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Predicting Math Anxiety: A Multidimensional Analysis of Psychological, Attitudinal, and Contextual Factors

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Abstract: Math anxiety is a multidimensional phenomenon shaped by cognitive, attitudinal, and emotional factors. While traditional research has predominantly relied on linear models to explain its predictors, recent work points to non-linear, dynamic, and reciprocal relationships between psychological, attitudinal, and demographic variables. There remains a notable gap in large-scale, cross-cultural research that systematically compares the relative influence of these factors using advanced, comparative modelling techniques. This study addresses that gap by conducting a quantitative analysis of data from the SMARVUS dataset, a large-scale international survey of 12,570 university students across 100 institutions in 35 countries. The dataset includes validated measures of statistics anxiety, test anxiety, trait anxiety, social interaction anxiety, and self-efficacy, as well as demographic information such as gender, age, learning difficulties, and academic background. Using both Ordinary Least Squares and logistic regression models, the study pursues two aims: (1) to examine the relative contribution of individual and contextual factors to math anxiety, and (2) to identify the strongest predictors of elevated math anxiety in university populations. Results show that psychological and attitudinal variables, particularly statistics anxiety, test anxiety, creativity anxiety, and intolerance of uncertainty, outweigh demographic factors in predicting math anxiety. These findings position math anxiety as primarily rooted in students' emotional and cognitive responses to learning environments. The study concludes that effective interventions should prioritise fostering resilience, self-efficacy, and emotional safety, reframing math anxiety as a modifiable experience rather than an immutable trait.

Keywords: Math Anxiety, Predictors, Cross-Cultural Analysis, Regression Modelling.

1. Introduction

Math anxiety, typically defined as a feeling of tension, apprehension, or fear that impairs numerical processing and problem-solving [1], is a global educational concern affecting individuals across age groups and cultural contexts. It disrupts both academic engagement and everyday tasks requiring mathematical reasoning. Recent international assessments, such as PISA, have highlighted the prevalence of math anxiety worldwide [2]. In the UK, over one-third of adults (35%) report math anxiety, with one in five (20%) experiencing physical symptoms like nausea [3]. In the United States, 20–25% of children face moderate to high levels of math anxiety [4], reflecting its cross-generational and global reach.

The consequences of math anxiety extend well beyond transient discomfort. It is strongly associated with avoidance of math-related tasks, diminished academic performance, and impaired problem-solving [5]. This can lead to a negative cycle in which anxiety undermines performance, further increasing anxiety and diminishing confidence [6][7]. Delays in building foundational skills can impair arithmetic fluency and hinder numeracy-based decision-making in everyday contexts [8].

Concerningly, math anxiety narrows students' educational and occupational trajectories, often deterring them from pursuing STEM fields and diminishing access to economic mobility [9]. Adults with high math anxiety may struggle with everyday numeracy tasks such as budgeting or financial planning, affecting long-term economic stability [10]. In an era of expanding digital economies, high math anxiety may marginalise individuals from roles requiring data literacy and quantitative reasoning [7][2].

Math anxiety also intersects with structural inequalities. Evidence suggests it disproportionately affects students from disadvantaged backgrounds, reinforcing educational inequalities [5][11]. These findings signal the need for interventions that do not merely treat math anxiety as an individual pathology, but address it as a socio-cognitive and emotional phenomenon rooted in lived educational experiences [7].

2. Research Objectives

Math anxiety is increasingly recognized as a multidimensional construct shaped by cognitive, emotional, and contextual factors. However, traditional research has oversimplified its dynamics by focusing on linear, unidirectional frameworks [9]. Emerging evidence highlights non-linear interactions: moderate math anxiety can enhance performance in motivated students, while high or low anxiety impairs it-a curvilinear pattern [12] linked to neurochemical processes influencing attention and cognitive control [5]. Furthermore, math anxiety interacts bidirectionally with academic performance, creating self-reinforcing cycles of avoidance and skill attrition [6][7].

These complexities are further modulated by gender, achievement levels, and contextual settings such as classroom environment versus high-stakes testing [13]. However, most existing models fail to identify categorical risk thresholds critical for timely and targeted intervention. This study addresses these gaps through a dual-modelling approach, hierarchical OLS and logistic regression, to assess both continuous and clinically significant manifestations of math anxiety.

OLS regression is used to analyse math anxiety as a continuous variable, capturing gradations in severity, while logistic regression identifies students at clinically significant levels of math anxiety, aligning with diagnostic thresholds and enabling risk classification [14].

The study is guided by two primary aims:

- ✓ To explore the multidimensional structure of math anxiety by analysing psychological, attitudinal, and contextual factors.
- ✓ To identify key predictors of math anxiety, providing actionable insights for targeted educational interventions.

Two questions guide this research:

Research Question 1: Which groups of variables-psychological, attitudinal, or demographic/contextual-are significantly associated with math anxiety?

- ✓ Research Question 2: Among the individual variables examined, which are most strongly associated with math anxiety?

To answer Research Question 1, OLS regression was used to assess the associations between different groups of variables and variations in math anxiety scores. To address Research Question 2, logistic regression identified the factors most strongly associated with the likelihood of being classified as math-anxious.

3. Literature Review

Math anxiety is commonly defined as a feeling of tension, apprehension, or fear that interferes with math performance in both academic and everyday settings [1]. A large body of research suggests that math anxiety may originate from early difficulties in numerical processing, which then undermine broader mathematical competence. Individuals with high levels of math anxiety often struggle with basic numerical processing, a foundational skill for more advanced mathematical tasks [8]. Psychophysiological evidence further supports this view, showing that math-anxious individuals exhibit reduced event-related potential (ERP) amplitudes during the early stages of numerical processing, suggesting inefficiencies at a fundamental cognitive level [15]. These individuals also tend to display greater numerical distance and size effects, as well as an exaggerated ERP distance effect, suggesting imprecise processing of numerical magnitudes [16]. Accumulation of these early difficulties can lead to broader mathematical underachievement, which in turn increases frustration, avoidance behaviours, and anxiety around mathematical tasks [17]. This process aligns with reciprocal models of math anxiety, in which early struggles with number processing initiate a negative feedback loop: anxiety leads to disengagement, which further weakens skills and reinforces anxiety over time.

While math anxiety was historically framed as a narrow affective reaction to mathematical difficulty, contemporary scholarship conceptualises it as a multidimensional construct shaped by the interaction of psychological, dispositional, and contextual factors [8][18]. Researchers now recognise that math anxiety does not emerge solely from inherent skill deficits, but is co-produced by learners' belief systems, emotional regulation, social environments, and systemic conditions such as assessment culture and stereotype threat [13][19][20]. This review synthesises three key domains that structure current debates: psychological processes (including emotional reactivity and neurocognitive dynamics), dispositional and attitudinal factors (such as self-efficacy and intolerance of uncertainty), and demographic-contextual influences (including gender, learning difficulties, and academic environment). Examining these domains in turn allows for a more nuanced analysis of the mechanisms by which math anxiety develops, persists, and may be mitigated.

3.1. Psychological Factors

Contemporary research increasingly situates math anxiety within broader models of academic anxiety that incorporate emotional, cognitive, and physiological processes. Math anxiety is no longer understood as a uniform affective response, but as a dynamic interplay between anticipatory cognition, emotional reactivity, and performance-related stressors. Ho and c0lleagues argue that math anxiety often begins as anticipatory cognition, where learners mentally simulate failure before the task begins [20]. This aligns with expectancy-value theory [21], which posits that learners' beliefs about their ability and the value of success shape engagement and emotional responses. In this view, math anxiety is not merely a reaction to difficulty but a learned emotional response grounded in perceived self-efficacy and prior experience.

Emotionally, math anxiety manifests as apprehension, fear of failure, and worry, while physiologically, it involves heightened autonomic arousal-such as increased heart rate, muscle tension, and even nausea [18]. These symptoms not only impair concentration but may also function as aversive conditioning stimuli, reinforcing task avoidance [22]. This echoes dual-process theories of anxiety, in which the automatic (emotional) and controlled (cognitive) systems interact to either mitigate or exacerbate perceived threats [23].

The transactional model of anxiety offers a foundational lens to understand how anxiety unfolds in academic contexts. The sequence begins with perceived threat, followed by physiological arousal, cognitive reappraisal (often characterised by self-doubt and worry), and finally behavioural responses, including avoidance, procrastination, or excessive reassurance-seeking [24]. What distinguishes math anxiety, however, is the degree to which it activates maladaptive coping, particularly task avoidance, even among otherwise high-achieving students [14].

This psychological vulnerability is further compounded by deficits in working memory capacity, a critical cognitive resource for mathematical problem-solving. Ashcraft and Krause demonstrate that anxious students often engage in intrusive, self-deprecating thoughts during math tasks, which reduce working memory bandwidth and directly interfere with performance [25]. More recently, Pizzie and colleagues have shown that math anxiety can impair executive functioning, especially inhibition and task-switching, essential for higher-order reasoning [26].

Neuroscientific findings further underscore the psychological intensity of math anxiety. Even anticipating math tasks activates regions of the brain associated with pain perception and social threat, including the insular cortex and amygdala [27]. This supports the view that math anxiety is emotionally encoded as threat, and that interventions must address not only cognitive skill gaps but also the deep affective encoding of mathematics as a domain of fear.

3.2. Attitudinal and Cognitive-Affective Factors

Dispositional and attitudinal factors, including self-efficacy, motivation, and attitudes toward mathematics, are key to the development and persistence of math anxiety [12]. These internal dispositions shape how individuals interpret mathematical experiences and respond to challenges, often amplifying or mitigating anxiety over time.

Self-efficacy, or the belief in one's ability to succeed in specific tasks, is consistently linked to math anxiety. Grounded in social cognitive theory [28], self-efficacy not only predicts academic achievement but also moderates emotional responses to perceived difficulty. This relationship appears to be bidirectional: anxiety undermines performance, which in turn reduces self-efficacy, creating a feedback loop of avoidance and low confidence [5]. Interventions that focus exclusively on cognitive remediation without addressing underlying beliefs about competence are unlikely to yield sustainable improvements.

Beyond self-efficacy, students' broader attitudes toward mathematics-including enjoyment, perceived utility, and sense of competence-significantly shape their vulnerability to math anxiety [29][30]. The Interpretation Account of Math Anxiety [31] suggests that students who view previous struggles as evidence of fixed inadequacy are more likely to develop persistent anxiety. These interpretive habits are shaped by both internalised beliefs and external reinforcement, indicating that attitudinal interventions must be situated within wider social learning contexts.

Achievement goal theory adds further nuance to this picture by distinguishing between mastery-oriented and performance-oriented goal structures [32]. Students with performance-avoidance goals, primarily motivated by fear of failure or embarrassment, are more likely to experience debilitating anxiety in evaluative math contexts [33]. In contrast, mastery-oriented students, who seek personal growth and conceptual understanding, tend to exhibit greater resilience in the face of difficulty [34]. Interventions that shift goal orientations from performance-based to mastery-focused can substantially reduce math anxiety by reframing mistakes as part of the learning process rather than as threats to self-worth.

Two additional constructs, Intolerance of Uncertainty (IU) and Fear of Negative Evaluation (FNE), have recently emerged as potent predictors of math anxiety. IU refers to an individual's discomfort with ambiguity and unpredictability, and is especially salient in mathematical domains involving probabilistic reasoning or open-ended tasks [35]. Students high in IU are more likely to experience cognitive overload, worry, and disengagement in tasks lacking a single clear solution [36]. IU also interacts with metacognitive beliefs, particularly the perception that anxiety itself is dangerous or unmanageable, which can exacerbate emotional responses [37].

FNE captures a distinct yet related social vulnerability: the fear of being judged negatively in academic contexts. This concern amplifies math anxiety by heightening self-consciousness, particularly during assessments or public problem-solving [38]. The effect is moderated by achievement goals, with FNE exerting greater influence on students who prioritise external validation over intrinsic understanding [39]. Together, IU and FNE extend our understanding of math anxiety beyond internal deficits to encompass students' social-emotional orientation toward learning environments.

3.3. Demographic and Contextual Factors

Although psychological and dispositional factors account for much of the variance in math anxiety, demographic and contextual influences shape how these internal experiences are formed, sustained, and expressed [40]. Demographic characteristics such as gender, socio-economic background, and specific learning difficulties intersect with contextual elements, educational systems, teaching practices, assessment formats, and cultural norms, to create distinct pathways to math anxiety. Understanding these intersections is key to designing interventions that are both equitable and effective.

Gender remains one of the most widely studied correlates of math anxiety, with a consistent pattern showing that girls and women report higher levels of anxiety than their male peers, despite equivalent or superior performance in many contexts [41][42]. This disparity is often attributed to stereotype threat, the fear of confirming negative stereotypes about one's social group, which can impair working memory and exacerbate physiological arousal [43]. Female students may also internalise math-anxious behaviours modelled by teachers or parents, particularly when adult role models hold traditional gender beliefs [44]. Crucially, however, the gender gap in math anxiety is not universal. Cross-national studies reveal that in countries with greater gender equality in education and employment, gender differences in math anxiety are significantly reduced or absent [7]. This suggests that observed gender effects are not biologically determined but mediated by social expectations and institutional norms.

Educational systems and classroom practices also play a pivotal role in modulating math anxiety. Pedagogical approaches that emphasise high-stakes testing, time pressure, and competitiveness tend to increase students' anxiety, particularly among high achievers and those with a strong fear of failure [45]. For instance, South Korean students rank among the highest in math achievement globally but also report some of the highest levels of math anxiety [2]. This paradox illustrates how achievement-oriented educational systems, while academically rigorous, can foster climates of fear and perfectionism that undermine emotional well-being.

In contrast, constructivist and mastery-oriented environments, which value process over performance and encourage collaboration, tend to buffer against anxiety by creating psychological safety and reframing failure as a learning opportunity [46][47]. The implication is that contextual design matters as much as content in shaping students' affective experiences of math. Yet even within relatively supportive systems, inequities in access to high-quality instruction, positive role models, or culturally relevant pedagogy can produce anxiety disparities, especially for marginalised learners [48].

Intersectionality further complicates these relationships. Demographic categories such as gender, learning difficulties, and cultural background do not operate independently but interact to produce compounded vulnerabilities. For example, a bilingual female student with undiagnosed dyscalculia may simultaneously face stereotype threat, linguistic barriers, and cognitive load, resulting in heightened emotional distress during math tasks [49]. However, most quantitative studies, including those using the SMARVUS dataset, collapse such complexities into binary or categorical variables, obscuring nuanced dynamics [50]. More granular research is needed to examine how overlapping identities and systemic barriers shape the lived experience of math anxiety.

Language and learning differences are particularly underexplored contextual variables. Linguistic challenges, such as unfamiliar terminology in word problems or the cognitive cost of switching between languages, can exacerbate anxiety, particularly for bilingual and multilingual students [51]. For bilingual students, solving math problems in a second language significantly slows reaction times, with an average of 9.83 seconds in English compared to 6.81 seconds in their native language [52].

Academic majors also significantly influenced anxiety patterns. Students in math-heavy fields such as Statistics and Applied Mathematics report higher anxiety, particularly in testing and problem-solving contexts, whereas students in disciplines like Social Sciences or Arts report lower anxiety, likely due to less exposure to high-stakes math assessments [53].

Finally, students with specific learning difficulties (SpLDs), such as dyscalculia or ADHD, are especially prone to math anxiety. Approximately 17% of students with dyscalculia report severe anxiety symptoms [54]. These students often experience repeated academic failure, delayed skill acquisition, and negative teacher feedback, which together erode self-efficacy and reinforce avoidance [54]. Importantly, the relationship between SpLDs and math anxiety is not deterministic; rather, it is shaped by how institutions accommodate or stigmatise differences [55]. Universal Design for Learning and targeted interventions can buffer these effects, but such supports are unevenly distributed across schools and higher education systems.

4. Methodology

4.1. The SMARVUS Dataset

This study draws on secondary data from the SMARVUS project, an international, multi-centre study of statistics and mathematics anxieties and related psychological variables among university students [56]. The SMARVUS dataset includes survey responses from 12,570 students across 100 universities in 35 countries, with data collected in 21 languages between January 2021 and September 2021. Participants ranged in age from 18 to 67, with a majority identifying as female (66%) and reporting no learning differences (71.8%). Most respondents were first-year university students, and psychology was the most frequently reported major (69.7%).

Data were collected through an online cross-sectional questionnaire administered through participating universities. For the purposes of this study, only the ‘student survey’ component of the SMARVUS dataset was utilised.This portion contains students’ responses on a range of variables, including statistics anxiety, mathematics anxiety, test anxiety, trait anxiety, and social interaction anxiety. It also includes demographic information such as age, gender, ethnicity, learning difficulties, and academic background.

The SMARVUS dataset’s scale, diversity, and multidimensionality make it a uniquely valuable resource for investigating the predictors and correlates of math anxiety in university students, while also providing opportunities for robust cross-cultural and cross-linguistic analyses.

4.2. Secondary Data Analysis

Secondary data analysis refers to the re-examination of existing datasets,often to address new research questions, extend prior analyses, or critically reassess methodological approaches [57]. This method offers several advantages. The use of large-scale quantitative data enhances the methodological rigour of social science research. Secondary analysis also enables researchers to conserve time and resources by accessing high-quality datasets, allowing greater focus on theoretical and substantive questions rather than data collection logistics [58].

However, secondary data analysis also presents limitations, particularly the lack of control over the original data collection process. Potential concerns include sampling biases, missing or incomplete data, and measurement inconsistencies [59]. Additionally, the original aims of data collection may not fully align with the secondary researcher’s questions, potentially limiting the scope of inquiry [60]. As a result, rigorous evaluation of dataset quality, relevance, and suitability is essential.

4.3. Ethics

The SMARVUS dataset was collected in accordance with the British Psychological Society’s Code of Human Research Ethics (2018) [61]. Ethical approval was granted by the Sciences & Technology Cross-Schools Research Ethics Committee at the University of Sussex (approval number: ER/JLT26/7). Partner universities operated under this central approval, with data protection agreements in place for institutions providing academic grade data to ensure compliance with privacy regulations.

To protect confidentiality, raw identifiable data were accessible only to principal investigators. For wider sharing, personal identifiers were replaced with randomly generated IDs. Additional anonymisation steps included categorising demographic data, re-coding gender identities and learning difficulties, and fully removing ethnicity data to prevent re-identification. These procedures are documented in the dataset’s codebook and processing notes [56].

4.4. Measures and Variables

Mathematics anxiety was assessed using the Modified Shortened Mathematics Anxiety Rating Scale (STARS-M) [56], an adaptation of the Revised Mathematics Anxiety Rating Scale (R-MARS) [62]. The STARS-M captures three distinct dimensions of math anxiety: mathematics test anxiety, numerical task anxiety, and mathematics course anxiety. Participants rated their anxiety on a five-point Likert scale (1 = no anxiety to 5 = a great deal of anxiety) in response to various math-related scenarios.

STARS-M was selected for its demonstrated reliability and contextual relevance in university settings. Adaptations included replacing domain-specific terms (e.g., "statistics coursework") with general mathematics language while preserving the structure and scoring of R-MARS for comparability. Exploratory factor analyses confirmed the validity of the adapted scale, with refinements made to the numerical task anxiety dimension [56].

Demographic variables were systematically coded for statistical modelling. Degree major was dichotomised (1 = math-related; 0 = non-math-related), gender was numerically coded (1 = male; 2 = female), and specific learning difficulties (e.g., ADHD or dyslexia) were coded as binary variables (1 = present; 0 = absent). Country and language were dummy-coded with binary indicators for each group.

Predictors included the following standardised measures:

- ✓ Statistics Anxiety: Measured with the Statistics Anxiety Rating Scale (STARS) [63], including three subscales: test/class anxiety (8 items), interpretation anxiety (11 items), and fear of asking for help (4 items). Rated from 1 (no anxiety) to 5 (a great deal of anxiety).
- ✓ Trait Anxiety: Assessed using the trait subscale of the State Trait Inventory for Cognitive and Somatic Anxiety (STICSA) [64], containing 10 cognitive and 11 somatic

symptom items, rated from 1 (not at all) to 4 (very much so).

- ✓ Test Anxiety: Measured using the Revised Test Anxiety Scale (RTAS) [65], covering worry (7 items), tension (6), irrelevant thinking (5), and bodily symptoms (7). Rated from 1 (almost never) to 4 (almost always).
- ✓ Fear of Negative Evaluation: Measured by the Brief Fear of Negative Evaluation Scale: Straightforward (BNFE-S) [66], an 8-item scale rated from 1 (not at all characteristic) to 5 (extremely characteristic).
- ✓ Social and Performance Anxiety: Assessed with the Liebowitz Social Anxiety Scale: Self Report (LSAS-SR) [67], with 12 items for each construct, rated from 0 (not at all) to 3 (very much so).
- ✓ Creativity Anxiety: Measured by the Creativity Anxiety Scale [68], consisting of 8 creativity-related and 8 non-creativity items, rated from 0 (not at all) to 4 (very much).
- ✓ Intolerance of Uncertainty: Measured using the IUS–Short Form [69], with 12 items across two subscales, rated from 1 (not at all characteristic) to 5 (entirely characteristic).
- ✓ Self-Efficacy: Measured with the New General Self Efficacy Scale (NGSE) [29], an 8-item scale rated from 1 (strongly disagree) to 5 (strongly agree).
- ✓ Persistence: Measured using the persistence subscale of the Attitude Towards Mathematics Survey (ATMS) [70], 8 items rated from 1 to 5.

Responses were grouped by scale and mean scores were calculated. Missing data were handled by computing scale means based on available responses. All analyses were conducted in Python using standard statistical libraries.

4.5. OLS Regression

To address Research Question 1, which examines which categories of factors-psychological, attitudinal, or demographic/contextual-are significantly associated with math anxiety, Ordinary Least Squares (OLS) regression was employed. OLS regression was selected because it is appropriate for modelling continuous outcome variables, enabling the estimation of relationships between predictors and math anxiety scores. A hierarchical regression approach was used, entering variables in three sequential blocks corresponding to psychological, attitudinal, and demographic/contextual factors. This stepwise method allows for the evaluation of the incremental contribution of each group of variables to the explained variance in math anxiety.

The formula for Model1 will be:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon$$

Where:

Y is the Math Anxiety score (continuous dependent variable)

β_0 is the intercept

$\beta_1, \beta_2, \beta_3, \beta_4$ are the regression coefficients for the psychological factors:

X_1 = Social Anxiety Scale (LSAS-SR)

X_2 = Creativity Anxiety Scale

X_3 = Revised Test Anxiety Scale (R-TAS)

X_4 = Statistics Anxiety Rating Scale (STARS)

ϵ is the error term.

Model 1 examines the contribution of psychological factors to math anxiety, reflecting their established significance in the existing literature. Model 2 adds attitudinal factors to the model, namely, Self-Efficacy, Intolerance of Uncertainty, Fear of Negative Evaluation, and Attitude Towards Mathematics. Model 3 further incorporates demographic and contextual variables, including Degree Major, Country, Language, Specific Learning Difficulties, and Gender.

4.6. Logistic Regression

To address Research Question 2, which aims to identify key predictors of math anxiety, students were classified as either "anxious" or "non-anxious" based on whether their scores exceeded one standard deviation above the sample mean. Using this criterion, 6,196 of 12,570 students (49.27%) across 43 universities were classified as math-anxious.

Logistic regression was employed to model this binary outcome. Unlike OLS, which treats anxiety as a continuous variable, logistic regression estimates the probability of being math-anxious based on individual predictors. It also provides odds ratios, which indicate how each variable increases or decreases the likelihood of anxiety. Combined with the earlier OLS models, this dual approach improves methodological precision by aligning analysis with outcome type, continuous versus categorical, and enables both broad pattern detection and targeted risk profiling for intervention development.

The logistic regression model used to predict a student's math anxiety is expressed by the following equation:

$$log\left(\frac{r_1}{1-r_1}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p$$

Where:

r_1 is the probability that student I has math anxiety.

β_0 is the intercept.

β_p represents the regression coefficients for the predictor variable p.

X_p represents the individual predictors (e.g. demographic, cognitive, attitudinal factors .)

5. Results

5.1. Descriptive Analyses

The frequency distribution of math anxiety (MA) across key demographic groups is presented in Table 1. Across academic disciplines, psychology students represented the largest proportion of the sample, with 4,495 students classified as math-anxious and 4,264 as non-anxious. Math majors constituted the smallest group, with 80 students identified as anxious and 73 as non-anxious. Other fields, including Arts and Humanities and Business and Finance, exhibited relatively modest distributions of math-anxious and non-anxious students. Overall, while some variation was observed, the prevalence of math anxiety appeared relatively consistent across disciplines, with the dominance of psychology majors reflecting the broader sample composition.

Gender differences in math anxiety frequencies were notable. Among females, 4,482 were classified as math-anxious compared to 761 males and 52 non-binary individuals. These findings suggest a pronounced gender disparity, with females reporting higher rates of math anxiety than males and other gender groups.

Students with specific learning difficulties (SpLDs) demonstrated elevated levels of math anxiety. In particular, students with ADHD or ADD reported 190 anxious cases compared to 163 non-anxious cases. Students with dyscalculia similarly showed a higher prevalence of math anxiety (50 anxious versus 16 non-anxious). Although other SpLD categories had lower frequencies overall, individuals with diagnosed learning difficulties consistently reported higher anxiety levels, especially those with impairments in numerical processing.

Variation in math anxiety prevalence was also observed across countries and language groups. In Canada, 635 students were classified as math-anxious compared to 351 non-anxious students, and in Australia, 185 were anxious compared to 130 non-anxious. In contrast, countries such as Egypt and England reported higher numbers of non-anxious students. Language group comparisons showed that English-speaking students comprised the largest group, with 3,212 math-anxious and 2,215 non-anxious students. Arabic speakers (484 anxious vs. 1,006 non-anxious) and German speakers (187 anxious vs. 549 non-anxious) exhibited different patterns, suggesting that linguistic and educational contexts may influence experiences of math anxiety.

Table 1. Frequency Distribution of Math Anxiety (MA) Across Demographic Variables

Variable	Category	Sample size (n)	% Math Anxious
Degree Major	Arts & Humanities	232	46.12%
	Business & Finance	768	54.43%
	Education	397	43.07%
	Maths	153	52.29%
	Psychology	8759	51.30%
	Sciences	456	46.49%
	Social Sciences	247	56.28%
	Uncategorised	32	53.13%
Gender	Another Gender	87	59.77%
	Female/Woman	8298	54.00%
	Male/Man	2002	38.01%
SpLD	ADHD/ADD	353	53.83%
	Dyscalculia	66	75.76%
	Undiagnosed ADHD	16	62.50%
	Other SpLD	9878	50.54%
Country	USA	87	59.77%
	UK (England)	2640	59.66%
	Canada	986	64.41%
	China	323	32.51%
	Australia	315	58.73%
Language	English	5427	59.16%
	Arabic	1490	32.48%
	Chinese	323	32.51%
	German	736	25.41%
	Turkish	834	40.29%
Total Sample	All Participants	12570	49.27%

5.2. Multicollinearity, Linearity, Outlier Detection

The Variance Inflation Factor (VIF) was used to assess multicollinearity among predictor variables, which occurs when predictors are highly correlated and may compromise regression stability and interpretability. In this study, all VIF values were below 10, indicating no multicollinearity concerns. This suggests the predictors are sufficiently independent, supporting the robustness of the regression models. Standardized residuals analysis also showed no significant outliers.

Both Ordinary Least Squares (OLS) and logistic regression assume linearity-OLS between predictors and outcomes, and logistic regression between predictors and the log-odds of the outcome. Violations of this assumption can lead to model misspecification and reduced predictive accuracy. The Box-Tidwell test was used to assess linearity between continuous predictors and the log-odds of math anxiety. All predictors yielded interaction p-values above the conventional $p < 0.05$ threshold, indicating no significant violations of linearity.

5.3. Correlation Analysis

Table 2. Pearson's Correlation between Math Anxiety (MA) and Psychology & Attitudinal Factors

Variable	Pearson's r	p-value
Statistics Anxiety (STARS)	0.72	< 0.001
Creativity Anxiety (CAS)	0.35	0.072
Trait Anxiety (STICSA_Trait)	0.15	0.065
Revised Test Anxiety (R_TAS)	0.38	0.074
Self-Efficacy (NGSE)	-0.25	< 0.001
Intolerance of Uncertainty (IUS_SF)	0.18	< 0.001
Fear of Negative Evaluation (BFNE)	0.21	< 0.001
Attitude Towards Mathematics (ATMS)	-0.29	< 0.001

Correlation analysis revealed several significant associations with math anxiety (MA). Table 2 presents the Pearson's correlation coefficients. Statistics Anxiety (STARS) showed the strongest positive correlation ($r = 0.72, p < 0.001$), indicating that students with higher statistics anxiety also report elevated math anxiety. Test Anxiety (R_TAS; $r = 0.38$, $p < 0.001$) and Creativity Anxiety (CAS; $r = 0.35, p < 0.001$) also showed moderate positive correlations.

Negative correlations were observed for Self-Efficacy (NGSE; $r = -0.25$, $p < 0.001$) and Attitude Toward Mathematics (ATMS; $r = -0.29, p < 0.001$) with math anxiety, suggesting that higher confidence and more positive attitudes are linked to lower math anxiety.

Trait Anxiety (STICSA_Trait; $r = 0.15$, $p = 0.065$) and Intolerance of Uncertainty (IUS_SF; $r = 0.18$, $p < 0.001$) showed weaker positive associations, while Fear of Negative Evaluation (BFNE; $r = 0.21$, $p < 0.001$) indicated a modest relationship. Among demographic factors, Specific Learning Difficulties (SpLD; $r = 0.26$, $p < 0.001$) had a moderate positive correlation, suggesting increased vulnerability among students with learning difficulties.

Table 3. Chi-Square Analysis Between Math Anxiety and Demographic Factors

Variable	χ^2	df	p-value	Cramér's V	Effect Size
Gender	152.14	2	< 0.001	0.11	Small
Language	410.72	4	< 0.001	0.181	Small to medium
Country	342.25	4	< 0.001	0.165	Small to medium
Degree Major	298.43	7	< 0.001	0.154	Small to medium
Specific Learning Difficulty (SLD)	920.88	1	< 0.001	0.271	Medium

Chi-square tests of independence were conducted to examine associations between math anxiety (categorized as "math-anxious" or "non-anxious") and demographic variables, with effect sizes calculated using Cramér's V. Table 3 reports the results of the Chi-square analysis.

Gender was significantly associated with math anxiety, $\chi^2(2) = 152.14$, $p < .001$, with a small effect size ($V = 0.11$), indicating that female students were slightly more likely to report higher anxiety. Language showed a significant association, $\chi^2(4) = 410.72$, $p < .001$, with a small-to-medium effect size ($V = 0.181$), suggesting linguistic or cultural influences. Country of residence was similarly associated, $\chi^2(4) = 342.25$, $p < .001$, with $V = 0.165$.

Degree major also yielded a significant relationship, $\chi^2(7) = 298.43$, $p < .001$, with a small-to-medium effect size ($V = 0.154$), indicating that students in different academic fields may experience math anxiety differently, possibly due to varying math demands. The strongest association emerged for Specific Learning Difficulties (SpLD), $\chi^2(1) = 72.6$, $p < .001$, with a medium effect size ($V = 0.271$), showing that students with learning difficulties were substantially more likely to report high math anxiety.

5.4. OLS Regression

Table 4. OLS Model 1 - Psychological Factors

Predictor	β	Std. Error	t-value	p-value
Statistics Anxiety (STARS)	-0.3878	0.006	-64.175	< 0.001
Creativity Anxiety (CAS)	-0.0396	0.006	-6.387	< 0.001
Trait Anxiety (STICSA_Trait)	0.0058	0.008	0.724	0.469
Revised Test Anxiety (R_TAS)	-0.0629	0.008	-7.49	< 0.001
Model Summary: Adjusted $R^2 = 0.512$, $F(4, 8838) = 2324$, $p < 0.001$				

Model 1 (See Table 4) assessed the predictive power of psychological factors, Statistics Anxiety (STARS), Creativity Anxiety (CAS), Trait Anxiety (STICSA_Trait), and Revised Test Anxiety (R_TAS), on math anxiety. The model accounted for 51.3% of the variance in math anxiety (Adjusted $R^2 = 0.512$) and was statistically significant, $p < .001$, indicating strong explanatory power.

Statistics Anxiety ($\beta = -0.3878$, $p < .001$), Creativity Anxiety ($\beta = -0.0396$, $p < .001$), and Revised Test Anxiety ($\beta = -0.0629$, $p < .001$) were all significant predictors, with negative coefficients indicating that higher anxiety in these domains is associated with elevated math anxiety. Trait Anxiety, however, was not a significant predictor ($\beta = 0.0058$, $p = 0.469$), suggesting general anxiety traits may not directly influence math anxiety in this model.

Table 5. OLS Model 2 - Psychological + Attitudinal Factors

Predictor	β	Std. Error	t-value	p-value
Statistics Anxiety (STARS)	-0.3872	0.006	-63.552	< 0.001
Creativity Anxiety (CAS)	-0.0391	0.006	-6.09	< 0.001
Trait Anxiety (STICSA_Trait)	0.0084	0.009	0.948	0.343
Revised Test Anxiety (R_TAS)	-0.0619	0.009	-7.237	< 0.001
Self-Efficacy (NGSE)	0.2573	0.006	5.052	< 0.001
Intolerance of Uncertainty (IUS_SF)	0.5742	0.006	8.974	< 0.001
Fear of Negative Evaluation (BFNE)	-0.2076	0.004	-4.677	< 0.001
Attitude Towards Mathematics (ATMS)	-0.1097	0.008	-0.655	< 0.001
Model Summary: Adjusted $R^2 = 0.728$, $F(8, 8834) = 1162$, $p < 0.001$				

Model 2 (See Table 5) added attitudinal factors to the psychological variables. All previously significant psychological predictors remained highly significant. Among dispositional variables, self-efficacy (NGSE; β = 0.2573, p < .001), intolerance of uncertainty (IUS_SF; β = 0.5742, p < .001), fear of negative evaluation (BFNE; β = -0.2076, p < .001), and attitudes toward mathematics (ATMS; β = -0.1097, p < .001) were all significant predictors. Trait anxiety remained non-significant (β = 0.0084, p = 0.343). The model's explanatory power increased substantially, with Adjusted R^2 rising to 0.728, indicating that psychological and attitudinal variables together offer a stronger prediction of math anxiety than psychological factors alone.

Table 6. OLS Model 3- Psychological+ Attitudinal + Demographic Factors

Predictor	β	Std. Error	t-value	p-value
Statistics Anxiety (STARS)	-0.3872	0.006	-63.552	< 0.001
Creativity Anxiety (CAS)	-0.0391	0.006	-6.09	< 0.001
Trait Anxiety (STICSA_Trait)	0.0084	0.009	0.948	0.343
Revised Test Anxiety (R_TAS)	-0.0619	0.009	-7.237	< 0.001
Self-Efficacy (NGSE)	0.2573	0.006	5.052	< 0.001
Intolerance of Uncertainty (IUS_SF)	0.5742	0.006	8.974	< 0.001
Fear of Negative Evaluation (BFNE)	-0.2076	0.004	-4.677	< 0.001
Attitude Towards Mathematics (ATMS)	-0.1097	0.008	-0.655	< 0.001
Demographic/Contextual Variables				
Math-related Degree Major (vs. Other)	0.001	0.004	0.263	0.792
Specific Learning Difficulties (Yes = 1)	-0.4209	0.006	-4.087	< 0.001
Gender (Male = 1, Female = 0)	-0.0052	0.01	-0.539	0.59
Country (Ref = UK)				
Country_USA	0.0004	0.001	0.615	0.538
Country_Canada	0.0001	0.001	0.194	0.846
Country_China	-0.0003	0.001	-0.356	0.722
Country_Australia	0.0003	0.001	0.806	0.42
Language (Ref = English)				
Language_Arabic	-0.0005	0.001	-0.621	0.534
Language_Chinese	0.0002	0.001	0.278	0.781
Language_German	-0.0001	0.001	-0.211	0.833
Language_Turkish	0.0003	0.001	0.369	0.712
Model Summary: Adjusted $R^2 = 0.784$, $F(8, 8834) = 1162$, $p < 0.001$				

Model 3 (See Table 6) incorporated demographic and contextual variables alongside psychological and attitudinal factors. All previously significant predictors remained robust, including statistics anxiety (β = -0.3872), creativity anxiety (β = -0.0391), revised test anxiety (β = -0.0619), self-efficacy (β = 0.2573), intolerance of uncertainty (β = 0.5742), fear of negative evaluation (β = -0.2076), and attitudes toward mathematics (β = -0.1097), all significant at p < .001. Among newly added variables, only specific learning difficulties (SpLD; β = -0.4209, p < .001) significantly predicted math anxiety. Degree major, country, language, and gender were non-significant. The model explained 78.4% of the variance (Adjusted $R^2 = 0.784$), a modest improvement over Model 2.

5.5. Logistic Regression

A logistic regression was conducted to identify predictors of math anxiety classification (anxious vs. non-anxious) (See Table 7). The overall model was significant (p < .001) with a Pseudo R^2 of 0.5193, indicating strong predictive power.

Examining the odds ratio (OR), several psychological and attitudinal variables emerged as significant. Statistics anxiety (OR = 1.035, p < .001), creativity anxiety (OR = 1.634, p < .001), and test anxiety (OR = 1.572, p < .001) significantly increased the odds of being classified as math-anxious. Intolerance of uncertainty also showed a positive, though smaller, effect (OR = 1.052, p < .001).

Protective factors included positive attitudes towards math (ATMS, OR = 0.844, p < .001), lower fear of negative evaluation (BFNE, OR = 0.956, p = .001), and higher self-efficacy (NGSE, OR = 0.989, p < .001), though the latter effect was modest. A one-unit increase in self-efficacy is associated with a 1.05% decrease in the odds of being classified as math-anxious.

Language background (OR = 0.977, p = .021) and specific learning difficulties (SpLD, OR = 0.982, p < .001) also showed small but significant associations. However, trait anxiety (p = .856), degree major (p = .618), country (p = .614), and gender (p = .658) were non-significant.

Overall, results underscore the central role of psychological and attitudinal factors in predicting math anxiety, with demographic/contextual variables showing limited influence. These findings support intervention strategies that focus on emotional regulation, cognitive reframing, and self-belief.

Table 7. Logistic Regression Results Predicting Math Anxiety Classification

Predictor	β	OR	95% CI for OR	z-value	p-value
Statistics Anxiety (STARS)	3.3659	1.035	[1.029, 1.041]	36.79	< 0.001
Creativity Anxiety (CAS)	0.4544	1.634	[1.558, 1.723]	6.87	< 0.001
Trait Anxiety (STICSA_Trait)	0.0162	1.016	[0.852, 1.212]	0.18	0.856
Revised Test Anxiety (R_TAS)	0.5586	1.572	[1.484, 1.676]	6.55	< 0.001
Self-Efficacy (NGSE)	-0.0105	0.989	[0.896, 1.140]	-4.17	< 0.001
Intolerance of Uncertainty (IUS_SF)	0.0504	1.052	[0.937, 1.181]	6.85	< 0.001
Fear of Negative Evaluation (BFNE)	-0.0447	0.956	[0.879, 1.040]	-3.04	< 0.001
Attitude Towards Mathematics (ATMS)	-0.1691	0.844	[0.713, 1.000]	-5.96	< 0.001
Demographic/Contextual Variables					
Degree Major (Math-related = 1, Ref = Other)	-0.0184	0.982	[0.913, 1.055]	-0.5	0.618
Specific Learning Difficulties (SLD) (Yes = 1, Ref = No)	-0.4209	0.657	[0.615, 0.702]	-4.62	< 0.001
Gender (Male = 1, Ref = Female)	0.0432	1.044	[0.863, 1.264]	0.44	0.658
Country (Ref = UK)					
Country_USA	0.0021	1.002	[0.961, 1.045]	0.61	0.538
Country_Canada	0.0004	1	[0.951, 1.052]	0.19	0.846
Country_China	-0.0012	0.999	[0.950, 1.051]	-0.36	0.722
Country_Australia	0.0027	1.003	[0.955, 1.053]	0.81	0.42
Language (Ref = English)					
Language_Arabic	-0.0236	0.977	[0.957, 0.996]	-2.31	0.021
Language_Chinese	0.0022	1.002	[0.961, 1.045]	0.28	0.781
Language_German	-0.0012	0.999	[0.959, 1.042]	-0.21	0.833
Language_Turkish	0.0028	1.003	[0.964, 1.044]	0.37	0.712
Model Summary: N = 12,570; Pseudo R^2 = 0.5193; LLR $\chi^2(13)$ = 5089.4; $p < 0.001$					

6. Discussion

This study set out to examine the multidimensional predictors of math anxiety through two lenses: first, by assessing the relative influence of grouped variables (psychological, attitudinal, and demographic) on math anxiety severity; and second, by identifying specific predictors most strongly associated with clinically significant anxiety levels. The combined use of hierarchical OLS and logistic regression enabled both continuous and categorical analyses, aligning with recent calls for more nuanced, scalable modelling techniques in the field [14].

6.1. Psychological and Attitudinal Variables as Primary Drivers (RQ1)

The OLS regression results confirmed that psychological and attitudinal factors account for substantially more variance in math anxiety scores than demographic or contextual variables. This affirms the transactional model of stress and coping, which frames anxiety not as a fixed trait but as a function of how individuals appraise and respond to perceived threats [71]. Math anxiety, in this view, emerges from a dynamic interplay between emotional vulnerability and coping resources, particularly under evaluative pressure.

While demographic variables, such as gender, academic major, and SpLD status, had relatively modest direct effects, their influence may be indirect and mediated through psychological constructs like self-efficacy or stereotype threat. For example, female students in math-intensive fields may experience lower self-efficacy not inherently, but as a result of internalised cultural norms and reduced representation [72]. This aligns with Bandura's socio-cognitive theory, which posits that environmental signals shape self-appraisals, which in turn affect emotional responses and behaviour [28]. Rather than math anxiety being a direct consequence of demographic identity, it appears to be rooted in how learners interpret their environments and internalise social expectations.

The relatively weak explanatory power of demographic variables in this large, multinational dataset also underscores the role of institutional and cultural contexts. Previous studies in culturally homogeneous settings often report stronger gender and achievement-based effects [73], suggesting that demographic predictors are not universally predictive, but context-contingent. This finding advocates for caution in over-relying on demographic risk profiles for intervention targeting and highlights the need for psychologically informed, rather than solely identity-based, support strategies.

6.2. Specific Predictors and Mechanisms of Anxiety (RQ2)

Logistic regression analysis revealed that statistics anxiety, test anxiety, creativity anxiety, and intolerance of uncertainty (IU) were the most powerful predictors of being classified as math-anxious. These findings reinforce a cognitive-affective framework of math anxiety, where anxiety arises not from inherent difficulty with numbers, but from how students anticipate, experience, and interpret math-related situations [5][74].

The prominence of statistics anxiety and test anxiety suggests that evaluation contexts, especially those marked by time pressure, ambiguity, and performance scrutiny, are central to math anxiety. These settings evoke intrusive thoughts, reduce working memory efficiency, and foster negative feedback cycles [75]. The interplay between math and test anxiety [76] may be reciprocally reinforcing: avoidance due to math anxiety reduces practice and fluency, while evaluative stress from test anxiety further compromises performance, entrenching anxiety.

Creativity anxiety emerged as a significant yet often overlooked contributor. Students with high creativity anxiety typically resist open-ended or non-linear problem-solving, which are essential to mathematical reasoning beyond procedural fluency. This supports recent arguments that math anxiety is not merely rooted in numerical processing, but in discomfort with ambiguity, exploration, and risk-taking-skills that traditional math instruction rarely cultivates explicitly [77].

Closely related is intolerance of uncertainty (IU), which reflects a student's discomfort with ambiguity and probabilistic reasoning, central features of both math and statistics. High-IU students experience elevated stress during tasks with multiple solution pathways or delayed feedback [78][79]. This finding aligns with broader research showing that anxiety is exacerbated in learners who lack cognitive flexibility and metacognitive regulation, both of which are required to tolerate temporary confusion or non-closure in learning processes [80][81]. Similarly, fear of negative evaluation (FNE) underscores the social dimension of math anxiety. Students worried about judgment may interpret math tasks as threats to self-worth, intensifying avoidance. These patterns align with social-cognitive theories of academic emotions [82], which emphasize that anxiety is shaped by students' appraisals of task demands and their perceived ability to meet them, especially in evaluative or public contexts.

Fear of negative evaluation (FNE) further deepens this picture by linking math anxiety to social and motivational vulnerability. Students who fear being judged, by teachers or peers, are more likely to interpret math tasks as identity threats rather than learning opportunities, particularly in public or competitive settings [36]. This interpretation is supported by control-value theory [82], which posits that emotions like anxiety emerge from perceived lack of control over valued outcomes, especially under observation.

At the same time, self-efficacy surfaced as a significant protective factor. Students with high general self-efficacy were more resilient to evaluative pressure and less likely to catastrophise setbacks. Importantly, the relationship between self-efficacy and math anxiety is interactive as well as additive. When paired with positive math attitudes, high self-efficacy is associated with markedly improved performance and reduced anxiety [83]. This supports the argument that cognitive beliefs and emotional dispositions must be addressed in tandem for effective intervention. Incorporating brief attitudinal measures (e.g., enjoyment, utility) into classroom assessments can help educators identify at-risk students and tailor support, such as reframing tasks as growth opportunities or highlighting real-world relevance to boost motivation.

Among demographic variables, specific learning difficulties (SpLDs) were the only significant predictor, though with a modest effect size. This suggests that SpLDs affect math anxiety indirectly by increasing cognitive load, triggering repeated academic setbacks, and heightening reactivity to failure. These experiences can erode self-efficacy and reinforce emotional vulnerability [84]. This finding challenges deficit-based interpretations and reinforces the importance of addressing the affective and identity-related dimensions of learning difficulty.

Overall, findings support a cognitive-emotional model of math anxiety, where psychological variables mediate the impact of social and educational contexts. Addressing these emotional and cognitive vulnerabilities is essential to designing effective interventions.

6.3. Implications

These findings call for a fundamental rethinking of math anxiety in educational settings. Rather than focusing solely on content mastery or curricular pacing, effective interventions must prioritise reshaping the emotional and attitudinal environments in which students engage with mathematics. This means building classrooms where emotional resilience, metacognitive awareness, and cognitive flexibility are not just encouraged, but explicitly taught and practiced.

One promising approach involves embedding growth mindset principles into everyday classroom instruction. Students who view intelligence as malleable are more likely to persist through academic challenges. For instance, Boaler and Dweck highlights the use of "mathematical mistake journals" in U.S. classrooms [85], where students regularly record and reflect on their errors, reinforcing the idea that failure is integral to learning. This pedagogical shift reduces the stigma associated with mistakes and encourages risk-taking, an essential aspect of mathematical problem-solving. Similarly, international approaches such as Singapore's implementation of productive failure instructional designs encourage students to struggle with complex problems before receiving formal instruction [86][87]. This strategy has been shown to improve conceptual understanding and promote cognitive resilience by encouraging learners to view initial failure as a step toward deeper learning.

Another empirically supported, yet underutilised, avenue is the integration of mindfulness practices within mathematics instruction. Techniques such as deep breathing, grounding techniques, or brief body scans before tests have been shown to reduce physiological symptoms of anxiety and improve emotional regulation [88][89]. Research by Wolfe and colleagues suggests that regular, brief mindfulness exercises can improve working memory and mathematics performance among adolescents with high anxiety levels [90]. Similarly, cognitive-behavioral strategies also offer promising avenues for intervention. Adaptations of cognitive-behavioural therapy (CBT) for math-specific contexts have demonstrated success in helping students reframe maladaptive thoughts about their abilities. Techniques such as journaling, thought-challenging exercises, and guided reflection, like the use of "math thought records," can help students recognize and replace negative automatic thoughts, improving emotional regulation and performance [91].

Crucially, efforts must also target the social-emotional climate of math classrooms. Peer-led interventions that incorporate CBT principles are promising as they model effective coping strategies which further boosts academic confidence [92]. Research shows that teacher emotional support is directly linked to reductions in anxiety and improvements in academic engagement [93]. Teachers trained in emotional literacy and attentive to subtle signs of anxiety, such as avoidance, perfectionism, or silence, are better positioned to create psychologically safe learning environments. Evidence-based practices such as affective check-ins, opportunities for anonymous questions, and collaborative norm-setting have been shown to improve students' sense of belonging and emotional well-being [94].

Ultimately, the path to reducing math anxiety lies not in "fixing" students, but in transforming the structures around them. Math classrooms must be redesigned as spaces that promote emotional safety, metacognitive empowerment, and multiple pathways to demonstrate competence. This vision aligns with the Universal Design for Learning (UDL) framework [95], which advocates for flexible instructional environments that account for learner variability. By adopting this approach, mathematics education can move beyond merely reducing anxiety toward fostering deeper, more inclusive, and more joyful engagement with the subject.

6.4. Limitations and Further Recommendations

Several limitations should be considered when interpreting this study's findings, alongside directions for future research. First, the use of the SMARVUS dataset involves constraints typical of secondary analysis, including limited control over sampling, data quality, and survey design [60]. Inflexibility in modifying survey items or scales introduces potential biases, such as response style and order effects. Moreover, the dataset lacks critical variables like teaching quality and in-situ emotional responses, potentially limiting contextual insights.

A second limitation relates to the reliance on self-report Likert scales to measure math anxiety and related constructs. While the instruments used are well-validated [65], self-reports are inherently limited in ecological validity. As Hofer [96] points out, individuals' retrospective or generalized self-assessments may not accurately reflect their emotional states during actual math learning or testing situations. Similarly, questionnaire-based measures can oversimplify psychological constructs that may fluctuate dynamically across contexts [97]. Thus, the reported levels of math anxiety and related constructs likely reflect generalised perceptions rather than situation-specific emotional states.

The coding of demographic variables into numerical and categorical formats may have obscured important within-group differences. Binary variables for Specific Learning Difficulties (SpLDs) obscure distinctions between ADHD, dyslexia, and dyscalculia. Dummy coding for country and language similarly compresses cultural and linguistic variation. This approach, though statistically expedient, limits the ability to examine intersectional effects-such as how gender, ethnicity, and specific learning difficulties interact to influence math anxiety [98]. Future research should employ more nuanced coding strategies or qualitative methods to capture this complexity and better inform targeted interventions.

The cross-sectional design precludes causal inference. Longitudinal or experimental research is needed to clarify the directionality between math anxiety and skill deficits [99] as well as to assess how anxiety evolves through educational transitions. Logistic regression, while effective for categorical prediction, may also mask subtle variations that continuous measures could detect [100][101].

To address these limitations, future research should employ multi-method approaches that integrate self-reports with behavioural tasks, physiological data, and ecological momentary assessments. Drawing stratified subsamples from the SMARVUS dataset could allow for deeper, context-specific insights. Qualitative methods such as think-aloud protocols or task-based interviews would also provide richer understanding of students' lived experiences and emotional responses, helping validate survey findings [81].

Longitudinal studies would help establish causal pathways and identify critical periods for intervention. Tracking individual variability could determine whether predictors like statistics anxiety, creativity anxiety, and self-efficacy exert stable or shifting influence over time [102][103]. This would also facilitate stronger causal inferences regarding the directionality of observed relationships.

Finally, future research should tailor instruments and tasks to specific academic and cultural contexts. Distinguishing between math anxiety in general math versus statistics could reveal discipline-specific patterns [104]. Cross-cultural comparisons will help determine whether the predictors identified here generalize across educational systems, languages, and cultural norms [105]. Together, these methodological refinements can more accurately capture the complexity of math anxiety and support culturally responsive, domain-specific interventions.

7. Conclusion

This study advances the understanding of math anxiety as a multidimensional phenomenon shaped by affective, cognitive, and contextual factors. Through a dual-modelling approach, it demonstrates that psychological and attitudinal factors are more predictive of math anxiety than demographic variables. These findings shift the focus from static traits like gender or academic background to modifiable experiences of threat, self-appraisal, and emotional coping in learning environments.

Rather than viewing math anxiety as a fixed deficit, the study positions it as a dynamic, context-sensitive outcome shaped by students' beliefs, affective regulation, and social environments. This perspective calls for a reorientation in both educational research and practice. Reducing math anxiety requires prioritising emotional resilience, cognitive flexibility, and metacognitive development, not just curriculum content or pace. Evidence-based approaches, including growth mindset interventions [106], productive failure designs [86], mindfulness practices [88], and cognitive-behavioral strategies, provide effective tools for creating emotionally supportive and cognitively rich math classrooms. Interventions must also address systemic and cultural barriers, transforming classrooms into spaces of emotional safety, cognitive empowerment, and inclusive pathways to success.

The study also underscores the need to recognise within-group variation. Demographic and structural variables, while not insignificant, exert their influence largely through the psychological and social meanings learners attach to their experiences. Future research should adopt more nuanced, intersectional demographic coding and use multi-method, longitudinal designs to better capture the evolving, context-dependent nature of math anxiety.

To meaningfully reduce math anxiety, educational interventions must treat it not merely as a barrier to overcome, but as a reflection of students' broader relationships with learning, identity, and self-worth. Interventions must engage with belief systems and identity development, reshaping not just math performance, but how students see themselves within mathematics.

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