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# The interplay between self-regulation, learning flow, academic stress and learning engagement as predictors for academic performance in a blended learning environment: A cross-sectional survey

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ABSTRACT

*Aim:* To examine the correlations between self-regulation, learning flow, academic stress and learning engagement as predicting variables for academic achievement in a blended learning environment in Namibia.
*Design:* Cross-sectional survey.
*Methods:* Data were collected from 166 randomly selected undergraduate nursing students through an online survey between January and February 2023, and were analysed using IBM SPSS AMOS version 28.0. The data were explored through factor, parallel and confirmatory factor analyses. The relationship between the study factors and the total score of the scale was analysed using the Pearson correlation coefficient.
*Results:* The results indicate that the two factors identified in the factor analysis are consistent with the theoretical proposition in this research. Factor 1 comprises items C1 to C24, which pertain to self-regulation (SR), while factor 2 consists of items D1 to D9, which relate to learning flow (LR). The findings demonstrate that self-regulation significantly predicts both flow and stress, as well as learning engagement. Additionally, there is a significant relationship between stress and self-regulated learning, as well as between stress and learning flow ($r = 0.23–0.26$; $p= < .05$). However, none of the study constructs were found to predict academic achievement.
*Conclusion:* Although self-regulation significantly predicted flow, stress and learning engagement, a non-significant association exists between all the study constructs and academic achievement. The results of this study have significant implications for improving the development of a positive learning environment that fosters active student engagement. Future studies should investigate correlation by conducting large-scale studies.
*Impact:* This study makes a valuable contribution to the current body of literature concerning academic achievement within the context of undergraduate nursing education. The insignificant relationship between the study variables and academic achievement indicate that these elements are not of considerable significance in enhancing educational achievements in blended learning surroundings in Namibia.

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*Patient or public contribution:* One hundred and sixty-six undergraduate nursing students participated in the survey. The data collected were analysed and interpreted by a skilled statistician.

## 1. Introduction

Higher education is known to be a path to economic success, social advancement and full participation in civic life [1,2]. Academic performance is thus a top priority for universities around the world [3], with student performance being essential for achieving success, including in the field of nursing [4]. Earning a degree entails confronting multiple challenges and being focused on one's chosen field of study. Due to this, educational institutions devise tactics to promote students' academic success, particularly in a blended learning environment. In order to stimulate students' involvement in higher education, the educational landscape has been slowly shifting from a teacher-centric to a student-focused approach [5,6].

The COVID-19 pandemic has had a significant impact on the learning environment, as it has on other sectors [7]. As a result, self-regulated learning (SRL) has become more popular and relevant. SRL is a meta-cognitive learning approach that enables learners to oversee and control their own academic learning [8]. It can be defined as the process of planning, monitoring and assessing one's own learning to meet a particular aim [9]. Self-regulation is seen as a cyclical procedure with three distinct stages: forethought, performance and self-reflection [10,11]. Forethought processes take place prior to learning and include a task analysis phase, such as goal setting and tactical planning, as well as self-motivational and self-reflection phases, which are impacted by self-control and self-observations [9]. The self-regulation process is cyclical because prior procedures of self-reflection impact future forethought processes [11]. Self-regulated learners are generally characterised as proactive learners who regulate their own learning processes in many different ways [11]. Recent research on self-regulation focused on a variety of components, such as goals, self-esteem, beliefs in self-efficacy, emotions, values, expected outcomes and self-assessments [12,13]. This research found SRL to improve students' cognitive, affective and behaviour components, such as organising, rehearsing, monitoring and time management [9,14].

Similar to SRL, learning flow, academic stress and learning engagement are also known as factors that have an effect on academic performance [15,16]. Flow can be defined as the seamless and uninterrupted progression from one moment to another, occurring naturally without any deliberate intervention [15]. Joo et al. [17], claimed that learning flow plays a significant role in enhancing a learner's active engagement in the learning process. As a result, it is crucial to promote both learning satisfaction and a learner's commitment to continue learning. Furthermore, the influence of learning time, students' active actions and space on learning flow is becoming increasingly important in the realm of teaching and learning, particularly in a blended learning environment [18].

On the other hand, academic stress encompasses individuals' perceptions, attitudes and behaviours towards academic demands within the academic setting [19]. The term "learning engagement" pertains to the active involvement and participation of students in the process of learning [20]. Medical students frequently experience academic stress due to the pressures imposed by significant individual or societal expectations, thereby leading to a prevailing state of mental strain [21]. There is substantial evidence indicating that engagement plays a vital role in establishing a connection between the learner and the learning resource [22]. Furthermore, it also contributes significantly to the achievement of objectives and the completion of tasks [20].

Despite studies pointing at SRL, flow, academic stress and student engagement as significant predictors of academic performance in a blended learning environment [15,18], few studies have integrated these constructs. Integrating the model of SRL, flow, academic stress and engagement would greatly contribute to the advancement of both research fields and foster a comprehensive understanding of students' academic performance. This cross-sectional study examined the correlations between self-regulation, learning flow, academic stress and engagement as predicting variables for academic achievement in a blended learning environment in Namibia.

## 2. Research question

What are the main predictors of academic performance among undergraduate nursing students in a blended learning environment at the University of Namibia, Rundu campus?

## 3. Theoretical framework

Zusho [23] conducted a recent study that contributed to the development of an integrated theoretical model of self-regulated learning (SRL) and cognitive engagement. This framework combines two dominant theories in the field, SRL and cognitive engagement, to enhance our understanding of what factors contribute to students becoming more efficient and effective learners in specific learning contexts [10,24]. Zusho [23] also argued that the interaction between cognitive factors contributes to our understanding of academic risk-taking, engagement, and achievement. Notably, this model aims to integrate three influential models of student learning: SRL, patterns of learning, and student engagement. By considering the strengths of each approach, this model emphasizes the use of cognitive and self-regulatory strategies and motivation, which are influenced by personal and contextual factors at different levels. These factors include stress and learning flow, which significantly impact a learner's active engagement in the learning process [17]. In our study both SRL, academic stress, flow and engagement were view it as an independent variables given their crucial role in influencing academic success, particularly in the context of flipped classrooms and online learning.

## 4. Research Methodology

### 4.1. Research design and study setting

This research employed a cross-sectional online survey to examine the determinants that influence the academic achievement of undergraduate nursing students at a satellite campus affiliated with the University of Namibia. The campus offers various undergraduate and postgraduate programmes, including education, health sciences, management and economics. All undergraduate courses were offered via blended learning following the COVID-19 pandemic. As a result, a cross-sectional online survey was necessary to acquire substantial and measurable data at a specific moment in time, as recommended Brink et al., [25].

### 4.2. Population and sampling

The participants in this study were 166 nursing students from the second to fourth year levels at a university campus in Namibia. Simple random sampling was used to select the respondents, whereby names were randomly drawn from a sampling frame to ensure an equal chance of selection for each person. In order to assess an adequate sample size for Confirmatory Factor Analysis (CFA), various criteria can be utilised. One such criterion is the use of cut-offs, which involve considering a minimum sample size of 200 [26]. The eligible criteria for participation in this study was being a second to fourth year undergraduate nursing student at the selected university campus in Namibia, who was willing to take part in the study.

### 4.3. Research instrument

The data in this study were collected through a structured online survey validated tool ($\alpha = 0.930$), which was adapted from literature. The demographic data tool consisted of six items ($\alpha = 0.88$) to collect demographic data, namely: sex, age, gender, grade, level of education and source of funding.

***Academic achievement:*** The assessment of academic performance was measured using the Perceived Learning Scale from the Cognitive Affective Psychomotor (CAP) framework, which was developed by Rovai et al., [27]. This domain consisted of nine items ($\alpha = 0.86$; KMO = 0.71; $\chi^2 = 162.22$; $p = <.001$), using a five-point Likert scale (1–5). The CAP perceived learning score has a scale of 0–45, where a higher score signifies a greater degree of academic accomplishment.

***Self-regulated learning*** (SRL): The measurement of the SRL level was conducted through the utilisation of the Online Self-regulated Learning Questionnaire (OSLQ) ($\alpha = 0.918$; KMO = 0.89; $\chi^2 = 1771.17$; $p = <.001$), a tool created by Barnard-Brak et al., [28]. A total of 24 items were assessed using a five-point Likert scale (5 strongly agree and 1 strongly disagree).

***Learning flow:*** The extent of learning flow was assessed using the Short Flow Scale ($\alpha = 0.89$; KMO = 0.77; $\chi^2 = 382.75$; $p = <.001$) adapted from Park et al., [15]. This particular scale comprises nine items, each rated on a five-point Likert scale that ranges from 1 (strongly disagree) to 5 (strongly agree). A higher score on this scale signifies a greater degree of learning flow.

***Academic stress:*** The level of academic stress was assessed using the Perception of Academic Stress (PAS) scale [29]. This scale comprises 16 items ($\alpha = 0.807$; KMO = 0.76; $\chi^2 = 862.77$; $p = <.001$), each of which is rated on a five-point Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree). A higher score on the scale indicates a lower degree of academic stress.

***Learning engagement:*** This measurement was conducted using a single item ($\alpha = 0.622$), using a five-point Likert scale. A greater numerical value on the scale signifies a greater level of involvement and dedication to the learning process.

All questions were presented in English and based on the pilot study findings, it was estimated that the survey would take approximately 10–15 min to complete. The instrument was reviewed by two nurse educators with expertise in quantitative study design.

### 4.4. Data collection procedure

After permission had been granted by the School of Nursing's Ethical Committee, the researcher randomly selected names from the sampling frame with the use of a Microsoft Excel select sheet, before approaching the potential respondents via WhatsApp with a link to the survey. The link provided detailed information on the study's purpose and significance, and sought their willingness and consent to participate. The data were collected via an online questionnaire during January and February 2023 at a satellite campus of the University of Namibia, Faculty of Health Sciences and Veterinary Medicine, School of Nursing and Public Health.

For a Confirmatory Factor Analysis (CFA) model with three to four indicators per factor, it is recommended to have a sample size (N) greater than 100 [30]. Of the 200 invitations that were sent, only 166 undergraduate nursing students voluntarily agreed to participate in this study. The remaining 34 were either not willing to participate or had challenges with internet access. Each respondent who agreed to participate in the study signed an informed consent by clicking the "agreed" button before continuing with the rest of the questions. All the respondents were informed that the survey would take about 10–15 min to complete.

### *4.5. Data analysis*

The data were first explored using Exploratory Factor Analysis (EFA) using IBM SPSS AMOS version 28.0. Firstly, the data were screened for reliability and validity, with the descriptive data being presented in tables as frequencies, percentages, means and standard deviations (mean ± SD). A factor analysis was performed using a principal component analysis and varimax rotation. The minimum factor loading criteria was set to 0.50. In order to account for the investigative nature of the study and the presence of non-normal distribution in certain variables, multiple factor analyses were performed using the Principal Axis Factoring (PAF) approach to identify and eliminate items that exhibited low communality with other items. The number of factors were identified by conducting McDonald's Omega or parallel reliability analysis of the tool in accordance with prior research [9,31]. As suggested by Alavi et al. [26], the Approximate Fit Indices (AFIs) were employed to assess the overall model fit. The relationship between the study's factors and the total score of the scale was analysed using the Pearson correlation coefficient using Amos.

## 5. Ethical considerations

Following approval from the School of Nursing Ethical Committee (ref no: SoN 173/2022), the study participants provided written informed consent prior to their participation, ensuring that ethical considerations were met. The individuals taking part in the study were asked to demonstrate their approval by selecting the "agree" option provided in the hyperlink prior to responding to the research questions. The participants were able to complete the survey from the comfort of their own homes, thereby ensuring their privacy. Participation was entirely voluntary and no personal identification data were required, thus ensuring complete confidentiality and anonymity. The electronic data collected were only accessible to the researchers. Thus the study upheld the principles of the revised Declaration of Helsinki.

## 6. Findings

### *6.1. Demographic data*

The study achieved an 83 % response rate, with a total of 166 participants falling within the age range of 18–45 years and a mean age of 1.16 (0.445). The largest proportion of respondents, accounting for 86.1 % (n = 143), were between the ages of 18 and 28, followed by 12 % (n = 20) in the age range of 29–39. Females constituted the majority of participants at 59 % (n = 98), while males accounted for 41 % (n = 68). This can be explained by the prevailing trend in which nursing is predominantly pursued by women (Sasa, 2019; Abbas et al., 2020; Saleh et al., 2020). Additionally, a significant number of respondents (31.3 %; n = 51) were in their fourth year of study. The majority of participants (89.2 % (n = 148) resided outside of the campus hostel, with only 10.8 % (n = 18) living on campus. Furthermore, most respondents had study loans (84.9 %; n = 141), while the majority also had employed parents or guardians, making up 72.9 % (n = 121) of the sample (see Table 1).

**Table 1**
Sociodemographic data.

| Variables | | Frequency | Percentage |
|---|---|---|---|
| Age in years | 18–28 | 143 | 86.1 % |
| | 29–39 | 20 | 12.0 % |
| | 40–45 | 3 | 1.8 % |
| *Mean age (SD) 1.16 (0.445)* | | | |
| Gender | Male | 68 | 41.0 % |
| | Female | 98 | 59.0 % |
| Education level | First year | 21 | 12.7 % |
| | Second year | 47 | 28.3 % |
| | Third year | 46 | 27.7 % |
| | Fourth year | 51 | 31.3 % |
| Residence | Outside campus | 148 | 89.2 % |
| | Hostel | 18 | 10.8 % |
| Funding | Self-funded | 25 | 15.1 % |
| | Study loan/bursary | 141 | 84.9 % |
| Family socio-economic status | Parent/guardian employed | 45 | 27.1 % |
| | Parent/guardian unemployed | 121 | 72.9 % |

**Table 2**
Mean scores.

| No. | Variables | N | Minimum | Maximum | Mean | SD |
|---|---|---|---|---|---|---|
| Section B | Academic Achievement | 166 | 1 | 6 | 2.437 | 1.189 |
| Section C | Self-regulation | 166 | 1 | 6 | 2313 | 1120 |
| Section D | Learning Flow | 166 | 1 | 6 | 2556 | 1074 |
| Section E | Academic stress | 166 | 1 | 6 | 2573 | 1192 |
| Section F | Learning engagement | 166 | 1 | 5 | 2.050 | 1.130 |

### 6.2. Means scores

Table 2 displays the average values for the key variables. The mean score of 2.43 ± 1.18 denotes academic achievement. Out of the five domains, academic stress obtained the highest score at 2.57 ± 1.19. The mean score representing the level of learning flow was 2.55 ± 1.07, the mean SRL score was 2.31 ± 1.12, and the lowest mean score indicating learning engagement was 2.05 ± 1.13.

### 6.3. The Approximate Fit Indices (AFIs)

Parallel analysis indicated that no more than four factors should be extracted rather than the predetermined five factors. The Approximate Fit Indices (AFIs) indicated a model fit with only three factors. Together with the fact that under-extraction is considered a worse problem than over-extraction, and because the three factor solution was clearer to interpret, the researcher proceeded with the two factor solution. Furthermore, the CFA model based on the three-factor solution had an adequate fit with the data: chi-square = 30.910, $p < .05$, BIC = 161.5761, RMSEA = 1.4334, CFI = 0.2017, TLI = 0.2527, and SRMR = 0.0437. The model fit was slightly worse in the three-factor model: chi-square = 25.044, $p < .05$, BIC = 85.3766, RMSEA = 1.3154, CFI = 0.2301, TLI = 0.2989 and SRMR = 0.0484, thus the two-factor solution was chosen (see Table 3).

### 6.4. The factor structure of items

A factor analysis was performed using a principal component analysis and varimax rotation. The minimum factor loading criteria was set to 0.50. The communality of the scale, which indicates the amount of variance in each dimension, was also assessed to ensure acceptable levels of explanation. The findings showed that not all communalities were over 0.50.

An important step involved weighing the overall significance of the correlation matrix through Bartlett's Test of Sphericity, which provides a measure of the statistical probability that the correlation matrix has significant correlations among some of its components. The findings were significant, $\chi 2$ (n = 166) = 4900.09 ($p < .05$), which indicates its suitability for factor analysis. The Kaiser–Meyer–Olkin measure of sampling adequacy (MSA), which indicates the appropriateness of the data for factor analysis, was 0.819. In this regard, data with MSA values above 0.800 are considered appropriate for factor analysis. Finally, the factor solution derived from this analysis yielded five factors for the scale, which accounted for 58.55 % of the variation in the data.

Nonetheless, in this initial factor analysis, 11 items (e.g., C5: I don't compromise the quality of my work; C11: I read instructional materials aloud to fight against distractions; D1: I have challenges with skill balance; D4: I give unambiguous feedback; E2: My lecturers are critical of my academic performance; E9: I have enough time to relax after work; E14: I fear failing courses this year) failed to load on any dimension significantly. "E11: I am confident that I will be a successful student" loaded onto a factor other than its underlying factor, hence the nine items were removed from further analysis.

The researcher repeated the factor analysis without including these items. The findings of this new analysis confirmed the three-dimensional structure theoretically defined in the research (see Table 4). The Kaiser–Meyer–Olkin MSA was 0.865. The three dimensions explained a total of 65.47 % of the variance among the items in the study. The Bartlett's Test of sphericity proved to be significant and all communalities were over the required value of 0.500. The two factors identified as part of this factor analysis aligned with the theoretical proposition in this research. Factor 1 gathers items C1 to C24, which represents self-regulation (SR), while Factor 2 includes items D1 to D9 on learning flow (LR).

**Table 3**
The approximate fit indices (AFIs).

Table 4: The Approximate Fit Indices (AFIs)

| | $\chi^2$ | *p-value* | Confidence Intervals | |
|---|---|---|---|---|
| Two-factor model | 30.910 | 0.032 | 95 % Cl (1645–2103) | BIC 161,5761; RMSEA 1,4334; CFI 0,2017; TLI 0,2527; SRMR 0,0437 |
| Three-factor model | 25.044 | 0.043 | 95 % Cl (1,82-2,39) | BIC 85,3766; RMSEA 1,3154; CFI 0,2301; TLI 0,2989; SRMR 0,0254 |
| Four-factor model | 34.692 | 0.015 | 95 % Cl (1671–2091) | BIC 120,7584; RMSEA 1,5188; CFI 0,8240; TLI 0,4518; SRMR 0,0484 |

**Table 4**
The factor structure of items.

| Items | F2 | F3 |
|---|---|---|
| C20. I am persistent in getting help from the instructor through e-mail. | | −0.554 |
| D7. I have Loss of self-consciousness | 0.484 | |
| E1. Competition with my peers for grades is quite intense | 0.422 | |
| E3. Lecturers have unrealistic expectations of me | 0.574 | |
| E4. The unrealistic expectations of my parents stress me out | 0.532 | |
| E5. The time allocated to class and academic is not enough | 0.447 | |
| E6. The size of the curriculum is excessive/overloaded | 0.525 | |
| E7. I believe that the amount of work assignment is too much | 0.628 | |
| E8. I am unable to catch up if getting behind my work | 0.519 | |
| E10. The examination questions are usually difficult | 0.572 | |
| E11. I am confident that I will be a successful student | | 0.434 |
| E15. I think that my worry about examinations is my weakness character | 0.479 | |
| E16. Even if I pass my exams, am worried about getting a job | 0.409 | |

**Table 5**
Correlations between self-regulation, learning flow, stress and learning engagement.

| Correlations | | | | | | |
|---|---|---|---|---|---|---|
| | | Achievement | Self-regulated learning (SRL) | Learning Flow | Academic stress | Engagement |
| Achievement | Pearson Correlation | 1 | .505** | .479** | .384** | .338** |
| | Sig. (2-tailed) | | <.001 | <.001 | <.001 | <.001 |
| Self-regulated learning (SRL) | Pearson Correlation | .505** | 1 | .731** | .413** | .496** |
| | Sig. (2-tailed) | <.001 | | <.001 | <.001 | <.001 |
| Learning Flow | Pearson Correlation | .479** | .731** | 1 | .511** | .486** |
| | Sig. (2-tailed) | <.001 | <.001 | | <.001 | <.001 |
| Academic stress | Pearson Correlation | .384** | .413** | .511** | 1 | .433** |
| | Sig. (2-tailed) | <.001 | <.001 | <.001 | | <.001 |
| Engagement | Pearson Correlation | .338** | .496** | .486** | .433** | 1 |
| | Sig. (2-tailed) | <.001 | <.001 | <.001 | <.001 | |

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

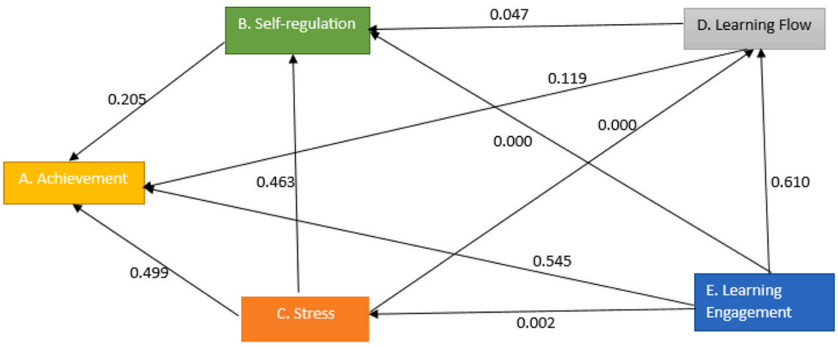


**Fig. 1.** The path model of the relationship between academic achievement, self-regulation, learning flow, stress and learning engagement.

### 6.5. Correlations analysis

The study found a correlation between self-regulation (SRL), learning flow, academic stress and learning engagement. A strong correlation was observed between SRL and flow ($r = 0.731$; $p = <.001$), while a moderate correlation was noted between achievement and SRL ($r = 0.505$; $p = <.001$) and between flow and academic stress ($r = 0.511$; $p = <.001$). Nevertheless, achievement displayed a relatively weak positive correlation with stress ($r = 0.384$; $p = <.001$) and engagement ($r = 0.338$; $p = <.001$) (see Table 5).

### 6.6. The path model of the relationship

A single path model (see Fig. 1) was utilised to examine the relationship between self-regulation, learning flow, academic stress and learning engagement, with academic achievement serving as the intervening variable. A superior fit of the model is indicated by a lower chi-square value in relation to the degrees of freedom, accompanied by a higher p-value [26]. Thus, the chi-square test was employed as a definitive measure of fit for the model, which revealed that it did not align perfectly with the data ($\chi^2 = 114.61$; p =

.001). Specifically, no significant relationship was found between SRL, flow, engagement academic stress with academic success. However, it is worth noting that learning flow and engagement were found to predict SRL ($p < .05$), whereas academic stress strongly predicted learning flow ($p = .002$).

## 7. Discussion

This study examined the correlations between self-regulation, learning flow, academic stress and learning engagement as predicting variables for academic achievement in a blended learning environment in Namibia. In line with existing research, this study found that SRL significantly impacts both flow of learning and engagement [15,32]. Karaca et al. [11], asserted that individuals classified as self-regulated learners tend to demonstrate proactive behaviours, actively overseeing and managing their own learning processes through diverse approaches. Similarly, insufficient control over one's own learning trajectory has been associated with detrimental academic findings, including unsuccessful completion of courses and withdrawal from educational programmes [33]. A recent study by Park et al. [15], reported fascinating findings indicating that students may actually lose track of time and their surroundings when they experience a deep sense of satisfaction and engagement while participating in a course. This finding suggests that when students are deeply engaged and fulfilled by their learning experiences, they become so absorbed in the material that their awareness of the passage of time and their physical surroundings diminish.

Moreover, a statistically significant correlation between academic stress, learning flow and learning engagement was found. Similar prior studies also demonstrated a positive correlation between learning engagement and stress [34]. These findings align with previous studies that assert that students' emotional well-being is impacted by their mental engagement in achieving success in a course [19,35]. This suggests that stress could be triggered by the responsibility for one's own learning and the choice of time and place to study. In recent studies, stress has been consistently linked to a decrease in engagement across various domains [19,36]. The observed findings can potentially be attributed to a transition from in-person to virtual learning settings, which may have adverse effects on behavioural engagement, cognitive engagement and emotional engagement [37]. Given these findings, it is imperative to encourage nursing students to prioritise ample time and a conducive environment to promote optimal academic outcomes.

Although there is a notable association between SRL, flow and engagement, as well as between academic stress, flow and engagement, the model's lack of satisfactory fit is indicated by a high chi-square value and a low p-value. This inadequacy can be attributed to the deviation from the expected chi-square distribution, primarily caused by the data's lack of multivariate normality and the small sample size [26]. However, this study's findings highlight that despite students' likeliness to lose track of time and place when engrossed in their tasks, learning flow was not found to significantly affect academic performance. This finding differs from a prior study conducted by Park et al. [15], which highlighted the importance of flow as a significant factor influencing academic achievement.

In regards to the relationship between SRL and academic performance, this research presents contrasting findings from previous studies, which indicated a favorable correlation between self-regulation and academic achievement [9,38]. The findings of this study possess clinical significance and theoretical relevance, despite not reaching statistical significance. It is possible that the differences observed in this study can be attributed to variations in the sizes of the study samples [26,39,40]. Interestingly, it was also discovered that there is a lack of significant association between academic achievement and self-regulation, learning flow, academic stress levels and learning engagement. While the reasons for this remain unexplained by the path model, existing literature suggests that individual or socioeconomic factors may play a role [41,42]. These factors encompass aspects such as students' socioeconomic status, emotional drive, fear of failure, adaptability to circumstances, commitment to completing assessments, and control over one's thoughts. Therefore, more research is needed to investigate these factors in relation to academic performance using large-scale studies.

In essence, this study has revealed a robust correlation between four constructs, namely SRL, stress, learning flow and academic engagement. The lack of observed correlation between all the study constructs and academic performance is concerning, especially considering existing evidence of the significance of SRL and academic engagement in enhancing academic performance [43,44]. It can be inferred from the study that the constructs being examined were not among the predictors of academic achievement within a blended learning context in Namibia. For this reason, it is essential that additional research is conducted to further examine the relationship between SRL, academic stress, learning flow, academic engagement and academic performance in all settings.

## 8. Limitations and recommendations

This study had several limitations, including that it did not specifically examine the influence of gender on the variables under investigation. Rather, it primarily centred on exploring the overall impact of self-regulated learning (SRL), flow, academic stress and engagement on academic performance, despite previous findings indicating the impact of gender [15]. Given the limitation of a single setting and a small sample size, nurse educators must diligently evaluate the correlation between self-regulated learning (SRL), flow, academic stress and engagement in this study. Due to the non-parsimonious character of the chi-square model fit, increasing the sample sizes in future studies could ameliorate the inadequate model fit observed in this study [26,45,46].

## 9. Conclusion

This research indicates that there is a significant correlation between SRL and academic stress levels with learning engagement. Additionally, a significant correlation was observed between stress and SRL with learning flow. These findings hold great significance in enhancing the creation of a conducive learning environment that encourages students' active participation. Furthermore, these findings can assist future studies in developing strategies to reduce stress related to SRL, learning flow and learning engagement in a blended learning environment at the university campus in Namibia.

Surprisingly, there was no significant association between academic achievement and self-regulation, learning flow, academic stress levels and learning engagement. Based on the limited evidence from literature, it is hypothesised that certain factors, such as individual or socioeconomic factors, may be related to the phenomenon being studied. These factors can include students' socio-economic status, emotional drive, fear of failure, adaptability to circumstances, commitment to completing assessments, and control over one's thoughts [41,42]. The assumption is that these variables are not significantly important in terms of improving academic performance within blended learning settings in Namibia. It is imperative that further investigation be undertaken to scrutinise the correlation between SRL, academic stress, learning flow, academic engagement and academic performance in various contexts within nursing education. Further research is also needed to explore the intricate relationship between these constructs and their impact on the observed outcomes.

## Implications for nursing practice

The findings of this study offer further insights into the integrated model theory proposed by Zusho [23]. The study identified a significant association between SRL, learning flow and stress. It is our contention that this favorable relationship can be comprehended as having a beneficial impact on students' ability to manage their academic learning, resulting in uninterrupted advancement in learning and subsequently heightening the level of stress experienced.

Surprisingly, we did not find a statistically significant relationship between SRL, flow, stress, engagement and academic achievement in blended learning environment in Namibia. These results were unexpected, considering the crucial role of SRL, flow and engagement on academic success [9,15]. These findings suggest that SRL, flow, academic stress and engagement had no substantial impact on nursing students' academic success in a selected blended learning environment in Namibia.

Our discoveries offer a framework for future research endeavors aimed at assessing the correlation between SRL, flow, academic stress levels, and engagement in relation to the academic achievement of student nurses. Furthermore, this breakthrough has the potential to offer invaluable insights that can be utilised to enhance the quality of nursing education.

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This study received no financial or material supports from any funding agency.

## Data availability

Has data associated with your study been deposited into a publicly available repository?
Please provide the name of the repository and the accession number here.
Mendeley, Mendeley Data, V1, https://doi.org/10.17632/vk6vyp7s62.1.

## CRediT authorship contribution statement

**Nestor Tomas:** Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Annarosa Poroto:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal interest appeared to influence the work reported in this paper.

## References

[1] M. Chankseliani, I. Qoraboyev, D. Gimranova, Higher education contributing to local, national, and global development: new empirical and conceptual insights, High Educ. 81 (2021 Jan) 109–127, https://doi.org/10.1007/s10734-020-00565-8.
[2] Rizzuto R. The Relationship of Perceived Learning and Self-Regulated Learning of Undergraduate Students and the Curiosity Scores Generated by Packback. Doctoral Dissertation. Libert Univesiy.
[3] F. Shirazi, S. Heidari, The relationship between critical thinking skills and learning styles and academic achievement of nursing students, J. Nurs. Res. 27 (4) (2019 Aug) e38, https://doi.org/10.1097/jnr.0000000000000307.
[4] K.D. Mthimunye, F.M. Daniels, Exploring the challenges and efforts implemented to improve the academic performance and success of nursing students at a university in the Western Cape, International journal of Africa nursing sciences. 2020 Jan 1 12 (2020) 1–8, https://doi.org/10.1016/j.ijans.2020.100196.
[5] A.B. Wilson, K.M. Brown, J. Misch, C.H. Miller, B.A. Klein, M.A. Taylor, M. Goodwin, E.K. Boyle, C. Hoppe, M.D. Lazarus, Breaking with tradition: a scoping meta-analysis analyzing the effects of student-centered learning and computer-aided instruction on student performance in anatomy, Anat. Sci. Educ. 12 (1) (2019 Jan) 61–73, https://doi.org/10.1002/ase.1789.
[6] S. Hoidn, K. Reusser, Foundations of Student-Centered Learning and Teaching. The Routledge International Handbook of Student-Centered Learning and Teaching in Higher Education, Routledge, 2020 Jul 28, pp. 17–46.

[7] N. Tomas, T. Munangatire, S. Ndinelago, Effectiveness of online assessments in higher education during the COVID-19 pandemic. Teaching and learning with digital technologies in higher education institutions in africa, Case Studies from a Pandemic Context (2022 Dec 9) 16, https://doi.org/10.4324/9781003264026-9.
[8] J. An, J. Oh, K. Park, Self-regulated learning strategies for nursing students: a pilot randomized controlled trial, Int. J. Environ. Res. Publ. Health 19 (15) (2022 Jul 25) 9058, https://doi.org/10.3390/ijerph19159058, 9058.
[9] H. Asikainen, T. Hailikari, M. Mattsson, The interplay between academic emotions, psychological flexibility and self-regulation as predictors of academic achievement, J. Furth. High. Educ. 42 (4) (2018 May 19) 439–453, https://doi.org/10.1080/0309877X.2017.1281889.
[10] T.J. Cleary, G.L. Callan, B.J. Zimmerman, Assessing self-regulation as a cyclical, context-specific phenomenon: overview and analysis of SRL microanalytic protocols, Education Research International. 2012 Oct 2012 (2012) 1–19, https://doi.org/10.1155/2012/428639.
[11] M. Karaca, O. Bektas, T. Celikkiran A, An examination of the self-regulation for science learning of middle school students with different achievement levels, Psychol. Sch. 60 (3) (2023 Mar) 511–540, https://doi.org/10.1002/pits.22776.
[12] A. Malkoç, A.K. Mutlu, Academic self-efficacy and academic procrastination: exploring the mediating role of academic motivation in Turkish university students, Universal Journal of Educational Research 6 (10) (2018) 2087–2093.
[13] S.A. Syapira, B. Budiman, M.N. Selamat, Self-efficacy and self-regulation with academic procrastination in muslim adolescents during the online learning period, Psikis: Jurnal Psikologi Islami 8 (1) (2022 Jun 30) 88–101, https://doi.org/10.19109/psikis.v8i1.11894.
[14] C.L. Lai, G.J. Hwang, Strategies for enhancing self-regulation in e-learning: a review of selected journal publications from 2010 to 2020, Interact. Learn. Environ. 31 (6) (2023 Aug 18) 3757–3779, https://doi.org/10.1080/10494820.2021.1943455.
[15] K. Park, S. Moon, J. Oh, Predictors of academic achievement in distance learning for nursing students, Nurse Education Today. 2022 Jan 1 108 (2022) 1–7, https://doi.org/10.1016/j.nedt.2021.105162.
[16] Ş.Ç. Özhan, S.A. Kocadere, The effects of flow, emotional engagement, and motivation on success in a gamified online learning environment, J. Educ. Comput. Res. 57 (8) (2020 Jan) 2006–2031, https://doi.org/10.1177/073563311882315.
[17] Y.J. Joo, S. Joung, J. Kim, Structural relationships among self-regulated learning, learning flow, satisfaction, and learning persistence in cyber universities, Interact. Learn. Environ. 22 (6) (2014 Nov 2) 752–770, https://doi.org/10.1080/10494820.2012.745421.
[18] S.H. Kim, S. Park, Influence of learning flow and distance e-learning satisfaction on learning outcomes and the moderated mediation effect of social-evaluative anxiety in nursing college students during the COVID-19 pandemic: a cross-sectional study, Nurse Educ. Pract. 56 (2021 Oct 1), 103197, https://doi.org/10.1016/j.nepr.2021.103197.
[19] M. Zhang, P. Zhang, Y. Liu, H. Wang, K. Hu, M. Du, Influence of perceived stress and workload on work engagement in front-line nurses during COVID-19 pandemic, J. Clin. Nurs. 30 (11–12) (2021 Jun) 1584–1595, https://doi.org/10.1111/jocn.15707.
[20] M.R. Chen, G.J. Hwang, Y.Y. Chang, A reflective thinking-promoting approach to enhancing graduate students' flipped learning engagement, participation behaviors, reflective thinking and project learning outcomes, Br. J. Educ. Technol. 50 (5) (2019 Sep) 2288–2307, https://doi.org/10.1111/bjet.12823.
[21] N. Joseph, A. Nallapati, M.X. Machado, V. Nair, S. Matele, N. Muthusamy, A. Sinha, Assessment of academic stress and its coping mechanisms among medical undergraduate students in a large Midwestern university, Curr. Psychol. 40 (2021) (2021 Jun) 2599–2609, https://doi.org/10.1007/s12144-020-00963-2.
[22] J. Shen, H. Yang, J. Li, Z. Cheng, Assessing learning engagement based on facial expression recognition in MOOC's scenario, Multimed. Syst. 28 (2022) (2022 Apr 1) 469–478, https://doi.org/10.1007/s00530-021-00854-x.
[23] A. Zusho, Toward an integrated model of student learning in the college classroom, Educ. Psychol. Rev. 29 (2017 Jun) 301–324, https://doi.org/10.1007/s10648-017-9408-4.
[24] S. Li, S.P. Lajoie, Cognitive engagement in self-regulated learning: an integrative model, Eur. J. Psychol. Educ. 37 (3) (2022 Sep) 833–852, https://doi.org/10.1007/s10212-021-00565-x.
[25] H. Brink, C. van der Walt, C.and G, G. van Rensburg, Fundamentals of Research Methodology for Health Professionals, Juta and Company Ltd, Cape Town, South Africa, 2012. Juta. 2012.
[26] M. Alavi, D.C. Visentin, D.K. Thapa, G.E. Hunt, R. Watson, M. Cleary, Chi-square for model fit in confirmatory factor analysis, J. Adv. Nurs. 76 (9) (2020) 2209–2211, https://doi.org/10.1111/jan.14399.
[27] A.P. Rovai, M.J. Wighting, J.D. Baker, L.D. Grooms, Development of an instrument to measure perceived cognitive, affective, and psychomotor learning in traditional and virtual classroom higher education settings, Internet High Educ. 12 (1) (2009 Jan 1) 7–13, https://doi.org/10.1016/j.iheduc.2008.10.002.
[28] L. Barnard-Brak, V.O. Paton, W.Y. Lan, Profiles in self-regulated learning in the online learning environment, Int. Rev. Res. Open Dist. Learn. 11 (1) (2010 Mar) 61–80, https://doi.org/10.19173/irrodl.v11i1.769.
[29] D. Bedewy, A. Gabriel, Examining perceptions of academic stress and its sources among university students: the Perception of Academic Stress Scale, Health Psychol. Open 2 (2) (2015 Jul 29), 2055102915596714, https://doi.org/10.1177/2055102915596714.
[30] T.A. Kyriazos, Applied psychometrics: sample size and sample power considerations in factor analysis (EFA, CFA) and SEM in general, Psychology 9 (8) (2018 Aug 24) 2207, https://doi.org/10.4236/psych.2018.98126.
[31] W. Widhiarso, Estimate reliability measurement for multidimensional scales, 2010, pp. 1–8. Available at SSRN 1597532. 2010 Apr 29. Available at SSRN, https://doi.org/10.2139/ssrn.1597532.
[32] E. Kim, E.H. Seo, The relationship of flow and self-regulated learning to active procrastination, SBP (Soc. Behav. Pers.): Int. J. 41 (7) (2013 Aug 1) 1099–1113, https://doi.org/10.2224/sbp.2013.41.7.1099.
[33] C.C. Chang, C.A. Warden, C. Liang, G.Y. Lin, Effects of digital game-based learning on achievement, flow and overall cognitive load, Australas. J. Educ. Technol. 34 (4) (2018 Sep 16) 155–167, https://doi.org/10.14742/ajet.2961.
[34] A. Adil, S. Ameer, S. Ghayas, Mediating role of flow and study engagement between academic psychological capital and perceived academic stress among university students, Pakistan Journal of Social and Clinical Psychology 17 (2) (2019) 12–18.
[35] R.J. Petillion, W.S. McNeil, Student experiences of emergency remote teaching: impacts of instructor practice on student learning, engagement, and well-being, J. Chem. Educ. 97 (9) (2020 Aug 6) 2486–2493, https://doi.org/10.1021/acs.jchemed.0c00733.
[36] Y. Ma, D. Bennett, The relationship between higher education students' perceived employability, academic engagement and stress among students in China, Educ + Train 63 (5) (2021 Jun 1) 744–762, https://doi.org/10.1108/ET-07-2020-0219.
[37] E.R. Wester, L.L. Walsh, S. Arango-Caro, K.L. Callis-Duehl, Student engagement declines in STEM undergraduates during COVID-19–driven remote learning, J. Microbiol. Biol. Educ. 22 (1) (2021 Apr 30) 10–128, https://doi.org/10.1128/jmbe.v22i1.2385.
[38] A. Jaramillo, J.P. Salinas-Cerda, P. Fuentes, Self-regulated learning and academic performance in Chilean university students in virtual mode during the pandemic: effect of the 4Planning app, Front. Psychol. 13 (2022 May 26), 890395, https://doi.org/10.3389/fpsyg.2022.890395.
[39] G. Di Leo, F. Sardanelli, Statistical significance: p value, 0.05 threshold, and applications to radiomics—reasons for a conservative approach, European Radiology Experimental 4 (1) (2020 Dec) 1–8, https://doi.org/10.1186/s41747-020-0145-y.
[40] C. Andrade, Sample size and its importance in research, Indian J. Psychol. Med. 42 (1) (2020 Jan) 102–103, https://doi.org/10.4103/IJPSYM.IJPSYM_504_19.
[41] J. De la Fuente, P. Sander, J.M. Martinez-Vicente, M. Vera, A. Garzón, S. Fadda, Combined effect of levels in personal self-regulation and regulatory teaching on meta-cognitive, on meta-motivational, and on academic achievement variables in undergraduate students, Front. Psychol. 8 (2017 Feb 23) 232, https://doi.org/10.3389/fpsyg.2017.00232.
[42] C.F. Rodríguez-Hernández, E. Cascallar, E. Kyndt, Socio-economic status and academic performance in higher education: a systematic review, Educ. Res. Rev. 29 (2020 Feb 1), 100305, https://doi.org/10.1016/j.edurev.2019.100305.
[43] S.K. Davis, A.F. Hadwin, Exploring differences in psychological well-being and self-regulated learning in university student success, Frontline Learning Research 9 (1) (2021) 30–43.

[44] H.J. Kim, A.J. Hong, H.D. Song, The roles of academic engagement and digital readiness in students' achievements in university e-learning environments, International Journal of Educational Technology in Higher Education 16 (1) (2019 Dec) 1–8, https://doi.org/10.1186/s41239-019-0152-3.
[45] D. Shi, A. Maydeu-Olivares, Y. Rosseel, Assessing fit in ordinal factor analysis models: SRMR vs. RMSEA. Structural Equation Modeling, A Multidiscip. J. 27 (1) (2020 Jan 2) 1–5, https://doi.org/10.1080/10705511.2019.1611434.
[46] D. Shi, C. DiStefano, X. Zheng, R. Liu, Z. Jiang, Fitting latent growth models with small sample sizes and non-normal missing data, IJBD (Int. J. Behav. Dev.) 45 (2) (2021 Mar) 179–192, https://doi.org/10.1177/016502542097936.