



Research article

Impact of intrapersonal and interpersonal emotional intelligence and self-directed learning on academic performance among pre-university science students

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ABSTRACT

Provision of equitable access to university education is the primary goal of pre-university education. Academically weak students stand to benefit more from pre-university program. However, available literature on effectiveness of the program revealed that high percentage of students still fail pre-university courses. Although the role of psycho-emotional factors on student academic performance has been highlighted, mechanism through which psycho-emotional factors impact on academic performance of pre-university science students is still not clear to offer adequate insights for proper intervention program. Therefore, we examined the pre-university students' academic performance in sciences in relation to Emotional Intelligence (EI) (Interpersonal EI and Intrapersonal EI) and Self-directed Learning (SDL). Specifically, a correlational study design was conducted to measure and gauge the level of relationships amongst Interpersonal EI, Intrapersonal EI, SDL and academic performance of pre-university students. The participants were 443 Nigerian students enrolled in pre-university science program. Students' self-report on EI and SDL were gathered and analyzed using SPSS 26 and AMOS 24. Exploratory and confirmatory factor analysis were performed to determine cross-cultural validity of the instruments in the Nigerian context. After controlling for gender and age, the hierarchical regression analysis reveals that student academic performance was positively predicted by perceived Interpersonal and Intrapersonal EI, whereas self-directed learning has an inconsistent predictive impact at different steps in the model. Overall, the predictor variables were able to explain substantial proportion of students' academic performance in pre-university program. Insightful suggestions were made.

1. Introduction

The prevalence of Pre-University Education (PUE) is well established in higher education literature (Chen, 2016; Sanabria et al., 2020; Turk, 2019). Of note, several definitions and conceptualization of Pre-University Education phenomenon have emerged, in which it has been viewed as 'pre-collegiate education', 'post-secondary basic skill', 'remedial course-taking', 'remediation', 'remedial education', 'developmental education' or 'alternate program' (Bahr, 2008; Chen, 2016; Turk, 2019). According to Chen (2016), pre-university education is defined as a program designed to offer customized support services and teaching of pre-university coursework, specifically, for the purpose of preparing the

underprepared students to succeed in university-level coursework. Indeed, there is an extensive participation in pre-university education among American students entering 2-year and 4-year college degree programs (Radford and Horn, 2012). For instance, about 39.6% of students enrolling into 4-year and 68% of students enrolling into 2-year degree programs in America have taken university remedial courses in all fields (Chen, 2016). The situation appeared to be similar in Sub-Saharan African countries like Nigeria where sizeable number of students who fail university entrance examination usually enroll into pre-university program (Aluede et al., 2012). Therefore, higher institutions should consider pre-university program as collegiate-responsibility and integrate same into the system.

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Of note, empirical evidence has revealed that failure in pre-university courses is a common experience associated with students who enroll in pre-university education (Bahr, 2008). In fact, Chen (2016) reported that about 51% and 40% of students enrolling in 2-year and 4-year degree program respectively were not successful in all the pre-university courses they take. Recently, another researchers also noted that more than 30% of pre-university course takers enrolling in both 2-year and 4-year degree programs failed pre-university courses (Sanabria et al., 2020). Consequently, the effectiveness of pre-university program has been questioned by the public due to large amount of money higher institutions spend on the program that does not add to post-secondary cumulative grade point average (Saxon and Boylan, 2001; Scott-Clayton et al., 2014). Yet, eliminating pre-university program will be hard because some regulations have made the developmental courses elective for students (Hu et al., 2016). Moreover, student failure has a negative impact on students' social cohesion, economic productivity and lifelong learning education. Given the significance of equitable access to university education in Sustainable Development Goal (SDG) 4, considerable efforts have been invested by many educators in identifying the likely barriers to pre-collegiate success (Webb et al., 2017).

Indeed, some authors have taken a deficit approach, underscoring the significance of demographic groups (e.g., blacks and Hispanic), poor academic background and low socio-economic status as the potential factors interfacing with student success in pre-university education (Chen, 2016; Sanabria et al., 2020). However, it is well established that the discrepancies observed in students' academic performance cannot be fully explained by students' cognitive and demographic differences (Adekitan and Noma-Osaghae, 2019). Consequently, a more strength-based approach to collegiate success emphasizes the importance of psychological factors in enhancing and sustaining interest and academic outcomes of students at risk of school failures (Bean et al., 2003; Cassidy and Johnson, 2002; Cruz, 2010). Specifically, an investigation of how students' social and emotional competencies influence various indicators of short and long term outcomes is one of the strength-based approach (Dymnicki et al., 2013). Indeed, these explorations have revealed that social and emotional competencies – collective capabilities known as emotional intelligence in psychological scholarship – are associated with academic performance (Thomas et al., 2017). Inferably, the ability of an individual to practice self-awareness, build and sustain close relationships with others, adapt to the changing and uncertain environments, and carefully manage the academic challenges, are vital skills required to navigate the huge obstacles periodically encountered by pre-university students.

Of note, expanding bodies of psychological literature have revealed that emotional intelligence is a crucial predictor of learner's capability to successfully regulate, control and manage the constant demands of academic environment (Chan, 2008; Thomas and Allen, 2020). However, studies investigating this assertion have reported mixed results. For instance, positive association of emotional intelligence has been linked to student' academic performance (Thomas and Allen, 2020; Zhoc et al., 2020). Furthermore, the findings from a meta-analytic review with 48 studies revealed that emotional intelligence was associated with Grade Point Average (GPA) (Perera and DiGiacomo, 2013). Accordingly, students who demonstrated high level of emotional intelligence also shown high level of retention and persistence in school (Snowden et al., 2018). Moreover, a highly emotional intelligence student is characterized with more adaptive strategies (MacCann et al., 2011), high self-efficacy (Chan, 2008), and ability to buffer against negative emotions (Thomas et al., 2017). On the contrary, some researchers found that emotional intelligence is not a significant predictor of student GPA in higher education (Zhoc et al., 2018). Similar findings were noted by another researcher who also found that dimensions of emotional intelligence were not associated with academic performance of undergraduate students (Engin, 2017). These mixed findings necessitated further investigation on the mechanism through which emotional intelligence impacts on academic performance of pre-university science students.

It is worthy to note that important to academic success of students is their ability to achieve autonomy in the learning process (Zhoc et al., 2018). Indeed, this becomes more crucial in the post-secondary education where greater academic responsibilities are shifted to students rather than the teachers (Smith, 2016). Empirical evidence has increasingly supported the fact that self-directed learners are more successful compared to those who have no capacity to self-monitor/regulate their learning (Zhoc and Chen, 2016; Zhoc et al., 2018). Several researchers have also noted the relationship existing between EI and self-directed learning given that EI could be a facilitative influence of self-directed learning in students (Engin, 2017; Guseh et al., 2015; Zhoc et al., 2018). This becomes very significant in understanding the joint impact of self-directed learning and EI would have on students' academic achievement. Literature appears to have inadequately captured this. Therefore, the present research was formulated to explore whether emotional intelligence, though the lens of Interpersonal and Intrapersonal EI, contributes to pre-university science students' capability to regulate day-to-day forms of academic stress and improve on their academic performance when moderated by self-directed learning.

2. Literature review

2.1. Emotional intelligence

The definitions and conceptualizations of emotional intelligence is yet to be agreed upon as several theoretical perspectives of emotional intelligence emerge in scholarly investigations, in which different views develop diverse measures of emotional intelligence (Hughes and Evans, 2018). Some authors adopt ability perspective, emphasizing that emotional intelligence involves the individual cognitive competencies to precisely express, evaluate and regulate diverse negative and positive emotions, and utilizes emotions to enhance cognitive functioning and problem-solving (Mayer and Salovey, 1997). Indeed, proponents of ability perspectives access emotional intelligence through emotions-achievement test (Bar-On, 2010). Secondly, there are some authors that endorse trait perspective of emotional intelligence. Supporters of this 'theoretical-view' suggest that emotional intelligence is individual psychological characteristics which enhance the chances that an individual will apply suitable responsive emotional and behavioral dispositions in the environment (Petrides et al., 2004). Supporters of trait perspective assess emotional intelligence using self-report emotions construct (Sanchez-Ruiz et al., 2013).

Of note, several researchers have argue against direct influence of trait perspective on academic performance (Mavroveli and Sánchez-Ruiz, 2011). However, careful examination of its theoretical content suggests that the relationship between affective dimensions of individual characteristics and academic performance is supported by theoretical mechanism. For instance, 'willingness factor' described by Webb (1915) is more likely to explain trait emotional intelligence relatedness to academic performance. Probably because high rate of performance in school is dependent on the individual willingness to perform. Ability to perform denotes declarative and previous cognitive intelligence, competences and skills of an individual while willingness to perform is inherent on individual dispositions, motivation, attitude and self-determination (Poropat, 2009). Logically, a person with high previous academic achievement records may not be willing to perform in a new task and this has the tendency of decreasing their performance. Low achievers may be motivated and develop a help-seeking behaviour that will assist them navigate through learning difficulties and improve on their performance. Therefore, students who demonstrate high level of trait emotional intelligence are likely to perform better academically than their counterparts.

The most widely adopted trait EI instrument was originally formulated by Schutte and partners on the basis of Salovey and Mayer (1990)'s proposed EI model (Schutte et al., 1998). The instrument was initially conceptualized as a one-factor construct and it has a good psychometric

properties. However, other studies adopting the measure have distinguished the construct into Intrapersonal and Interpersonal EI (Chan, 2008; Gignac et al., 2005). In relation of EI to academic performance, Sellars (2006) classified Intrapersonal EI as individuals' driving ability to enhance and sustain inner motivating factors to perform and Interpersonal EI as individual capabilities and willingness to perform by seeking for help through social relationships and interactions. Additionally, Chan (2008) also noted that Intrapersonal EI is individual's coping ability while encountering academic stress and Interpersonal EI as support seeking behaviours from others in stress management. Moreover, Chan (2008) further noted that these two dimensions of EI enhances student self-efficacy and academic performance. Therefore, it is of substantial interest to explore how perceived Intrapersonal and Interpersonal emotional intelligence are associated with pre-university students' academic performance.

2.2. Self-directed learning

Self-directed learning is another personality characteristic factor that is related to students' academic achievement in higher education (Zhoc et al., 2018). Self-directed learning is relevant in post-secondary education because it underlines that individual autonomy, self-responsibility and personal growth encompasses the fundamental principles of post-secondary learning (Zhoc et al., 2018). Additionally, the shift from teacher-centred to student-centred mode of content delivery in higher education underscores the crucial role of self-directed learning in promoting individual autonomy (Smith, 2016). Moreover, other related constructs to self-directed learning such as autonomous learning and lifelong learning are very vital in student retention and persistent till college graduation (Salleh et al., 2019). Hence, a self-directed learner takes ownership of his learning by personally initiating, planning, regulating and evaluating learning process as well as recognising help-seeking and social interactions as recourses for learning (Dagal and Bayindir, 2016; O'Shea, 2003). Moreso, a student who is a self-directed learner develops attributes of willingness to perform such as achievement and mastery goals, personal motivation and high self efficacy in learning (Jennings-Arey, 2020). Indeed, Salleh et al. (2019) also noted that self-awareness, learning strategies, learning activities, evaluation and social interaction skills are constructs embodied in self-directing learning.

It is crucial to note that prior empirical studies have highlighted positive association of self-directed learning with academic performance (Lounsbury et al., 2009; Zhoc and Chen, 2016; Zhoc et al., 2018), as well as lifelong learning (Salleh et al., 2019), in higher education. In their meta-analysis, Boyer et al. (2014) found that self-directed learning has a positive relationship with a range of personality factors such as intrinsic motivation, internal locus of control, academic achievement and help seeking behavior. Therefore, students who regulate and take control of their own learning are more likely to develop intrinsic motivation, sense of confidence, think critically and establish social interaction as well as help-seeking tendencies in the learning environment.

2.3. Emotional intelligence and self-directed learning

Of note, some research findings have suggested that emotional intelligence is a facilitating factor of self-directed learning in higher education (Guseh et al., 2015; Zhoc et al., 2018). For instance, Engin (2017) explore the association of emotional intelligence and self-directed readiness with a sample of 259 Turkish first year undergraduate students. The study revealed that emotional intelligence is strongly related to self-directed learning readiness. Similarly, Zhoc et al. (2018) appraised the emotional intelligence in relation to self-directed learning using higher education students from Hong Kong. The study revealed a strong association between the two constructs, and more importantly, self-directed learning appeared to be the path through which emotional intelligence impact on student GPA. Studies investigating the association

of EI and SDL have adopted trait measure of emotional intelligence developed by Schutte and colleagues. However, the dimensions of the construct used have not been consistent in academic literature. For instance, scale adopted by Engin (2017) consists of four sub-constructs, namely, emotional perceptions, self-emotional management, emotional management of others and emotional usage. On the contrary, Zhoc et al. (2018) assessed emotional intelligence using six sub-constructs which include the following: emotional appraisal in self, emotional appraisal in others, expression of emotions, regulation of self-emotions, regulation of others emotions and emotional usage in problem solving. Indeed, two dimensions of Schutte's emotional intelligence, namely, Intrapersonal and Interpersonal EI have also been validated in the previous studies (Chan, 2008; Gignac et al., 2005). Nevertheless, the association of Interpersonal and Intrapersonal dimensions of EI with self-directed learning still remain unexplored. Hence, it is unclear if both constructs will jointly impact on academic performance in a single study. The present study aims to provide the need answers using data collected from pre-university science students in Nigeria context. This study is timely because pre-university students may likely be facing psychological challenges like managing academic stress, anxiety and burnout. Understanding how the students regulate, control and manage their emotional personalities and develop help-seeking and emotional supportive behaviors will have a tremendously potential in informing intervention pathways to enhance their academic performance.

2.4. Purpose of the present study

The intent of the current research was to investigate pre-university science students' academic performance in relation to perceived emotional intelligence (Interpersonal and Intrapersonal) and self-directed learning. In other words, the present research considered the correlative functions of the predictor variables in explaining students' academic achievement. For the purpose of analyzing the relative contributions of students' demographic factors (age and gender), perceived Interpersonal EI, Intrapersonal EI and self-directed learning in predicting students' academic performance, predictor variables were entered in a stepwise order. The control variables (students' age and gender) were entered first as the predictor variable. This is to validate the previous research findings which suggested that gender and age are potential factors influencing students' academic achievement (Haist et al., 2000; Prajapati et al., 2011). Based on the prior studies, perceived aspects of emotional intelligence may influence self-directed learning (Zhoc et al., 2018), therefore we entered self-directed learning at the second step. Among the aspects of emotional intelligence examined, Interpersonal EI has higher prediction power of students' attributes (Chan, 2008), and was added at the third step which follows by Intrapersonal EI as the final predictor at the final step. The present study is therefore anchored on the following research questions:

Does the perceived self-directed learning predicts students' academic performance, after accounting for age and gender?

Does the perceived Interpersonal EI predicts students' academic performance, after accounting for age, gender and perceived self-directed learning?

Does the perceived Intrapersonal EI predicts students' academic performance, after accounting for age, gender, perceived self-directed learning and Interpersonal EI?

3. Methods

The current study utilized correlational research design to examine and measure the level of the relationships amongst Intrapersonal EI, Interpersonal EI, self-directed learning and academic performance of pre-university science students (Seeram, 2019). Given the relationships, we proceeded to examine the predictive dimensions of the exogenous variables on the endogenous variable using hierarchical regression analysis (Lewis, 2007). The use of hierarchical regression in the present research

offered two main advantages to us. First, we were able to analyze the unique contribution of each exogenous variables on the endogenous variable under investigation. Second, the procedure offers us a chance to explore the incremental validity of the exogenous variables at the same time. Hence, hierarchical regression allowed us to explore and gauge the contributions of Intrapersonal EI, Interpersonal EI and self-directed learning to academic performance of pre-university science students.

3.1. Research participants

The population in the present study comprised 443 prospective university undergraduates who successfully finished the pre-university science program in one of the South-Eastern Universities in Nigeria. Prior to data collection, ethical approval was obtained from the Nnamdi Azikiwe University Research Ethics Committee. Subsequently, we followed the ethical standard specification of American Psychological Association. For instance, we got the consent of the students to take part in the study and we explain the research aims to them. We also informed them that their data/responses will be kept confidential within the confines of the law and international best practices. Furthermore, we informed them that they can opt out at any time if they felt so but we also encouraged them to take part in the study. Complete removal of participants' identification data were also ensured as well. We distributed questionnaires to only one participating university within the first year registration period. Given that universities in Nigeria have the autonomy to organize their own pre-university programs and this could account for variances in emotional and learning climates, we considered one university for data collection. Hence collecting data from other universities demands that these variances are taken into consideration. The participants were selected using convenience sampling method. The choice of convenience sampling technique is predicated on the issue of willingness of students to participate in the study. We used students who were not just available at the time but were also willing to participate in the study. Those who, after explaining the essence of the study, are still not willing to be part of the study, were not included in the study. There were 165 (37.2%) males and 278 (62.8%) were females. Their age range was 16–25 years with mean age of 19.2 years and Standard Deviation (*SD*) of 1.70.

3.2. Data collection instruments

3.2.1. Emotional intelligence scale (EIS)

We adopted 33-items questionnaire originally formulated by Schutte et al. (1998) on the basis of Salovey and Mayer (1990)'s theoretical model of EI. The questionnaire is a one-dimensional construct. A five-point Likert-type response scale ranging from strongly disagree (1) to strongly agree (5) was used to measure emotional intelligence behavior (Zhoc and Chen, 2016). Sample item of EIS is 'I know when experience my emotions'. The scale has a sound psychometric properties with 0.90 alpha value (Schutte et al., 1998). Subsequent efforts have been made to revalidate the factor solution of the construct and the analysis revealed its multifaceted nature with significance variability in the number of dimensions (Chan, 2008; Zhoc and Chen, 2016). However, two sub-dimensions of EIS, namely, Interpersonal EI and Intrapersonal EI, were examined in the current study. The alpha value of the two EI sub-dimensions are Interpersonal EI, $\alpha = .67$, Intrapersonal EI, $\alpha = .60$ and they are adequate for exploratory factor analysis (Hair et al., 2010). The composite reliability (CR) scores of the two sub-constructs ranged from .68 to .72 and exceeded the .60 desired standard, confirming high internal consistency.

3.2.2. Self-directed learning scale (SDLS)

We adopted 10-items SDLS formulated by Lounsbury and Gibson (2006) from personality perspective model (Brockett, 1983). The questionnaire is a one-dimensional construct. A five-point Likert-type response scale ranging from strongly disagree (1) to strongly agree (5) was used to measure student's self-directed learning behavior (Lounsbury

et al., 2009). The reliability coefficients of the scale ranges from 0.84 to 0.87 when used for high school and college students (Lounsbury et al., 2009). In the current research, the alpha value of the self-directed learning scale exceeded 0.70 required standard ($\alpha = .77$). The composite reliability (CR) value of the construct is .77 and exceeded the minimum cut-off of .60, reflecting high internal consistency.

3.2.3. Background variables and achievement scores

The background variables captured in the current study are student demographic variables (age and gender). The academic performance of the students were determined by the achievement scores students obtained at the end of the academic session and it ranges from 0 to 400. Each student was expected to offer four science courses and each course is allocated a maximum score of 100. We used the academic records of the students and the achievement scores were culled from the official result records of these students. The scores of these students were tallied with their responses in the questionnaire using their registration number. The age and gender were retrieved from the bio-information the students supplied when they were completing the questionnaires during data collection.

3.2.4. Methods of data analysis

The present study considered several data screening-related issues. Missing data and outliers were identified in each sub-construct through boxplot (Kwak and Kim, 2017). Univariate normality test for each item was done using skewness and kurtosis with a range of +1.90 to -1.90 at the significance level of 0.05 (Hair et al., 2010). Multivariate normality assumption was check by considering the homoscedasticity issues. In addition, multicollinearity problem was tested using tolerance and variance inflation factor (VIF) (Pallant, 2020).

Exploratory Factor Analysis (EFA) was implemented using SPSS 26 to revalidate the factor structures of the EIS and SDLS in Nigerian context (Lorenzo-Seva and Ferrando, 2006). Subsequently, confirmatory factor analysis were employed to determine the measurement model of EIS and SDLS using AMOS 24.0 (Byrne, 2010). Apart from chi-square test (χ^2) and the ration of Chi-square to degrees of freedom (χ^2/df) which have the limitation of rejecting a model with a huge sample size, other fit indices we employed to gauge the fitness of the model include, Comparative Fit Index (CFI), Goodness of Fit Index (GFI) and Root Mean Square Error of Approximation (RMSEA) (Awang, 2012). According to (Awang, 2012), the cut-off point for the various fit indices included the following; ($\chi^2, p > 0.05$), ($\chi^2/df < 5.00$), (CFI > 0.90), (GFI > 0.90) and (RMSEA < 0.08). Reliability of the scales were determined using Cronbach's alpha coefficient and composite reliability. Due to exploratory factor analysis, alpha value ranges from .60 to .70 is acceptable (Hair et al., 2010), and composite reliability value of .60 and above is satisfactory (Awang, 2012). The unique contributions of predictor variables on the outcome variable and the incremental validity were examined through hierarchal regression analysis.

3.3. Statistical assumptions

Hair et al. (2010) suggested that statistical assumption should be performed to ensure the adequacy and accuracy of the data. Statistical assumptions performed include handling the missing data, univariate normality, multivariate normality and multicollinearity. Initial screening of the data reveals that there is no missing data. As Kline (2005) suggested, we checked the univariate normality of the data using skewness and kurtosis. The range of +2.035 to -.247 for skewness and kurtosis showed that normality of data were accepted. In addition, residual values examination shown that there is no homoscedasticity problem, indicating that we met the assumption of multivariate normality. We further examined the scale to identify if multicollinearity issues exist using 'tolerance and variance inflation factor (VIF)' (Pallant, 2020). The present study has no multicollinearity problems since tolerance and VIF fall

within the acceptable range (tolerance (T) values ranges from .831 to .865, $T > .20$; VIF ranges from 1.156 to 1.275, $VIF < 5.0$).

3.4. Exploratory factor analysis of SDLS and EIS

We first employed EFA and analyze the factor structure of the EIS with principal components analysis (PCA) by varimax rotation. Based on eigenvalue greater than 1 and item loading of .4 and above, an initial extraction produced 11 factors-solution, accounting for the total variance of 55.25%. Scree plot in Figure 1 further illustrated the distinct dimensions of EIS, affirming that EIS is multi-dimensional construct. We repeated the principal component analysis using varimax rotation by fixing 2 as the number of factor expected. A clear 2-factor solution of EIS which can be easily interpreted were produced from a sample of Nigeria pre-university science students. We checked the missing data, the determinant was $<.00001$ and >0 , Kaiser-Meyer-Olkin (KMO) measure was .785, the Bartlett test of sphericity was significant at 0.000 indicating that the variables are highly correlated providing a justifiable basis for factor analysis. The Communalities table showed that items loaded above .20. In the factor 1, the descriptions of items with highest and lowest loading were 'expectation of good performance why I try' and 'easy problem solving on a positive mood' respectively. These descriptions explicated students understanding of their own emotions which is the basic principle of intrapersonal emotional intelligence. For the factor 2, the items with the highest and lowest loadings were 'recognitions of peoples' emotion by their facial expression' and 'Support to others when they are emotional down' respectively. These descriptions shed more light on understanding emotions of others which is the central proposition of interpersonal emotional intelligence. This EFA yielded similar factorial structure earlier identified by (Chan, 2008). The total of 16 items were retained while 17 items which loaded below 0.4 were omitted from the initial 33-items. Factor 1 with 11-items and factor 2 with 5-items show clear distinct dimensions of EIS and were used in the further analysis. The summary is shown in Table 1:

We also applied principal components analysis (PCA) on the response of SDLS using varimax rotation. We checked the missing data, the determinant was $<.00001$ and >0 , Kaiser-Meyer-Olkin (KMO) measure was .805, the Bartlett test of sphericity was significant at 0.000 indicating that the variables are highly correlated providing a justifiable basis for factor analysis. The Communalities table showed that items loaded above

.20. Based on eigenvalue greater than 1 and retention of items loaded with .4 and above, an initial extraction produced 2 factors-solution, accounting for the total variance of 35.16%. Only two items loaded in the factor two. This is further illustrated in scree plot in Figure 2. The EFA was repeated fixing the number of factor as 1. A clear one-dimensional scale self-directed learning emerged. All the items were well loaded and had loadings $>.50$. This finding supports the factor structure earlier identified by previous researchers (Lounsbury et al., 2009; Zhoc and Chen, 2016). The summary of the analysis is illustrated in the Table 2 and the scree plot as shown in Figure 1.

4. Results

4.1. Preliminary correlational analysis

The results revealed a significant correlation amongst Interpersonal EI, Intrapersonal EI, self-directed learning and students' academic performance (Table 3). Interpersonal EI had a low positive significant relationship with Intrapersonal EI ($r = .343$), self-directed learning ($r = .255$); and moderate positive significant relationship with academic performance ($r = .661$). Similarly, Interpersonal EI had a low positive significant relationship with self-directed learning ($r = .391$), and a high positive significant relationship with academic performance ($r = .798$). Additionally, self-directed learning had a low positive significant relationship with academic performance ($r = .420$).

We took further step to determine the discriminant validity. The results indicated that the discriminant validities for all the latent variables were significant (.46–.60) (Table 3). Careful examination of the correlation matrix also revealed that the latent variable correlations were less than the square root of AVE which validates that the current research presents an acceptable discriminant validity. Finally, the mean scores amongst the variables varies as shown in the Table 3:

4.2. Measurement models

Measurement model was utilized to confirm that the latent factors were measurable by the observable indicators. The measurement model of EIS revealed an acceptable fit indices, with the expectation for chi-square (χ^2) (189.545**) which is statistical significant at probability of .01. Furthermore, the confirmatory factor analysis (CFA) revealed that

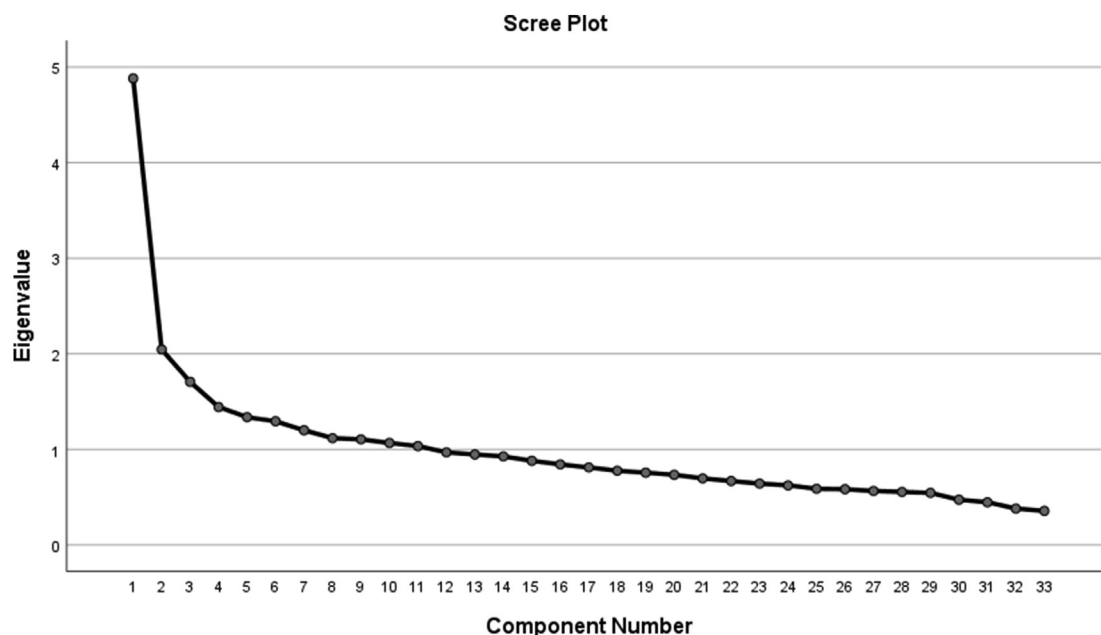


Figure 1. Scree plot on factor number of EIS.

Table 1. Factor loadings from principal component analysis for a two-factor solution for the emotional intelligence questionnaire.

S/N	Item descriptions	Factors		Commonality
		1	2	
EIS3	I expected to perform well	.605		.311
EIS28	I easily lose hope of success when I encounter difficulties	-.541		.226
EIS12	I know how to sustain a positive emotion I experience	.518		.330
EIS27	I develop new ideas when I experience change in emotions	.512		.277
EIS20	I usually come up with new thoughts when I am in a positive mood	.492		.240
EIS23	I encourage myself when I take new task by imagining a positive outcome	.487		.265
EIS2	I use past experience to overcome obstacles when I face similar situation	.478		.217
EIS21	I am in charge of my emotional experiences	.474		.286
EIS7	When I have change in frame of mind, I see new hope	.466		.486
EIS17	In my positive mood, I easily solve problems	.456		.439
EIS16	I present myself in a manner that creates positive feelings on others	.435		.286
EIS18	I acknowledge others emotional experience by observing their facial looks		.506	.410
EIS29	When I look at others, I easily recognize their emotions		.696	.466
EIS30	I assist others when they are emotionally down		.679	.375
EIS32	When I listen to other people, I can tell their emotional experience		.638	.307
EIS25	I have knowledge of the nonverbal communications other people pass across		.535	.335

Note: factor 1 is Intrapersonal EI and factor 2 is Interpersonal EI; items shown on the table are those make .40 cut-off loading and they are arranged in a descending order based on the magnitude of each item. Items number are the same as the number in original Schutte et al. (1998) scale.

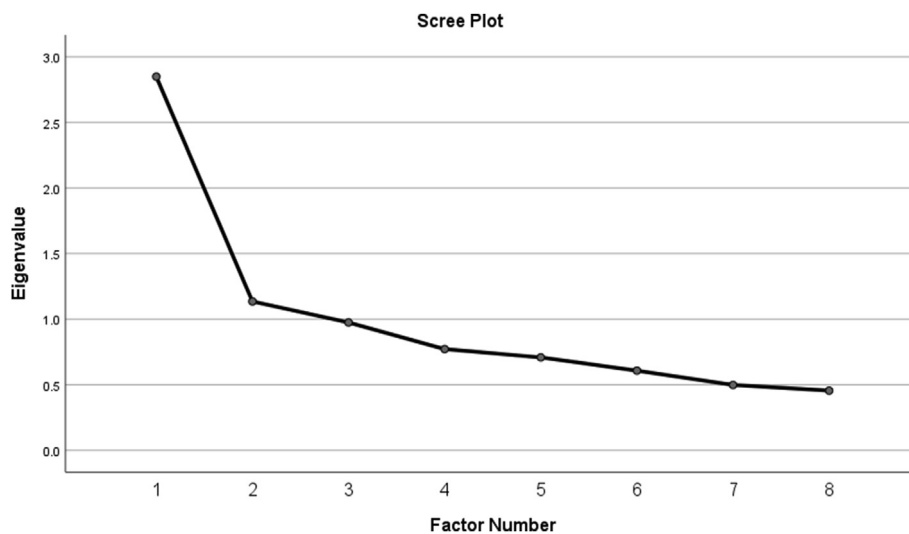


Figure 2. Scree plot on factor number of Self-directed Learning.

Table 2. Factor loadings from principal component analysis for a one-factor solution for the self-regulated learning questionnaire.

S/N	Item descriptions	Factor	
		Factor	Commonality
SDLS1	I acquire knowledge on my own regularly outside of class teachings	.636	.328
SDLS2	I easily find the solutions to what teacher didn't explain on my own	.607	.367
SDLS3	I device a way to learn what I do not understand in the class	.606	.282
SDLS4	I am proficient at finding the best learning resources that will assist me academically	.573	.405
SDLS5	I perceived self-directed learning as important for success in school	.572	.327
SDLS6	I outline my personal learning goals for what I will learn	.563	.306
SDLS7	I like to control my learning activities and when to learn	.553	.275
SDLS8	I device a way to learn something I consider important	.549	.369
SDLS9	I can learn things on my own better than my peers	.531	.317
SDLS10	I am encouraged to learn personally without having to depend on others	.525	.302

Note: all the items have loadings of 0.4 and above and they arranged in descending order based on the magnitude of their factor.

Table 3. Inter-correlation, mean, standard deviation and discriminant validity of the variables.

S/N	Variables	1	2	3	4
1	Interpersonal EI	.57**			
2	Intrapersonal EI	.343**	.60**		
3	Self-directed learning	.255**	.391**	.48**	
4	Academic Performance	.661**	.798**	.420**	
	Mean	3.54	3.69	3.86	119.8
	SD	.69	.45	.55	11.97

Note: ** correlation is significant at 0.01 level (2-tailed).

emotional intelligence scale is significantly associated with the indicators as shown in Figure 3. Of note, some items loaded below .50 standard loading proposed by (Awang, 2012), however, other researchers have accepted factor loading of .40 (Garson, 2009; Erdim and Zengin, 2020). Moreover, some authors accepted a factor loading of .30 for regression analysis (Chan, 2008). The measurement model of SDL showed an acceptable fit, with exception of chi-square (χ^2) (80.328**) which is statistically significant. In addition, Figure 4 reveals statistical association between the self-directed learning latent and its indicator variables. The results on the measurement model are summarized in Table 4:

4.3. Hierarchical regression analysis

We conducted hierarchical regression analyses to examine the impact of emotional intelligence and self-directed learning in predicting students' academic performance in pre-university science program. The regression analyses were done by entering the exogenous variables in the following stepwise manner: (i) age and gender, (ii) perceived self-directed learning, (iii) perceived Interpersonal EI, and (iv) perceived Intrapersonal EI.

As shown in Table 5, comparison of relative influence of different exogenous variables on students' academic performance in pre-university

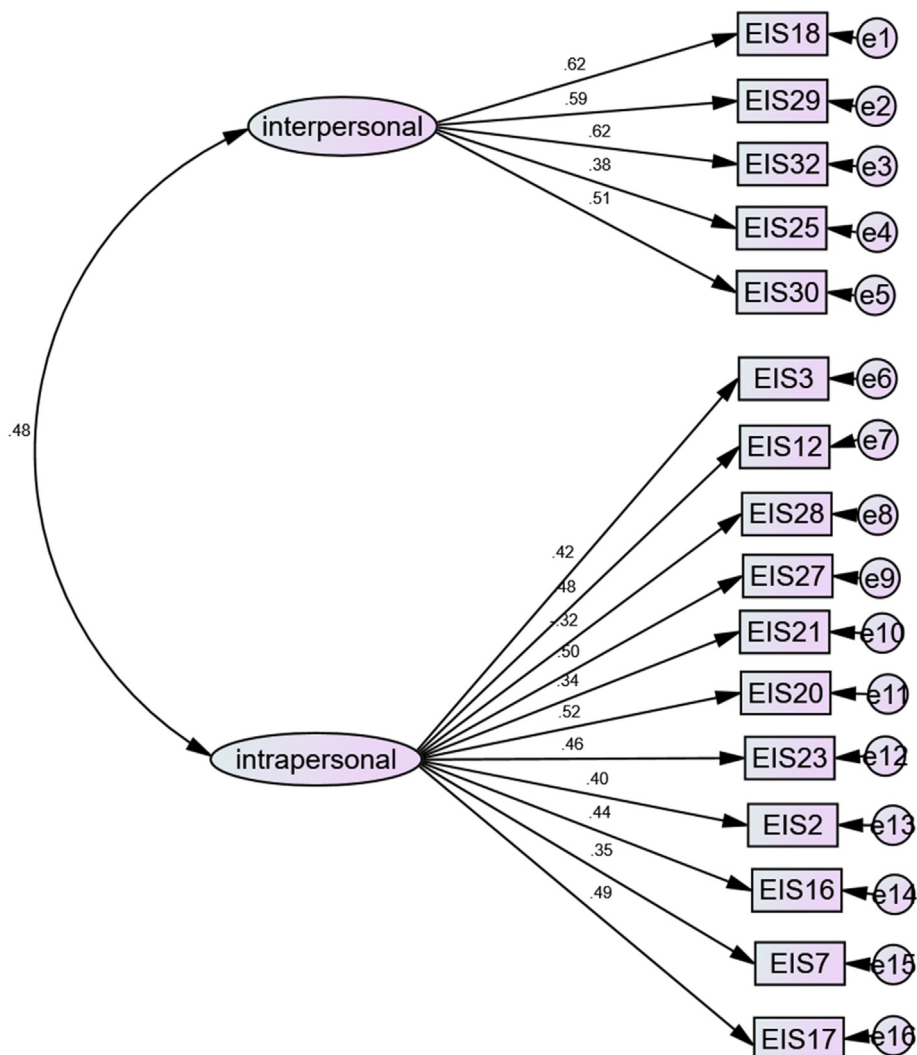


Figure 3. CFA of emotional intelligence scale.

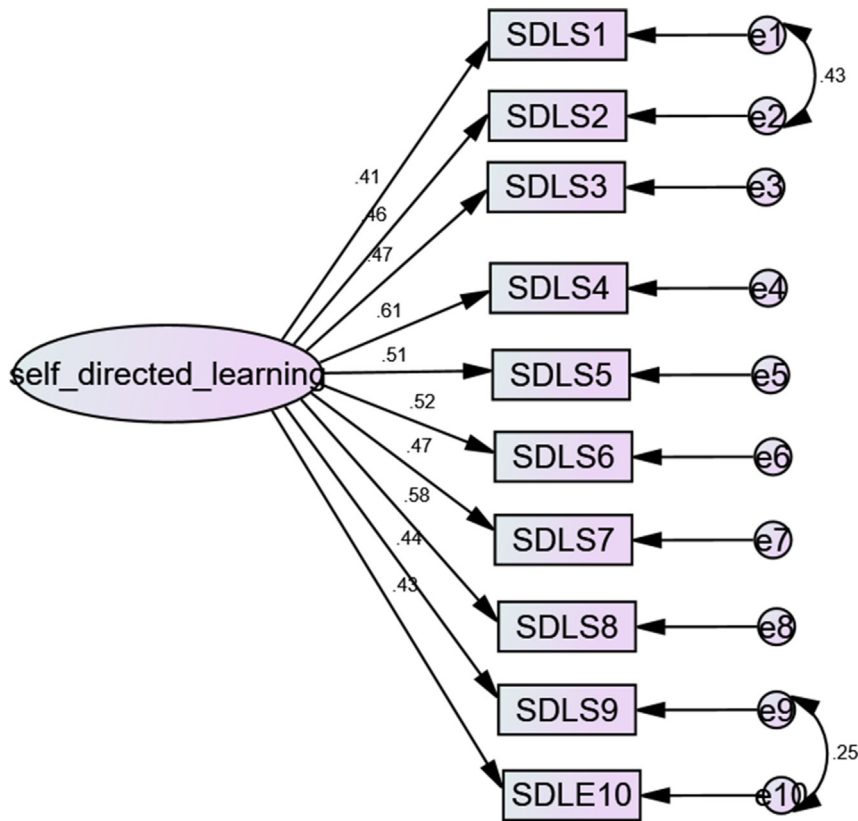


Figure 4. CFA of self-directed learning scale.

Table 4. Measurement model (CFA) results of SEI and SSDL.

Measures	χ^2	Df	χ^2/df	RMSEA	GFI	CFI
EIS (two-factor)	189.545**	103	1.84	.044	.949	.901
SDL (one-factor)	80.328**	33	2.434	.057	.965	.939
Acceptable Cut-off	$P > 0.05$		< 5.00	< 0.08	$> .90$	$> .90$

Note: χ^2 is significant at ** $p < 0.01$, df = degree of freedom.

science program were examined. Gender and age were entered in the step 1 as the potential predictor variables. The result reveals that both the gender ($\beta = -.080, t = -1.677, p > 0.01$) and age ($\beta = .099, t = 2.087, p > 0.01$) did make significant impact on students' academic performance. Then, self-directed learning was added into the model. The result reveals significant and positive predictive impact of self-directed learning ($\beta = .417, t = 9.684, p < 0.01$) on students' academic performance. Furthermore, self-directed learning was able to account for additional 17.3% changes in students' academic performance. In step 3, we added perceived Interpersonal EI, which accounted for extra 32.4% of the variance in student academic performance. The result reveals predictive impacts of Interpersonal EI ($\beta = .590, t = 17.115, p < 0.01$) and self-directed learning ($\beta = .266, t = 7.735, p < 0.01$) on academic performance, when other exogenous variables are controlled. Finally, perceived Intrapersonal EI was added into the model, accounting for additional 29.7% of the variance in students' academic performance. Furthermore, the result shows that Intrapersonal EI ($\beta = .619, t = 26.324, p < 0.01$) and Interpersonal EI ($\beta = .429, t = 19.256, p < 0.01$) have significant impacts on academic performance. The final model reveals a quite interesting but rather surprising result because the predictive impact of self-directed learning on academic performance is no more significant.

5. Discussion

Our study, primarily, set out to investigate the predictive powers of emotional intelligence and self-directed learning on students' academic performance in pre-university science program using hierarchical regression analysis. We separated the dimensions of the emotional intelligence into Interpersonal and Intrapersonal emotional intelligence in the regression model. Four regression models emerged in our study showing the predictive nature of our variables. Results showed that gender, age, self-regulated learning, intrapersonal and interpersonal emotional intelligence have significant impacts on students' academic achievement; with the final model indicating that the significant impact of self-regulated learning on students' academic achievement is significantly affected by including students' emotional intelligence in the model. Our finding is an indication that our variables are theoretically relevant to understanding students' academic success.

Our preliminary findings revealed significant relationship between self-directed learning and academic performance of students. Interpersonal EI and Intrapersonal EI were significantly related to academic performance. The relative influence of different independent variables on students' academic performance in pre-university science program was

Table 5. Hierarchical regression analysis predicting academic performance of pre-university students.

Steps	Predictors	B	SE B	β
1	(Constant) ($R^2 = .018$)	109.746	6.869	
	GENDER	-1.972	1.176	-.080*
	AGE	.697	.334	.099
2	(Constant) ($\Delta R^2 = .173$)	74.688	7.213	
	GENDER	-1.533	1.069	-.062
	AGE	.675	.304	.096
3	(Constant) ($\Delta R^2 = .324$)	55.490	5.702	
	GENDER	-1.766	.829	-.071
	AGE	.446	.236	.063
	Self-directed learning	.576	.074	.266**
4	(Constant) ($\Delta R^2 = .297$)	22.021	3.771	
	GENDER	-.492	.518	-.020
	AGE	.268	.147	.038
	Self-directed learning	.147	.049	.068
	Interpersonal	1.500	.078	.429**
	Intrapersonal	1.506	.057	.619**

Note: ** $p < 0.01$, * $p < 0.05$, $\Delta R^2 = R$ square change, B = unstandardized beta, SE B = standard error for unstandardized beta, β = standardized beta, gender is coded 1 for female and 2 for male, real age is used.

examined. Findings showed that Interpersonal EI was the highest predictor of academic achievement followed by Intrapersonal EI. Gender also made significant impact on the students' academic performance. What this implies is that these demographic variables when entered do accounted for variances in students' academic achievement. Similar studies have demonstrated that gender, gender-related stereotypes and age could impact on students' academic achievement in science related courses (Amelink, 2009; Awofala, 2011; Jabor et al., 2011; Niederle and Vesterlund, 2010; Wang and Degol, 2017). However, researchers have observed that the gender gap differences in achievement in science related subjects are beginning to decline in recent time (Niederle and Vesterlund, 2010; Wang and Degol, 2017). However, in the Nigerian context, the patriarchal nature of the society tend to attribute superior knowledge to male students. There is the stereotype that science subjects are the reserve of male students though this has been tapering currently (Daniel, 2008).

Furthermore, when self-directed learning was entered in the model, finding revealed a significant impact accounting for 17.3% on students' academic performance. This is in agreement with previous findings that have shown that self-regulated learning predicts students' academic achievement in sciences (Ho, 2004). Furthermore, Ho (2004) also noted that self-regulated strategies are positive predictors of students' achievement in science domain in Hong Kong. This implies that pre-university students who are more self-regulated are likely to do better in their studies than those who are not. This could be that higher academic achievement in itself demands that students are able to pay attention to more relevant issues that impact their studies. This has been also demonstrated in both online and traditional learning settings of undergraduate students by some researchers (Broadbent and Poon, 2015; Dunnigan, 2018). In their review, Broadbent and Poon (2015) further indicated that the relationships existing between self-regulated learning and academic achievement were stronger in the traditional learning setting than in the online setting. However, the study by Ningrum et al. (2018) revealed a weak non-significant positive relationship among medical students even though they concluded that students who are more self-regulated are likely to achieve more.

In steps 3 and 4, our findings showed that Interpersonal and Intrapersonal emotional intelligences are positive predictors of students' academic achievement in pre-university program. This finding is supported by recent meta-analysis which has shown that, overall, emotional

intelligence impacts students' academic success (MacCann et al., 2020). In relating how emotional intelligence impact on students' academic achievement, Malik and Shahid (2016) stated that emotional intelligence helps the individual to prioritize thinking which facilitates academic success. Though there exists a paucity of literature on the interpersonal and intrapersonal emotional intelligences being separately associated with students' academic achievement, Zahed-Babelan and Moenikia (2010) found that Intrapersonal emotional intelligence is a positive predictor of distance learning students' academic achievement while Interpersonal emotional intelligence negatively predicted their academic achievement. Our findings is in partial agreement with that of (Zahed-Babelan and Moenikia, 2010), given the fact that only their findings on Intrapersonal emotional intelligence and academic achievement tallied with ours. This contradiction might have arisen from the fact that the population of these two studies differ in their make-up. Distance learning students study from outside the university environment while pre-university students stay and learn within the university premises. The interactions with their peers could be an enabler in their academic achievement. Studies have shown that students who live in university environment score higher in Interpersonal emotional intelligence (Falahzadeh, 2011). Therefore, their development of this intelligence becomes important for their academic success.

The final model reveals a quite interesting but rather surprising result because the predictive impact of self-directed learning on academic performance was no more significant when the Interpersonal and Intrapersonal EI were entered. This appears to indicate that emotional intelligence could be so strong a factor among our sample that it can moderate the impact of self-regulated learning. This could be a reflection of Rager (2009)'s assertion that emotional intelligence is a foundation for learning process and revealed in self-regulated learning. Considering the fact that emotional intelligence is an alterable state of being which is highly influenced through interventions and training programmes (Di Fabio and Kenny, 2011), the inclusion of emotional intelligence in the pre-university orientation programme and curriculum development has a practical implication for the current study.

5.1. Limitations

Despite the fact that our study provided an insight into the predictive abilities of emotional intelligence and self-directed learning on academic

achievement among pre-university science students in Nigeria, the generalizability of its findings could be limited by the following factors. First is the fact that our finding is derived from data collected from a single university in Nigeria. This could limit the generalization of the finding to other universities. For the finding to be generalized to pre-science students in Nigerian universities, there is the need that data are collected from other institutions in Nigeria. Second, our sample size is limited to only the successful students in the program and they comprised primarily of female students accounting for more than 62% of the sample size. These also affect the generalizability of the findings and might lead to significant gender difference in the responses of our sample. Finally, the study adopted only quantitative design. For more robust findings, there could be the adoption of mixed method approach with an inclusive sample so that students could also be interviewed. Therefore, we suggest that further studies to be conducted should adopt a mixed method approach; and data collected beyond a single university in Nigeria factoring in the differences in the program operations in the universities.

6. Conclusion

Notwithstanding the aforementioned limitations, our finding is significant given that it revealed the association between perceived students' emotional intelligence and their academic achievement in Nigeria. We learned that students' emotional intelligence plays critical role in improving pre-university science students' academic achievement. This is an indication that students in the pre-university program who are lagging in their academics could be provided with intervention programs that can build on their emotional intelligence.

Furthermore, the findings that showed significant predictive ability of students' self-directed learning and their academic achievement revealed the importance of self-directed skills for these students. For them to improve on their academics, there is the need that they are accountable for their learning. They have to develop strategies that can position them for independent study. Therefore, there is the need that intervention programs on self-directed learning skills are mounted for them to improve on their learning. Finally, the finding that showed that the impact of self-directed learning was significantly moderated by students' emotional intelligence is quite instructive. This shows that higher scores in emotional intelligence could be a substitute for self-regulation. Interventionist could borrow from this by first equipping students with emotional intelligence that help them regulate their actions. It could be concluded from this study that the academic achievement of pre-university science students could be impacted by their emotional intelligence and self-directed learning skills.

Declarations

Author contribution statement

Emmanuel Nkemakolam Okwuduba: Conceived and designed the experiments; Wrote the paper.

Nwosu Kingsley Chinaza: Performed the experiments; Wrote the paper.

Ebele Chinelo Okigbo: Analyzed and interpreted the data.

Naomi Nkiru Samuel, Chinwe Achugbu: Contributed reagents, materials, analysis tools or data.

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Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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