loadings of 0.5 and above for the multivariate, and the hierarchical models (1-factor and 4-factor hierarchical models) were kept. Items with standardized residual covariances greater than 2 were excluded from the analyses, while care was taken to guard against model misspecifications. This process reduced the total number of items included in each of the four models from 63 to 54, as 9 items were excluded from the analyses following pescribed guidelines. Despite these exclusions, the item-to-factor ratio of between '5:1' and '10:1' as recommended by Goretzko *et al*. (2023) [25] were still achieved in all four models. The items that were excluded during the data analyses in all four models included, PSM4, TS5, TS7, TM3, PP5, CHE2, MA2, MA3, and MA8. In addition, the multivariate, 1-factor hierarchical, and the 4-factor hierarchical model structures were presented in figure 1, 2 & 3 below. The multivariate, and the hierarchical models presented below illustrates the structural arrangement of nine correlated first order, one second order, and four second order hierarchical latent factors respectively. Four different hierarchies were presented in Fig 3 for the 4-factor hierarchical model. These hierarchies, as mentioned earlier included; curricular, cognitive, affective, and environmental.

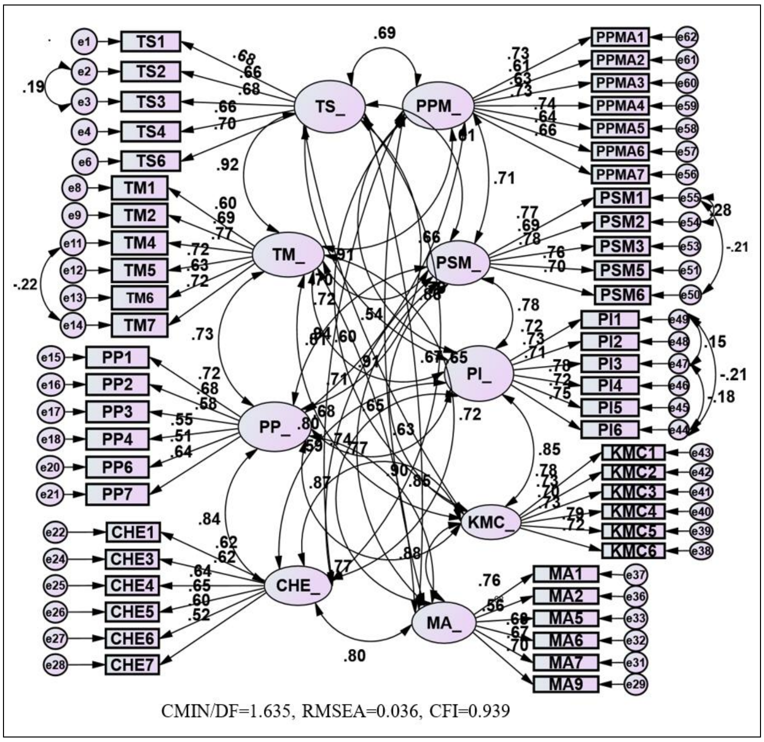


Fig 1: Results Output for the Multivariate Model

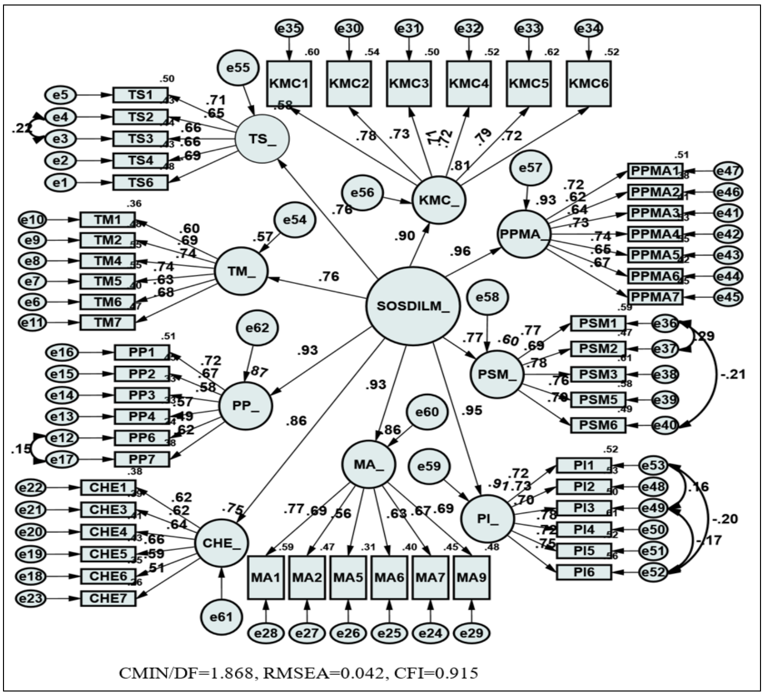


Fig 2: Results Output for the 1-Factor Hierarchical Model

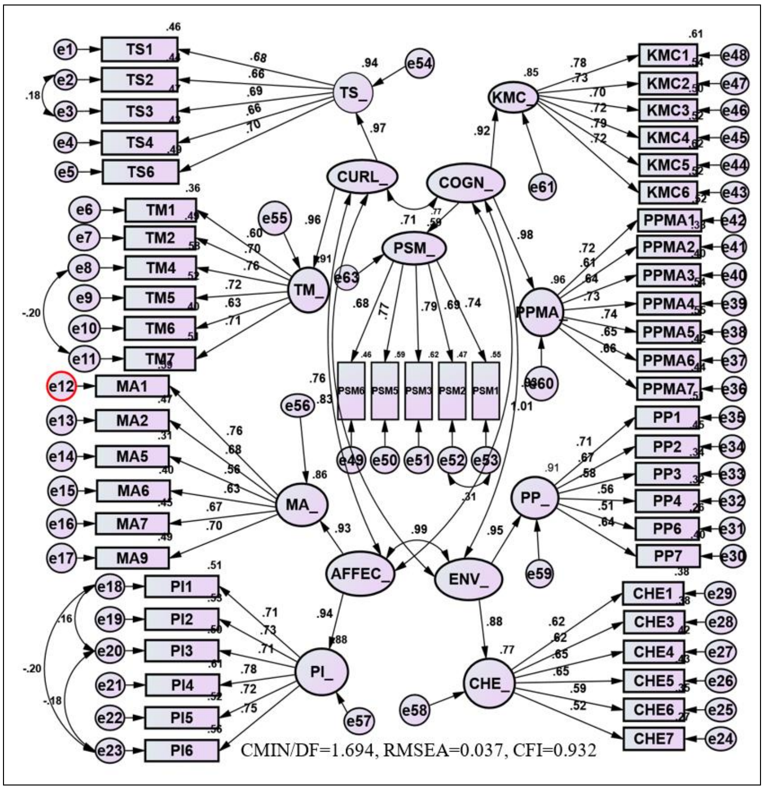


Fig 3: Results Output for the 4-Factor Second Order Model

Research Question Two: Which is the most valid factorial structure for sources of students' difficulties in learning mathematics among secondary school students in Cameroon?

In this section, findings from the confirmatory factor analyses outputs for the three models illustrated above were presented in a number of tables. Firstly, information on the CFA model fit indices and their corresponding cut off values for the initial and finalized, univariate, multivariate, 1-factor hierarchical, and 4-factor hierarchical models were presented. Fit indices were presented under the three categories in CFA models; the absolute fit, comparative fit, and the parsimonious correction fit indices. Secondly, the measurement quality of factors in the respective models consisting of item standardized factor loadings, cronbach reliability coefficients, average variances extracted (AVEs), and composite reliability (C.R) were also presented in table 4 below. Moreover, the different estimates of the corelated first order factors in the multivariate, and second order factors in the 4-factor hierarchical models were also presented. Finally, the various variances in the first order factors explained by second order factors in the hierarchical models known as the squared multiple correlations were also presented in this section.

Table 2: Initial Model Fit Indices of the Univariate, Multivariate, 1-Factor Hierarchical, and 4-Factor Hierarchical Models for the SOSDILMS *(N=500, 62 Items)*

Fit index Category	Model fit index	Obtained value				Cut off values Acceptable Fit
		Univariate Model	Multivariate Model	1-Factor Hierarchical Model	4-Factor Hierarchical Model	
Absolute fit indices	CMIN	5388.748	3588.086	2559.834	3633.697	
	DF	1829	1793	1316	1811	>1
	P-Value	0.000	0.000	0.000	0.000	>0.05
	SRMR	0. 0586	0.0550	0.0500	0.0560	<0.08
	RMSEA	0.066	0.045	0.044	0.045	<0.08
	GFI	0.671	0.795	0.830	0.793	>0.9
	AGFI	0.649	0.777	0.815	0.777	>0.8
Comparative fit indices	CFI	0.755	0.877	0.907	0.875	>0.9
	TLI	0.747	0.870	0.902	0.869	>0.9
Parsimonious Correction fit index	PNFI	0.687	0.741	0.789	0.746	>0.5
	CMIN/DF	2.946	2.001	1.945	2.006	<3
	AIC	4720.481	3908.086	2789.834	3906.000	Smallest
Decision		Rejected	Rejected	Rejected	Rejected	

The initial fit indices for all the four models initially hypothesized in the study were not satisfactory as seen in Table 2 above. This led to the rejection of all four models. In accordance with suggestions on the improvement of fit indices listed above, error terms with modification indices 10 and above were correlated, items with low factor loadings (less than 0.4), and standardized residual covariances greater than 2, were deleted from all four model structures (McIntosh, 2012; Savalei, 2020) [39, 55]. In the univariate model, nine items with factor loadings less than 0.4 were excluded from the analysis, and over 270 error terms with covariances greater than 10 were correlated to obtain new fit indices for the model. In both the multivariate model and in the hierarchical models, nine items with standardized factor loadings less than 0.4 were also excluded from the analyses. There were over 14 error terms with covariances greater than 10 that were correlated in both the multivariate model and in the 1-factor hierarchical model, whereas over 12 error terms were correlated in the 4-factor hierarchical model to obtain new fit indices for all three finalized models. After this was done, model fit indices were improved considerably for all four models as presented in the Table 3 below.

Table 3: Finalized Model Fit Indices of the Univariate, Multivariate, 1-Factor Hierarchical, and 4-Factor Hierarchical Models for the SOSDILMS *(N=500, 62 Items)*

Fit index Category	Model fit index	Obtained values				Cut off values Acceptable Fit
		Univariate Model	Multivariate Model	1-Factor Hierarchical Model	4-Factor Hierarchical Model	
Absolute fit indices	CMIN	1966.067	2096.514	2445.335	2208.551	
	DF	1190	1282	1309√	1304	>1
	SRMR	0.0394	0.0381√	0.0481	0.0407	<0.08
	RMSEA	0.036√	0.036√	0.042	0.037	<0.08
Comparative fit indices	CFI	0.942√	0.939	0.915	0.932	>0.9
	TLI	0.933	0.934√	0.910	0.928	>0.9
Parsimonious Correction fit index	PNFI	0.748	0.798	0.792	0.804√	>0.5
	CMIN/DF	1.652	1.635√	1.868	1.694	<3
	AIC	2448.067	2394.514√	2689.335	2462.551	Smallest taken
Decision		Acceptable	Acceptable	Acceptable	Acceptable	

Abbreviations: CMIN, *chi square*; DF *degrees of freedom*; P-value, *probability value*; CFI, *comparative fit index*; TLI, *Tucker-Lewis index*; GFI, *goodness of fit index*; AGFI, *adjusted goodness of fit index*; RMSEA, *root mean squared error of approximation*; PNFI, *parsimonious-adjusted measures index;* SRMR, *standardized root mean squared residual*; AIC, *Akaike's information criterion*.

The model sizes and sample sizes utilized in all four models in the present study were considerably large (over 62 measures and 500 respondents), and as such it became impossible to obtain a nonsignificant chi-square (indicative of good fit) given that the Chi-square statistic is affected by model size and model sample size, in which models with more variables and larger sample sizes (greater than 200) tend to have larger chi-square values (Newsom, 2023, p. 1) [44].

Table 4: Standardized Factor Loadings, Average Variances Extracted and Composite Reliability for the Multivariate, 1-Factor Hierarchical, and 4-Factor Hierarchical Models

		Multivariate: 9-Factor 1st Order			1-Factor Hierarchical: 1-Factor 2nd Order			4-Factor Hierarchical: 4-Factor 2nd Order			
Factors	Items	CFA Standardized Loadings	C.R	AVE	CFA Standardized Loadings	C.R	AVE	Standardized CFA Loadings	C.R	AVE	Cronbach Reliability
Pre-secondary school myths	PSM1	0.770	0.86	0.55	0.769	0.86	0.55	0.745	0.86	0.54	0.76
	PSM2	0.691			0.687			0.687			
	PSM3	0.780			0.779			0.786			
	PSM5	0.760			0.764			0.769			
	PSM6	0.702			0.700			0.680			
Teaching Strategies	TS1	0.684	0.81	0.45	0.709	0.81	0.46	0.663	0.82	0.46	0.73
	TS2	0.663			0.654			0.697			
	TS3	0.679			0.661			0.686			
	TS4	0.657			0.658			0.656			
	TS6	0.700			0.693			0.698			
Teaching Methods	TM1	0.601	0.84	0.47	0.601	0.84	0.47	0.602	0.84	0.47	0.79
	TM2	0.694			0.692			0.697			
	TM4	0.766			0.740			0.760			
	TM5	0.721			0.739			0.724			
	TM6	0.626			0.630			0.629			
	TM7	0.716			0.684			0.711			
Personal Interest	PI1	0.719	0.88	0.54	0.718	0.88	0.54	0.714	0.88	0.53	0.78
	PI2	0.731			0.730			0.731			
	PI3	0.708			0.705			0.705			
	PI4	0.777			0.780			0.780			
	PI5	0.720			0.721			0.721			
	PI6	0.750			0.748			0.749			
Peer Pressure	PP1	0.717	0.78	**0.37**	0.717	0.78	**0.38**	0.715	0.88	**0.32**	0.80
	PP2	0.678			0.672			0.672			
	PP3	0.582			0.576			0.582			
	PP4	0.553			0.575			0.564			

	PP6	0.506			0.489			0.507			
	PP7	0.636			0.619			0.635			
Classroom and Home Environment	CHE1	0.617	0.78	**0.37**	0.617	0.78	**0.37**	0.619	0.78	**0.37**	0.74
	CHE3	0.617			0.621			0.615			
	CHE4	0.642			0.644			0.647			
	CHE5	0.650			0.656			0.655			
	CHE6	0.596			0.594			0.588			
	CHE7	0.525			0.514			0.522			
Mathematics Anxiety	MA1	0.764	0.83	0.45	0.770	0.83	0.45	0.765	0.80	0.46	0.83
	MA2	0.684			0.685			0.684			
	MA5	0.562			0.555			0.558			
	MA6	0.633			0.629			0.633			
	MA7	0.669			0.669			0.670			
	MA9	0.697			0.695			0.697			
Knowledge of Math concepts	KMC1	0.779	0.88	0.64	0.777	0.88	0.55	0.779	0.88	0.55	0.84
	KMC2	0.730			0.734			0.731			
	KMC3	0.703			0.705			0.704			
	KMC4	0.725			0.724			0.723			
	KMC5	0.791			0.788			0.789			
	KMC6	0.720			0.720			0.723			
Prior Mathematics Achievement	PPMA1	0.730	0.86	0.46	0.716	0.88	0.46	0.721	0.87	0.46	0.77
	PPMA2	0.614			0.619			0.615			
	PPMA3	0.635			0.637			0.636			
	PPMA4	0.734			0.729			0.735			
	PPMA5	0.741			0.741			0.742			
	PPMA6	0.644			0.650			0.647			
	PPMA7	0.656			0.669			0.662			

CFA, *confirmatory factor analysis*; C.R, *composite reliability*; AVE, *average variances extracted. The missing items (PSM4, TS5, TS7, TM3, PP5, CHE2, MA3, MA4, MA8) indicate that the standardized factor loadings of those items in the respective models were lower than the cut off (0.4) and were therefore excluded from the analyses*

The standardized factor loadings which represents correlations between individual latent factors and their respective items were between 0.4 and 0.75. For the multivariate and the hierarchical models, standardized factor loadings were considerably high and ranged between 0.5 and 0.8. According to Stucky *et al*. (2014) [58], loadings of small sizes in one model compared to bigger size loading in the other models suggests a multidimensional nature for the construct for a reduced set of factors. In the present study, the univariate model had standardized factor loadings that were small in magnitude compared to the multivariate and the hierarchical models, thus suggesting a multidimensional nature for the SOSDILM as a construct. The composite reliability estimates for all latent factors in each of the four models were above the cut-off of 0.7, and signified that items that loaded onto individual latent factors in the respective models had excellent internal consistency. In the univariate model, five factors had AVEs far below the 50% cutoff (less than 0.4), but that notwithstanding, their C.R values were all relatively high. Regardless of the fact that AVEs for two of the latent factors (peer pressure and classroom/home environment) in all four models in the study did not make the cutoff of 0.5, the majority of the AVEs were significantly greater than 0.40. Irrespective of the fact that not the best possible fits were obtained for the data in all four initially hypothesized models, there however were within the acceptable threshold. In conclusion, the fits statistics indicated that all four hypothesized models offered a reasonable but not a sufficient (or the best) explanation of the data. Following that, any confirmatory question that was asked about the factorial structure of the SOSDILM therefore could be answered statistically as demonstrated in the three models with the multivariate model providing a better fit for the data of the four models (SRMR= 0.0381, RMSEA=0.036, TLI=0.934, CMIN/DF= 1.635, smallest AIC). Under such circumstances it became difficult for the researchers to conclude on the exact structure of the SOSDILM. To that effect a bifactor model analysis was performed (output and loadings not presented) to rescue the situation. The bifactor model was a multidimensional model which hypothesized that nine sub-domain specific factors accounted for much of the unique variance in the items, above and beyond the variance accounted for by a single general factor. Surprisingly, the bifactor model still did not yield any fit indices that were better than those obtained in the four models presented above (CFI=0.926, RMSEA=0.039, CMIN/DF=1.763). Hence there was dire need for a more parsimonious factorial structure (resolved by regression analysis under research question three).

Table 5: Correlations of First Order Factors in the Multivariate Model

Factors	**PSM**	**TS**	**TM**	**PI**	**PP**	**CHE**	**MA**	**KMC**	**PPMA**
PSM	1								
TS	0.609	1							
TM	0.543	**0.923**	1						
PI	**0.784**	0.695	0.714	1					
PP	0.719	0.790	0.731	0.903	1				
CHE	0.678	0.655	0.720	0.805	**0.837**	1			
MA	0.738	0.665	0.631	**0.868**	0.851	0.802	1		
KMC	0.648	0.605	0.588	0.848	0.771	0.771	0.877	1	
PPMA	0.713	0.694	0.661	0.913	0.859	0.809	0.914	**0.938**	1

PSM, *presecondary school myths*; TS, *teaching strategies*; TM, *teaching methods*; PI, *personal interest*; PP, *peer pressure*; CHE, *classroom and home environment*; MA, *mathematics anxiety*; KMC, *knowledge of mathematical concepts*; and PPMA, *perceived prior mathematics achievement*.

Table 5 revealed moderate to very high statistically significant correlations ($0.5<r>0.95$, $p=0.000$) between latent factors in the multivariate model. In particular, very high correlations were found between the following pair of latent factors; teaching strategies and teaching methods, personal interest and mathematics anxiety, peer pressure and classroom/ home environment, and knowledge of mathematical concepts and perceived prior mathematics achievement. Despite very high correlations between the above-mentioned factors in the multivariate model, presecondary school myths did not have the recommended levels of association with other factors (r_{max}=0.784), and that was part of the rationale for initially leaving it as a special hierarchy in a 5-factor hierarchical structure (model was abandoned in favour of the 4-factor hierarchical model due to negative error variances). However, on a conceptual basis it was placed under the cognitive hierarchy. In the 4-factor hierarchical model, second order factors had high to very high correlations with each other (0.7≤r≥0.9).

Table 6: Correlations of 2nd Order Factors in the 4-Factor 2nd Order Model

Factors	AF	CG	CU	EN
AF	1			
CG	0.760	1		
CU	0.760	0.709	1	
EN	0.987	0.927	0.825	1

AF=Affective, CG=Cognitive, CU=Curricular, EN=Environmental

Table 7: Squared Multiple Correlations for the 4-Factor Hierarchical and the 1-Factor Hierarchical Models

Factors	Squared Multiple Correlations		
	4-Factor Hierarchical Model		1-Factor Hierarchical Model
Affective	**MA**	0.857	0.865
	PI	0.881	0.905
Cognitive	**KMC**	0.852	0.805
	PPMA	0.964	0.925
	PSM	0.591	0.600
Curricular	**TS**	0.936	0.585
	TM	0.913	o.570
Environmental	**PP**	0.907	0.869
	CHE	0.773	0.746

Additionally, in the 4-factor hierarchical model (see Fig 3 and Table 7), the affective factor explained 85% and 88% of the variance in mathematics anxiety and personal interest respectively. Moreover, cognitive factors, explained 85%, 96% and 59% of the variances in knowledge of math concepts, perceived prior mathematics achievement, and presecondary school myths respectively. The curricular factor explained 94% and 91% of the variances in teaching strategies and teaching methods respectively, while the environmental factor, explained 91% and 77% of the variance in peer pressure and classroom/home environment respectively.

Research Question Three: Which are the salient and mythical sources of students' difficulties in learning mathematics among secondary schools in Cameroon?

The four models that were initially hypothesized in the study did not provide convincing fit indices for the data for a valid factorial structure for the SOSDILM. To classify the SOSDILM, a multivariate regression analysis of nine factors was performed. In this analysis, the datasets for each of the nine factors were utilised as predictor variables while students' scores of the regional mock for mathematics for three consecutive years (2020-2022) were utilised as the response variable data set. To begin, a forward stepwise regression was first performed to identify the most useful set of predictors of mathematics performance. This resulted in the selection of the combination of variables that best explained the changes in students' performance. Out of the nine variables, four variables consisting of presecondary school myths, personal interest, mathematics anxiety, and perceived prior mathematics achievement, were found to be the most useful set of contributors and were then selected and retained. In addition, as a stepwise criterion, these variables were selected in steps based on p-values less than or equal to 0.05. Those with p-values greater than 0.05 were removed from the finalized model. Following the selection, a multivariate regression analysis of four predictor variables and students' scores of the regional mock examination for mathematics as the response data set was performed. The model summary, model fit, and the regression weights for the associations were presented in the tables below.

Table 8: Regression Model Summary

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.698[a]	.487	.482	18.16240
a. Predictors: (Constant), PPMA, PSM, MA, PI				

Table 9: Model Fit

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	142151.161	4	35537.790	107.732	.000[b]
	Residual	149762.320	454	329.873		
	Total	291913.480	458			
a. Dependent Variable: MSCORES						
b. Predictors: (Constant), PPMA, PSM, MA, PI						

Table 10: Regression Weights for Model Predictors

Coefficients[a]									
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Correlations**		
		B	**Std. Error**	**Beta**			**Zero-order**	**Partial**	**Part**
1	(Constant)	-12.236	3.802		-3.218	.001			
	PSM	.144	.071	.095	2.020	.044	.519	.094	.068
	PI	.253	.079	.206	3.191	.002	.642	.148	.107
	MA	.282	.084	.177	3.369	.001	.601	.156	.113
	PPMA	.422	.086	.303	4.908	.000	.656	.224	.165
a. Dependent Variable: Regional Mock Mathematics Scores									

Findings from the model summary table above (Table 8) revealed that presecondary school myths, personal interest, mathematics anxiety, and perceived prior mathematics achievement were significant predictors of mathematics performance. Together, the four predictors accounted for 48.7% of the variance in mathematics performance. The regression model revealed a good fit for the data (F(4, 454)=[107.732], p=0.00). In addition, given that all p-values for the effect of each predictor variable on mathematics performance were below the cut off value of 0.05, the null hypotheses were all rejected and it was concluded that all four predictors individually had statistically significant effects on mathematics performance. The variables were then sorted according to the sizes of their regression weights and classified as valid sources of difficulties in learning mathematics. The valid sources of difficulties in learning mathematics for secondary school students in Cameroon were classified from the most to the least salient as follows; perceived prior mathematics achievement (.422), personal interest (.253), mathematics anxiety (.282), and presecondary school myths (.144). The results provided evidence of convergent validity given that weak positive relationships were found between individual salient sources and mathematics performance. Moreover, prior to performing a stepwise regression to narrow the factors to a useful set of predictors, multivariate analysis of all nine factors and mathematic performance had revealed that all nine predictors accounted for 49.1% of the variance in mathematics performance. This revealed that the set of five factors eliminated by the stepwise regression analysis were non-salient SOSDILM (teaching methods, teaching strategies, knowledge of mathematical concepts, peer pressure, and classroom/home environment) given that they only accounted for 0.4% of the variance in mathematics performance. Furthermore, comparing this value (0.4%) with that from the four salient sources of difficulties which accounted for the bulk of the variance (48.7%) revealed that the five discarded factors were the most salient mythical reinforcers of mathematics being a difficult academic discipline to learn (invalid sources) in secondary schools in Cameroon.

Finally, the classification of the SOSDILM could only be finalized if and only if the valid and invalid factors could separately produce factorial structures with parsimonious fit indices. Following this, as a final confirmatory step, two new models (salient and mythical models) consisting of; a 4-factor 1st order (salient) model, as the set of valid sources of students' difficulties in learning mathematics, and a 5-factor 1st order (mythical) model, as the set of mythical sources of students' difficulties in learning mathematics, were then generated. The goal was to fit the hypothesized new models. In other words, the arrangements (measurement and structural) of factors in the new models had to be proven reliable and correctly specified if and only if the two new models produced parsimonious fits for the data (CMIN/DF<3, CFI≥0.95, RMSEA<0.05). After that was done, fit indices were improved significantly in both models. The best fits were obtained for both new models.

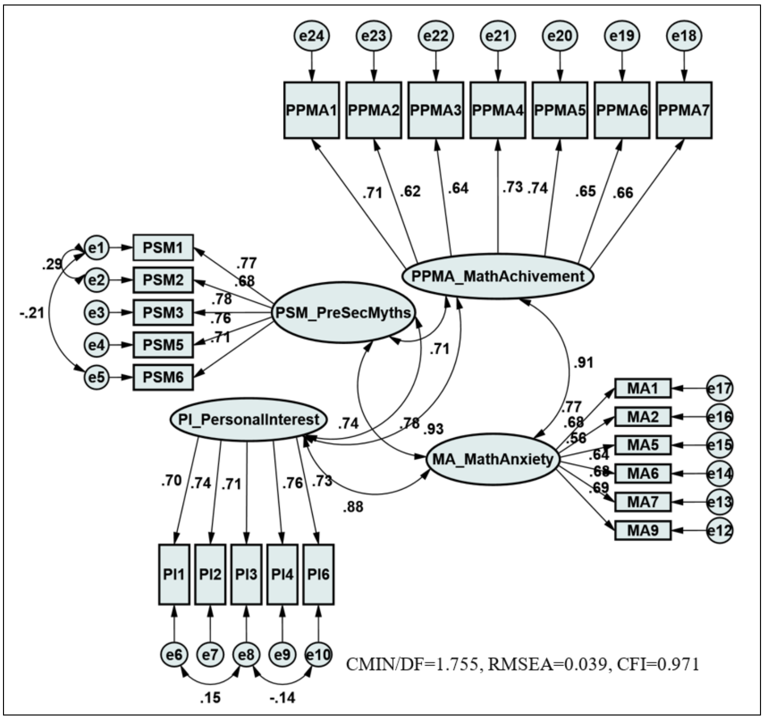
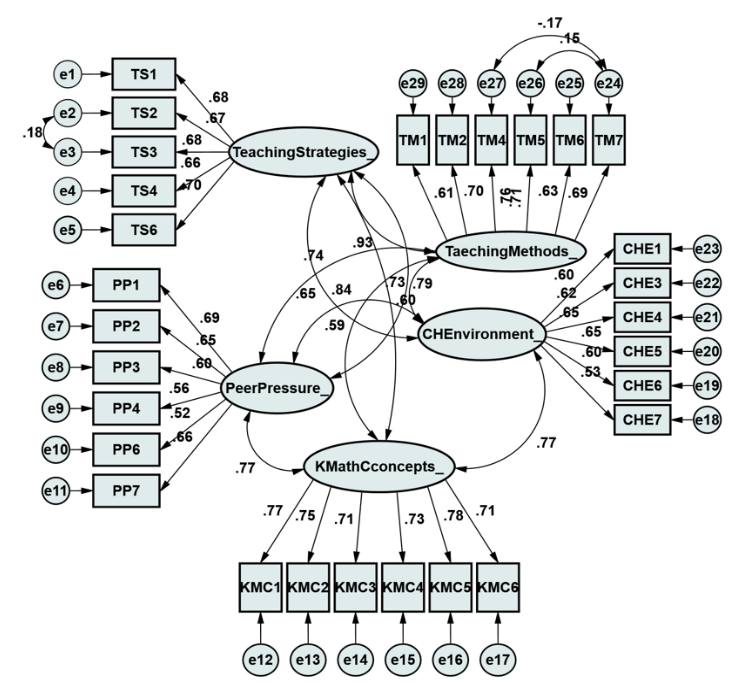


Fig 4: Results Output for the Salient Model (Valid SOSDILM)



CMIN/DF=1.770, RMSEA=0.039, CFI=0.954

Fig 5: Results Output for the Mythical Model (Mythical SOSDILM)

The results from the analyses outputs for both the salient and the mythical models revealed that the categorisation of the two models and the structural arrangement of factors in each of the two models were indeed correct. The results confirmed that; perceived prior mathematics achievement, personal interest, mathematics anxiety, and presecondary school myths were valid and most salient SOSDILM, while teaching methods, teaching strategies, knowledge of mathematical concepts, peer pressure, and classroom/home environment were mythical SOSDILM. The standardized factor loadings, AVEs, C.Rs, and model fit indices for both models were presented in the tables below.

Table 11: Standardized Factor Loadings, Average Variances Extracted, Composite Reliability and Model Fit Indices for the Salient and Mythical Models

		Salient Model: 4-Factor 1st Order Model					Mythical Model: 5-Factor 1st Order Model		
Salient Factors	**Items**	**Standardized CFA Loadings**	**C.R**	**AVE**	**Mythical Factors**	**Items**	**Standardized CFA Loadings**	**C.R**	**AVE**
Presecondary School Myths	PSM1	0.766	0.80	0.55	**Teaching Strategies**	TS1	0.676	0.68	0.46
	PSM2	0.684				TS2	0.665		
	PSM3	0.779				TS3	0.685		
	PSM5	0.764				TS4	0.660		
	PSM6	0.705				TS6	0.700		
Personal Interest	PI1	0.696	0.79	0.53	**Teaching Methods**	TM1	0.608	0.71	0.47
	PI2	0.739				TM2	0.698		
	PI3	0.713				TM4	0.762		
	PI4	0.765				TM5	0.706		
	PI6	0.731				TM6	0.627		
Mathematics Anxiety	MA1	0.767	0.77	0.50		TM7	0.689		
	MA2	0.676			**Peer Pressure**	PP1	0.693	0.79	0.48
	MA5	0.564				PP2	0.652		
	MA6	0.636				PP3	0.599		
	MA7	0.676				PP4	0.562		
	MA9	0.691				PP6	0.524		
Prior Mathematics Achievement	PMA1	0.714	0.81	0.56		PP7	0.659		
	PMA2	0.618			**Classroom and Home Environment**	CHE1	0.601	0.78	0.47
	PMA3	0.637				CHE3	0.621		
	PMA4	0.734				CHE4	0.650		
	PMA5	0.744				CHE5	0.655		
	PMA6	0.649				CHE6	0.595		
	PMA7	0.661				CHE7	0.528		
					Knowledge of Mathematical Concepts	KMC1	0.773	0.62	0.55
						KMC2	0.745		
						KMC3	0.711		
						KMC4	0.732		

						KMC5	0.783		
						KMC6	0.707		

The table above details the quality of measurement and standardized factor loadings for every factor and item in the salient and mythical models respectively. Most AVEs in the mythical model did not make the cutoff of 0.5. That however was not problematic since they were all closed to 0.5 and in addition, the corresponding C.R values were high. The salient and the mythical models had best fits for the data. Fit indices for the salient model were as follows; CMIN/DF=1.755, RMSEA=0.039, CFI=0.971. The fit indices for the mythical model also showed best fit for the data with the following values; CMIN/DF=1.770, RMSEA=0.039, CFI=0.954.

Table 12: Finalized Model Fit Indices for the Salient and Mythical Models

Fit Index Category	Model Fit Index	Salient Model: 4-Factor 1st Order Model	Mythical Model: 5-factor 1st Order Model	Cut off Values Best Fit
Absolute Fit Indices	CMIN	386.173	644.344	-
	DF	220√	364√	>1
	P	0.000	0.000	>0.05
	SRMR	0.0323√	0.0381√	<0.05
	RMSEA	0.039√	0.039√	<0.05
	GFI	0.937√	0.914√	>0.9
	AGFI	0.921√	0.900√	>0.9
Incremental Fit Indices	CFI	0.971√	0.954√	>0.95
	TLI	0.966√	0.950√	>0.95
Parsimonious Fit Indices	PNFI	0.813√	0.807√	>0.5
	CMIN/DF	1.755√	1.770√	<3
	AIC	498.173	786.344	
Decision		**Best Fit: Accepted√**	**Best Fit: Accepted√**	

Discussion

The thematic analyses of interview transcripts revealed nine sub-themes as supposed sources of difficulties in learning mathematics for secondary school students in Cameroon. The findings of the present study supported findings by Gafoor and Kurukkan (2015) [24]. They also utilised mixed methodology for a sample consisting of 200 students and 14 teachers, and established that teaching strategies, personal interest, and knowledge of mathematical concepts were main sources of difficulties involve in the learning of mathematics. In addition, the findings from the present study also supported findings by Acaharya (2017), who established that sources of difficulty in learning mathematics for students consisted of teaching strategies, teaching methods, math anxiety, and school/home environment. Moreover, findings from the present study equally supported findings from several other studies including; Sakilah *et al.* (2017); Jega *et al.* (2019) [28]; Guner (2020) [26]; Bhusal (2021) [10]; Bringula *et al.* (2021); and Kauffmann and Ryve (2022). The methodology utilised in the present study in classifying SOSDILM, was similar to that utilised by Sugilar and Achmad (2020). The authors classified SOSDILM according to the regression weights from the association between sources and mathematics performance. In terms of the study's statistical method of data analysis, the findings from the present study supported findings by Rameli and Kosnin (2017) [48] who also utilised a data validation measurement model to establish a similar 5-factor 1st order model to be the most parsimonious for SOSDILM. Furthermore, the findings also supported those of Safiih and Azreen (2016) [53]. They utilised a correlated CFA model of 4-factors and established that motivation, teacher's role, attitudes, and self-confidence were salient predictors of students' difficulties in learning mathematics. Contrary to the findings of the present study which found that the 4-factor 1st order was the most parsimonious model for the data, Sugilar and Achmad found a hierarchical model (1-factor 2nd order) to be the most parsimonious for SOSDILM. In the present study however, the univariate, multivariate, 1-factor hierarchical, 4-factor hierarchical, and the bifactor models all had acceptable but not the best fits for the data. Finally, the present study, set a precedence by establishing that other than the 1-factor hierarchy of Sugilar and Achmad for SOSDILM, a 4 factors hierarchy also exist with acceptable fit for the data on the SOSDILM.

Conclusion

Contrary to students' claims, teaching methods, teaching strategies, knowledge of mathematical concepts, peer pressure, and classroom/home environmental factors proved not to be reliable sources of students' difficulties in learning mathematics. This have serious implications for social representation, given that myths surrounding mathematics learning are constructed early in primary education, and as a consequence, pupil transition into secondary education already imagining, thinking and talking negatively about mathematics. In addition, students' prior performances appear to be strongly associated with future performances. There are implications for the expectancy-value theory of achievement emotions, in that students' emotions for failure or success and the value which they attach to the knowledge influences future performance. Finally, finding regarding personal factors including personal interest and mathematics anxiety have implications for performance in that each time students encounter the subject or specific learning situations in the subject, anxiety occupies attentional resources, leading to frustration. Subsequently, students worry, and resent their mathematics experiences which negatively affect mathematics learning and performance.

Recommendations

Firstly, the cronbach alpha values, composite reliability coefficients, and the average variances extracted (see tables 4 & 11) by all latent factors especially in the four initialized models revealed good measurement quality for the Q-SOSDILM. Secondly, an ancillary bifactor analysis of the instrument revealed a unidimensional internal structure for the Q-SOSDILM (Explained Common Variance=0.751, Percentage of Uncontaminated Correlations=0.909) making the instrument a reliable scale for measuring overall sources of difficulties in learning mathematics for any group of secondary school students. Thirdly, given that, both Creswell (2014) [15] and Shiyanbola *et al.* (2021) [57] amongst others, highly recommends the exploratory sequential design utilised in the present study as the best strategy to develop and adapt a questionnaire; the researchers therefore recommend the use of the Q-SOSDILM by classroom teachers of mathematics in identifying sources of students' difficulties in learning mathematics. In addition, the findings indicate that students benefit from not just situational but personal interest in learning mathematics given that students' performances improved as their interest in the subject surged. It was recommended that teachers should keep students motivated in learning mathematics and should consistently encourage curiosity, and build and grow students' interest for the reason that sufficient evidence exist supporting the fact that interest deepens with increasing participation and is significantly positively impacted by achievement (Azmidar *et al*., 2017; Eriksson, 2020) [8, 19]. Moreover, the study revealed that students' performance improved with improvement in prior mathematics performance. This implies that students' expectancy for success and the value they place on knowledge contribute to positive achievement and learning trajectories" (Wigfield, 1994, p. 49; Middleton *et al*., 2013, p.2) [61, 41]. It was recommended that teachers should vary assessment strategies and rely on scores from various assessment instruments so as to break the cycle of failure for poorly performing students. This will lead to attitude change towards the subject. Furthermore, it has been shown that students' poor performances in mathematics leads to mathematics anxiety (Tobias, 1986); it was recommended that teachers should help students to actively construct knowledge on their own by introducing scaffolds when necessary which make learning in mathematics to be interesting, interactive and meaningful. Given that presecondary school myths among students were a significant predictor of mathematics performance, the researchers recommend that teachers should develop interventions targeting students' mindsets so that attitudes towards the subject and in specific learning situations in the subject can be improved. Finally, the AVEs for most factors in the initial four models, and in the mythical model were below the cutoff value of 0.5, which according to Fornell and David (1981) [22], still indicates that the convergent validity is reliable as long as the AVEs are close to 0.5 and the C.Rs are above 0.6 (which was the case in this study), the researchers however noted that and recommends that replication is needed in the study so as to further ascertain the validity of the constructs.

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