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Scale development and investigation of self-directed learning readiness in Mathematics among Filipino college students

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Abstract

The global shift in higher education brought about by the pandemic has underscored the importance of self-directed learning for academic success, particularly in challenging subjects like mathematics. To assess the self-directed learning readiness in Mathematics among Filipino college students, this study aimed to develop a monitoring instrument that is both structurally valid and reliable. Through an extensive literature review, key indicators relevant to measuring self-directed learning were identified. Subsequently, a 120-item questionnaire was administered to a sample of 326 first-year college students enrolled in Mathematics courses. The data obtained from the questionnaire were subjected to exploratory factor analysis using the Principal Axis Factoring method. This analysis led to the identification of three correlated factors, each consisting of 10 indicators: self-confidence and intelligence, self-monitoring and responsibility, and attitude towards Mathematics learning. These factors collectively explained 56.63% of the observed variation. Furthermore, Pearson correlation analysis revealed direct associations among the identified factors. Notably, students scored significantly lower in the domain of self-confidence and intelligence. The developed instrument demonstrated both simple structure and excellent reliability. These findings provide valuable insights into the self-directed learning readiness of Filipino college students in the context of Mathematics education and lay the foundation for future research and interventions aimed at enhancing self-directed learning practices and promoting academic achievement in this subject area.

Keywords: Factor, mathematics, scale, self-directed learning, Filipino

Introduction

The pandemic-induced shift to distance learning in Philippine higher education has compelled college students to adopt a self-directed approach to learning. Self-directed learning, as defined by Knowles (1975), involves individuals taking initiative in identifying their learning needs, setting goals, employing suitable strategies, and evaluating their learning outcomes. This concept holds significant importance in mathematics education, particularly in a remote learning environment where students are responsible for their own progress (Laine et al., 2021; Kleden, 2015). Mathematics plays a vital role in daily life, enabling individuals to understand the world and meet its demands (Kunnathodi Abdul Gafoor & Abidha Kurukkan, 2015; Peter, 2011). Consequently, learners must develop mathematical skills to navigate these demands. The sudden transition to remote learning disrupted the teaching-learning process and placed greater responsibility on students for their own learning. Educators are now challenged to cultivate students' self-directed learning skills and design engaging activities that promote self-direction (Long & Agyekum, 1983). Thus, monitoring students' readiness for self-directed learning, particularly in mathematics, which is often perceived as a challenging and disliked subject (Kunnathodi Abdul Gafoor & Abidha Karukkan, 2015), becomes crucial. This monitoring ensures that students continue to acquire knowledge and skills even in a remote learning setting, with appropriate instructional support. Thereby, the use of a scale is necessary to monitor students' self-directed learning readiness in mathematics.

Self-directed learning readiness related scales

Several studies attempted to establish the factor structure of self-directed learning readiness. Guglielmino and Associates (n.d.) developed the first and currently the most popular SLDR scale to measure the complexity of attitudes, abilities and characteristics which involves self-direction. The questionnaire is composed of 58 items grouped into eight factors. These factors are: (1) attitude toward and joy of learning (2) self-confidence in abilities and skills for learning (3) complexity, adventure and independence in learning (4) attraction to new and unusual situation (5) openness to learning situations (6) internal control (7) self-understanding and (8) responsibility for own learning.

Hoban et al. (2005) identified four underlying factor structure of the SDLRS for entering medical students. This includes (1) learning being a tool for life, (2) self-confidence in abilities and skills for learning, (3) responsibility for own learning and (4) curiosity. On the other hand, in the scale termed Self-Directed Learning Readiness Scale for Nursing Education by Fisher, King and Tague (2001), SDLR has only three sub-factors; namely (1) Self-Management, (2) Desire for Learning and (3) Self-Control.

In the study conducted by Khiat (2015), ten factors were found to diagnose the self-directed learning of the adult learners. The developed scale comprises the factors namely (1) Assignment Management, (2) Online Learning Proficiency, (3) Stress Management, (4) Technical Proficiency, (5) Procrastination Management, (6) Online Discussion Proficiency, (7) Seminar Learning Proficiency, (8) Comprehension Competence, (9) Examination Management and (10) Time Management. On the other hand, the Self-Directed Learning Skills Scale developed by Ayyildiz and Tarhan (2015) have identified nine factors of SDLR which define (1) Attitude towards learning, (2) Learning responsibility, (3) Motivation and Self-confidence, (4) Ability to plan learning, (5) Ability to use learning opportunities, (6) Ability to manage information, (7) Ability to apply learning strategies, (8) Assessment of learning process and (9) Evaluation of learning success/results. The scale was developed to measure the self-directed learning skills of high school students in Turkey.

Previously, a standard scale termed “Self-Directed Learning Preparation Skills Scale” was developed by Gunduz and Selvi (2016) to determine the SDL skills of the primary students and found to have four factors which explained 45.65% of the total variance. These factors are: (1) Continuity in learning skills, (2) Planning in learning skills, (3) Awareness towards learning skills and (4) Management of learning environment and learning resources skills.

Another study conducted by Lim et al. (2018) aimed to explore the construct of SDLR among foundation students from high and low proficiency levels to learn English language. The developed scales consisted of three sub-factors namely, (1) Motivation, (2) Awareness and (3) Language learning strategies.

The Research Gap

It is evident that the factor structure of self-directed learning readiness scales varies depending on the study field and participant setting. Various scales, such as those developed by Guglielmino and Associates (n.d.), Khiat (2015), Hoban et al. (2005), Fisher, King, and Tague (2001), Ayyildiz and Tarhan (2015), Gunduz and Selvi (2016), and Lim et al. (2018), have been designed for specific groups such as adult learners, medical students, nursing students, high school students, primary students, and foundation students learning English language. However, there is a gap in research regarding the self-directed learning readiness of college students in the Philippines, particularly in the context of mathematics education within the new normal scheme. Most studies have been conducted internationally, with no specific focus on self-directed learning readiness in mathematics as a domain-specific measure. This highlights the necessity to develop a scale tailored for Filipino college students.

Research Purpose

The current study aimed to extend the self-directed learning readiness in Mathematics (SDLR-M) scale in Philippine higher education and provide evidence toward quality of the instrument. In particular, it sought to explore the underlying factors of SDLR-M, provide evidence for the validity and reliability of the instrument, and assess the SDLR-M of college students. By achieving these aims, this study intends to provide valuable insights that can enhance teaching and learning practices, inform educational interventions, and address the specific needs of Philippine college students in Mathematics education.

Methods

Research design

The current study employed exploratory factor analysis (EFA) as a crucial step in the early development of an instrument aimed at measuring self-directed learning readiness in college mathematics. EFA is a powerful multivariate statistical approach commonly used to identify and validate influential factors within a set of interrelated variables (Watkins, 2018). By reducing the extensive dataset into a smaller set of variables that reflect the respondents' characteristics, EFA facilitates the identification of the underlying factor structure that characterizes the specific phenomenon under investigation. In this study, the application of EFA successfully reduced the initial pool of 120 variables pertaining to self-directed learning readiness, yielding a condensed set of factors. Moreover, EFA served to assess the validity and reliability of these factors, ultimately contributing to the development of a robust measurement tool.

Respondents of the study

The target population for the current study were first-year students enrolled in mathematics subjects during the first semester of the school year 2021-2022 in higher education institutions (HEIs) across the Philippines. A cluster random sampling method was employed to select the respondents. All first-year students within the chosen clusters were invited to participate in an online survey. Out of the total invited participants, a total of 326 qualified respondents completed the survey.

Scales preparation and development

An extensive review of literature was done to examine the existing scales and for the compilation of attitudes, characteristics, skills and abilities of a student related to self-directed learning. After a thorough review of literature, 120-items that could measure the SDLR of the college students were prepared upon revision. To ensure the comprehensibility of each item and its appropriateness for the participants, the opinions of three knowledgeable others from the field of mathematics teaching and research were elicited. They were asked to assess if the constructs make sense with the chosen respondents as well as to evaluate and carefully check the suitability of the language and terms used in each item for better understanding and comprehensive reading of the participants. Some of the items were then modified and transformed into shorter and simple sentences conforming to the experts' feedbacks and suggestions. Subsequently, the final version of the questionnaire was administered to all the first-year college students at Isabela State University who are enrolled in a mathematics subject.

Data gathering procedure

The data-gathering procedure was carefully followed adhering to the research ethics. Prior to the online survey, the researcher asked permission to the authorities through request letter. Upon approval, a survey via online was conducted to collect data for this study. The questionnaire was transcribed in the Google Form and the link of the form was sent to the participants along with the consent statement to inform them about the nature of their involvement in the study. In answering the survey questionnaire, the students were asked to rate themselves using a five-point scale: 5 = strongly agree, 4 = agree, 3 = neither agree nor disagree, 2 = disagree, 1 = strongly disagree. The students were given enough time to accomplish the 120-item questionnaire. The data obtained from the respondents was stowed electronically and kept with the utmost confidentiality and anonymity.

Data analysis

IBM Statistical Packages for Social Sciences (SPSS) version 20 for windows was utilized in analyzing the data obtained from the respondents. Initial tests were conducted to justify factor analysis. Correlation Matrix and Bartlett's test of Sphericity were used to validate the factorability of the data set while Kaiser-Meyer-Olkin (KMO) was used to measure the sampling adequacy. The optimal number of factors to be retained in the scale was determined by using scree plot. Factor Correlation Matrix was requested using Direct Oblimin rotation to check the correlation of the factors and to identify the right rotation to be applied (oblique or orthogonal) for the better interpretability of the data. EFA was re-run to re-assess the construct validity of the scale having a three-factor solution (10 variables retained per factor) while Cronbach alpha reliability test was done to measure the extent to which the items in the scales measures the same construct.

Furthermore, the SDLR of the first-year college students in mathematics was measured by utilizing quantitative approach. The data obtained from the respondents using the questionnaire that was structured in this study were analyzed by the application of several statistical techniques. The mean (*M*) and standard deviation (*SD*) of each subscale was calculated. Pearson correlation analysis was run to determine the degree of association between the three subscales of SDLR in college mathematics. The correlation coefficients (*r)* were interpreted using the criteria recommended by Cohen (1998) i. e., .10 was small; .30 was medium; and .50 was large.

Results

To assess the inter-correlation between variables, a correlation matrix was examined. According to Hair et al. (2010), it is recommended to have a significant number of correlations exceeding 0.30 in order to justify the application of exploratory factor analysis (EFA). Table 1 demonstrates a substantial number of correlations surpassing the .30 threshold. Additionally, Bartlett's test of sphericity was performed to verify the factorability of the variables. The results revealed a significant chi-square value (30453) at $p<0.001$, indicating that the data is suitable for factor analysis. Furthermore, the Kaiser-Meyer-Olkin (KMO) measure yielded a value greater than .50 (.951), suggesting that the sample size is adequate for the analysis.

Table 1 *KMO and Bartlett's Test*

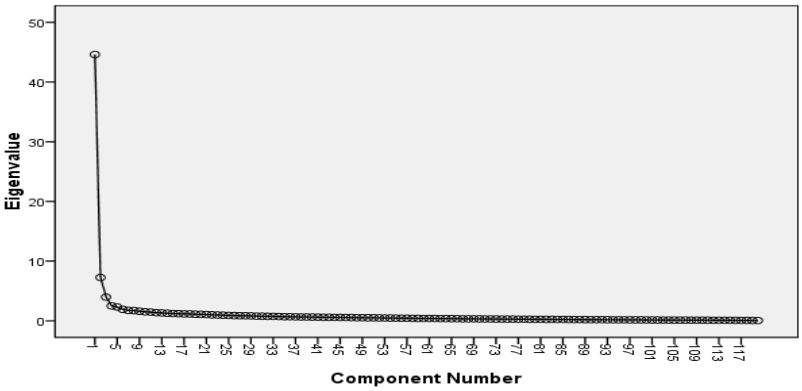
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.951
Bartlett's Test of Sphericity (BTS)	Approx. Chi-Square	30453.154
	Df	7140
	Sig.	.000

Note. The data was factorable, KMO = .951, BTS = 30453, $p < .001$

To assess the variance shared by the variables, communalities were examined prior to factor extraction. The results indicated that all variables had good fit with the factor solution, as all values exceeded .50. Costello and Osborne (2005) suggest that a communality value greater than .40 is favorable.

The Kaiser-Criterion Method initially suggested the retention of 22 factors. However, this might be an overestimation of the number of factors. To determine the appropriate number of factors, a scree plot was employed. Factors above the breaking point or elbow on the scree-plot were extracted. Figure 1 illustrates the scree plot, which suggests a three-factor solution for SDLR-M.

Figure 1 *Scree Plot*



To determine the appropriate rotation method, the recommended approach involves generating a Factor Correlation Matrix using Direct Oblimin rotation in SPSS (Tabachnick & Fidell, 2019; Brown, 2009). The Factor Correlation Matrix provides insights into the intercorrelations among the factors (see Table 2). As per Tabachnick and Fidell (2019), if the correlations fall below .32, orthogonal rotation is advised, whereas correlations of at least .32 indicate the need for an oblique rotation (Tabachnick & Fidell, 2019). In this case, since two of the correlations exceed .32, an oblique rotation method, such as Direct Oblimin or Promax, would be appropriate.

Table 2 *Factor Correlation Matrix*

Factor	1	2	3
1	1.000	.594	.451
2	.594	1.000	.155
3	.451	.155	1.000

Note. Extraction method: Principal Axis Factoring, Rotation method: Oblimin with Kaiser Normalization

Promax rotation is the most widely used oblique rotation strategy when factors are highly correlated (Hetzel, 1996; Costello & Osborne, 2005). Promax (Oblique) rotation, sorted by size and suppressing absolute values (factor loadings) less than .30 was then requested to obtain a clear and simple structure that is more interpretable. According to Berkman and Reise (2012), factor loading less than .30 are less important and removing them will generate simplified output. From the result of the analysis, the structure matrix contains the variables that load in each factor with their corresponding factor loadings. There are 52 items that loads in factor 1, 42 items in factor 2 and 26 items in factor 3. The items in each factor contain loadings ranging from .387 to .768, .495 to .739 and .533 to .730 respectively.

Research recommends several rules of thumb in terms of the respondents to variables ratio. Tabachnick and Fidell (2019) and Gorsuch (1983) propose that the minimum ratio of sample size per variable should be at least 5:1. On the other hand, Nunnally (1978) suggests a ratio of at least 10:1 which is widely used by researchers. Following the rule of thumb of Nunnally (1978), the number of variables was reduced into 30. In each factor, 10 items were retained with their highest possible factor loadings (refer to Table 3). For factor 1, ten items with factor loadings from .711 to 768 retained; factor 2, ten items that ranged from .681 to .739 retained; factor 3, 10 items having factor loadings .675 to .710 retained.

Table 3 *Variables retained in each factor*

Factor	Variables to Retain	*No. of Items*	Factor Loadings
1	var108, var107, var113, var116, var115, var90, var119, var85, var114, var93	10	.711 to .768
2	Var31, var39, var37, var36, var32, var52, var44, var73, var35, var58	10	.681 to .739
3	var13, var18, var5, var16, var20, var19, var14, var10, var15, var12	10	.676 to .710

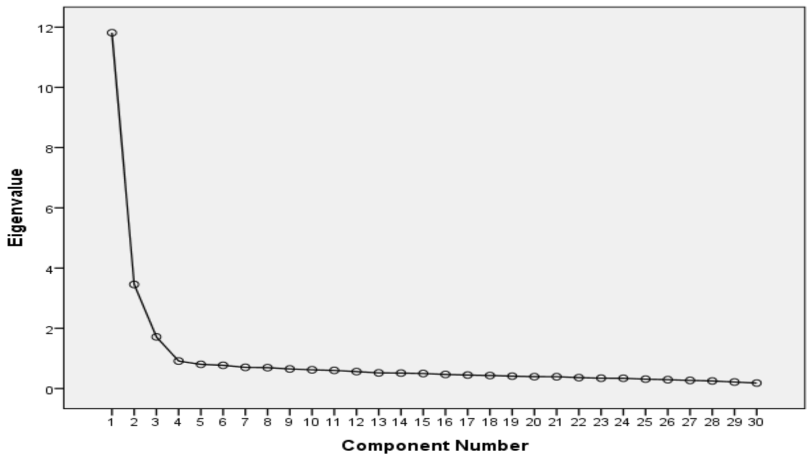
EFA was re-run to re-assess the factorability and reliability of 30 retained variables (as shown in Table 4). Result shows that the data is factorable. The KMO value (.946) is greater than .50 and the Bartlett's test statistic (5524.469) was significant at 0.01 level.

Table 4 *KMO and Bartlett's Test*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.946
Bartlett's Test of Sphericity	Approx. Chi-Square	5524.469
	Df	435
	Sig.	.000

Scree plot was again used as the basis in deciding the number of factors to be retained. Figure 2 still shows that there are three factors (with eigen value greater than 1) that should be extracted.

Figure 2 *Scree plot*



Factor Correlation Matrix was requested once more by performing Direct Oblimin rotation to check the correlations among the factors and to determine the right rotation to be used. As shown in Table 5, two out of three correlations are greater than .32. This suggests the use of Promax (Oblique) rotation.

Table 5 *Factor Correlation Matrix*

Factor	1	2	3
1	1.000	.250	-.514
2	.250	1.000	-.501
3	-.514	-.501	1.000

Note. Extraction method: Principal Axis Factoring, Rotation method: Oblimin with Kaiser Normalization

Promax rotation was again requested to attain a simple structure and for a more pronounced interpretation of the variables. Table 6 shows that the same variables were retained in each factor. The loadings of the three factors ranged from .697 to .762, .693 to .803, and .660 to .773, respectively.

Table 6 *Structure Matrix*

	Factor		
	1	2	3
37. I am confident working on math homework.	.762		
31. I feel confident enough to ask questions in my math class.	.761		
36. Working on math homework is not stressful for me.	.760		
32. I believe I am the kind of person who is good at mathematics.	.756		
39. I believe I can think like a mathematician.	.741		
44. I have a deep understanding about math concepts.	.727		
35. I feel confident when I work on math tasks.	.723		
52. I think logically when I study math.	.708		
58. I can clearly explain and present my work on a math task.	.698		
73. I have high personal standards in mathematics.	.697		
107. I evaluate myself about things I do in math.		.803	
116. I evaluate my own learning in math by trying to solve other examples.		.802	
108. I know what I want to achieve in learning from my math subject.		.797	
115. I reflect on what I have learned during our math class.		.780	
113. I understand what my instructor says during our math class.		.773	
114. I focus on the lesson being discussed in math class.		.754	
93. I find time to study the learning materials in my math subject.		.731	
119. I monitor my own learning progress in math.		.731	
90. I set specific time for my study in math.		.718	
85. I am responsible for my own decisions and actions in math.		.693	
20. I want to do better in math when I see kids who excel in math.			.773
18. I want to improve my mathematical intelligence.			.757
19. I want to do better in math when I see adults who do well in math.			.744
14. I want to improve my grade in math.			.730
5. I want to improve my mathematical skills.			.720
13. I want to learn how to use math in real-life effectively.			.715
15. I want to study math because I want to participate in our activities.			.701
12. I want to continue learning math for as long as possible.			.701
16. I want to find more than one solution to a math problem.			.665
10. I think about what I should study to learn more about math.			.660

Note. Extraction method: Principal Axis Factoring, Rotation method: Promax with Kaiser Normalization

The three subscales explained 56.36% of the total variance. The factor 1 shared 39.38%, factor 2 contributed 11.53%, and factor 3 was accounted for 5.78% variance (refer to Table 7). Samuels (2017) recommends that the proportion of the overall variance explained should account for at least 50% for a scale to be acceptable. Hence, the current scale with an explanatory power of 56.63% is acceptable.

Furthermore, the reliability coefficients of the subscales were requested by running a Cronbach alpha reliability test to check if the scale instrument can measure the same latent constructs. Nunnally (1978) suggests .70 as a minimum Cronbach alpha value that is acceptable. According to the results of the analysis, the Cronbach alpha values of the three subscales ranged from .869 to .920 while the overall reliability coefficient is .945. This indicates that the instrument attained an excellent reliability.

Table 7 *Subscales' Reliability Coefficients and Variance Explained*

Factor	Scales	No. of Items	Cumulative Variance (%)	Cronbach Alpha
1	Self-Confidence and Intelligence	10	39.382	.907
2	Self-Monitoring and Responsibility	10	50.909	.920
3	Attitude towards Mathematics Learning	10	56.631	.869
Overall	Self-Directed Learning Readiness	30	56.631	.945

Correlation analysis using Pearson-r was conducted to investigate the relationship among the factors. Table 8 shows the correlation coefficients between the three underlying constructs and their corresponding mean and standard deviation. Based on Cohen's interpretation, there exist a strong, positive correlation between factor 1 (Self-confidence and Intelligence) and factor 2 (Self-monitoring and Responsibility), $r = .678$. Similarly, factor 2 (Self-monitoring and Responsibility) and factor 3 (Attitude towards Mathematics Learning) have a strong, direct correlation, $r = 0.596$, while factor 1 (Self-confidence and Intelligence) and factor 3 (Attitude towards Mathematics Learning) are moderately associated with each other, $r = 0.403$. It can be observed also that the students indicated the highest score in factor 3 ($M = 3.96$; $SD = .54$), followed by factor 2, ($M = 3.52$; $SD = .58$) and then least in factor 1 ($M = 3.31$; $SD = .60$).

Table 8 *Correlation of the SDLR factors*

		1	2	3	4
1	Self-Confidence and Intelligence	1			
2	Self-Monitoring and Responsibility	$.678^{**}$	1		
3	Attitude Towards Mathematics Learning	$.403^{**}$	$.596^{**}$	1	
4	Self-Directed Learning Readiness	$.835^{**}$	$.904^{**}$	$.781^{**}$	1
	M	3.31	3.52	3.96	3.60
	SD	.60	.58	.54	.48

*Note. ** Correlation is significant at the 0.01 level (2-tailed).*

Discussion

This study attempted to establish the factor structure and reliability of SDLR-M scale while measuring the SDLR-M of college students. Through rigorous data analysis, the study revealed three correlated factors within the SDLR-M scale and the instrument exhibited excellent reliability. Henson and Roberts (2006) assert that defining the factors will rely in the interpretation of the researcher. However, the descriptive labels that will be given should reflect its conceptual meaning. Additionally, it should represent all the variables included in that factor. Therefore, the three factors were named descriptively and defined accordingly as follows: Self-confidence and Intelligence (SCI) for factor 1, Self-monitoring and Responsibility (SMR) for factor 2, and Attitude toward Mathematics Learning (AML) for factor 3.

Self-confidence and Intelligence (SCI) is defined as one's belief to his/her own learning abilities in mathematics. Mathematical confidence signifies a growth mindset by which the learner fosters a positive disposition regarding the subject matter, shows willingness to take risks, determined and self-reliant. On the other hand, intelligence is defined as one's capability in dealing with mathematical challenges. It involves the intellectual capacity and the ability of the learner to comprehend, analyze, evaluate a given information and apply the appropriate methodology in solving a mathematical problem. Extensive research has highlighted the significant influence of both self-confidence and intelligence on students' mathematics performance (Izzata Maghfirah & Osly Usman, 2021; Arum et al., 2018; Kunny Kunhertanti & Rusgianto Heri Santosa, 2018).

Self-monitoring and Responsibility (SMR) encompass the essential practices of tracking one's own learning progress in mathematics. It involves utilizing tools such as reflective journaling, behavior checklists, and other monitoring techniques that promote metacognition and enhance self-regulation, ultimately leading to improved mathematics achievement. Responsibility is closely intertwined with self-monitoring, as it necessitates learners to take initiative in assessing their progress based on learning goals and understanding what they need to learn in mathematics. Effective self-monitoring also requires time management skills and consistency to meet the expectations of mathematics learning. Previous case studies have consistently demonstrated that learners who engage in self-monitoring and take responsibility for their learning process in mathematics are more likely to achieve academic success (DiGiacomo, 2014; Chairil Faif Pasani, 2018). These findings further align with the research conducted by Jakobsen (2001), which showed that implementing a self-monitoring program enhanced students' academic responsibility.

Attitude towards Mathematics Learning (AML) refers to how learners respond to their own learning experiences in mathematics. A positive attitude has a favorable impact on learners' mathematics achievement, while a negative attitude can hinder their performance. Attitude comprises two components: cognitive and affective. The cognitive component reflects learners' perceptions and beliefs about the subject of mathematics, while the affective component encompasses their emotions and feelings towards mathematics. It is important to recognize that learners' attitude towards mathematics can significantly influence their overall achievement. While mental abilities play a role in learning mathematics, the attitude of learners also plays a crucial part in their success.

The findings of the study demonstrate similarities with existing scales developed for other fields. Factors identified in the current study align with those found in the scales developed by Guglielmino and Associates (n.d.) and Ayyildiz and Tarhan (2015), as previously discussed. Additionally, Meng et al. (2019) explored the interconnectedness of SDLR, learning attitude, and self-efficacy, which are closely related to self-confidence. Their findings indicated that low SDLR in students was influenced by these factors. These results corroborate the findings of Izzata Maghfirah and Osly Usman's (2021) case study, where self-confidence, mathematical logical intelligence, and student learning independence explained a significant variation in students' learning outcomes (79.5%). In contrast, Khaled Alotaibi and Sultan Alanazi (2020) proposed that students' mathematical thinking and generalization could impact their performance, but it may not be a sufficient predictor of their mathematical achievement.

Moreover, the study revealed a significant, direct relationship between SCI and SMR. This finding aligns with Moenikia and Adel Zahed-Babelan's (2010) study, which identified intelligence quotient and a sense of responsibility as strong predictors of academic achievement, particularly in mathematics. Additionally, Omolola reported that the combined contributions of self-efficacy and self-monitoring accounted for 69.2% of the explained variance in students' mathematical interest.

Similarly, a positive correlation was observed between SMR and AML. Langat (2015) examined the impact of students' effort and behavior on their mathematics performance, concluding that effort (e.g., completing assignments, dedicating time to practice concepts) and behavior (e.g., attentiveness in class, preparation even in the teacher's absence) significantly predicted mathematics achievement. Notably, Langat found that 55% of students sometimes utilized class time for other subjects when their mathematics teacher was delayed, indicating a lack of interest that could contribute to underachievement in mathematics.

Literature also highlights a significant association between SCI and AML, with both factors serving as predictors of students' mathematics achievement (Nicolaidu & Philippou, 2003; Arup Kundu & Aditi Ghose, 2016; Laranang & Bondoc, 2020; Hwang & Son, 2021). Renalas Repuya and Sumalinog Repuya (2018) further explored the implications of attitude towards mathematics (ATM) and mathematics self-efficacy (MSE) on students' performance, finding a significant association and impact on achievement. They noted that negative ATM was primarily influenced by teacher behavior and pedagogy, while low MSE stemmed from students' personal ability, fear of making mistakes, and destructive feedback from teachers.

All three factors (SCI, SMR, and AML) exhibited a significant relationship with SDLR (Saeid & Eslaminejad, 2017; Prabjanee & Inthachot, 2013). However, this finding contradicts the study by Arslantas and Kurnaz (2017), which investigated the effect of self-monitoring strategies in a Social Studies course on students' self-monitoring, self-regulation (related to self-directed learning), and academic levels. Their research indicated that self-monitoring, one of the factors examined in this study, did not have a significant effect on students' self-regulation skills.

Moreover, the findings indicate that the respondents scored higher in attitude towards Mathematics learning and self-monitoring and responsibility compared to self-confidence and intelligence. This suggests that the respondents recognize the practical applications of mathematics and acknowledge the importance of taking initiative and self-assessment in their learning process, which positively contributes to their mathematics achievement. These results support the significance of fostering a positive attitude towards mathematics (Peteros et al., 2019) and promoting self-paced individualized learning (Christine, 2015) for success in mathematics.

On the other hand, the lower score for self-confidence and intelligence highlights the need for collective efforts to enhance students' self-confidence and intelligence in mathematics. This emphasizes the importance of implementing instructional approaches that encourage active student engagement, such as demonstrating learning and innovation skills (e.g., critical thinking, problem-solving, communication, collaboration, creativity). These skills should serve as foundational elements in curriculum development and content creation, as self-confidence and intelligence were found to be the primary factors influencing self-directed learning readiness, a crucial determinant of mathematics achievement.

Conclusions

The present study aimed to develop and investigate the Self-Directed Learning Readiness in Mathematics (SDLR-M) scale among college students in the Philippines. Through exploratory factor analysis, three distinct factors of SDLR-M were identified, namely self-confidence and intelligence, self-monitoring and responsibility, and attitude towards Mathematics learning. These factors were found to be interrelated, suggesting the interconnected nature of self-directed learning in the mathematics context. Additionally, the results indicated that the respondents scored higher in attitude towards Mathematics learning and self-monitoring and responsibility, while scoring lower in self-confidence and intelligence. This emphasizes the importance of addressing and enhancing students' self-confidence and intelligence in mathematics through collaborative efforts.

The developed SDLR-M instrument demonstrated excellent reliability, making it a valuable tool for higher education teachers to monitor their students' SDLR in mathematics. By utilizing this instrument, teachers can gather data that will guide them in making informed instructional decisions, tailored to the specific needs of their students. Furthermore, future research should aim to further investigate the psychometric properties of the instrument. Specifically, the reliability of the scale could be re-evaluated after removing certain items, and expert input could be sought to review and potentially reintroduce items that may provide valuable insights into students' learning readiness. Moreover, a confirmatory factor analysis could be conducted to validate and refine the developed instrument, ensuring its robustness and applicability in measuring SDLR-M.

The findings of this study contribute to the understanding of SDLR-M among college students in the Philippines. The developed instrument provides a reliable means of assessing students' self-directed learning readiness in mathematics, enabling teachers to make informed instructional decisions. Future research endeavors should focus on refining the instrument, exploring additional factors influencing SDLR-M, and investigating the impact of enhancing self-confidence and intelligence in mathematics on students' overall academic achievement.

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