Predictive Power of Study Skills on Concentration among University Students: Evidence from a Ghanaian Context

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ABSTRACT

Study skills are vital for academic achievement in higher education, as they help students improve and manage their learning processes. Understanding these strategies is essential for educators, policymakers, and students to develop interventions that promote effective, lifelong learning. Despite extensive research, there remains a limited understanding of how diverse study strategies interact to influence concentration, particularly within non-Western educational settings like Ghana, where students often rely on rote memorisation and surface learning approaches. Guided by Self-Regulated Learning theory, which posits that effective study skills and concentration stem from cyclical processes of forethought, performance, and self-reflection, this cross-sectional study examined the multidimensional structure of study skills and their ability to predict students' concentration. Data were gathered from 273 Level 400 students at the University of Cape Coast, Ghana, using the Study Skills Assessment Questionnaire (SSAQ). Confirmatory Factor Analysis (CFA) supported a seven-factor model- Concentration, Information Processing, Motivation and Attitude, Study Aid/Note-taking, Time Management, Test Strategies, and Writing Skills. Hierarchical regression showed that Time Management, Study Aid/Note-taking, and Information Processing were significant predictors of concentration, collectively explaining over half of its variance. Test Strategies, Motivation and Attitude, and Writing Skills were not significant. These findings emphasise the importance of organisational and cognitive strategies in maintaining attention during learning. They have implications for higher education teaching, especially the development of targeted workshops on time management, note-taking, and deep information processing, to foster enhanced student engagement and academic success. The limitations of the cross-sectional and self-report methods are acknowledged, with suggestions for future longitudinal and experimental research.

Keywords: Study Skills Strategies, Concentration, Time Management, Confirmatory Factor Analysis,

INTRODUCTION

Study skills strategies include a variety of cognitive, metacognitive, motivational, and behavioural techniques that university students use to improve their learning and academic performance (Almoslamani, 2022). These strategies involve time management, note-taking, reading comprehension, and test preparation, all of which are vital for students' academic success (Fadhil et al., 2022; Miller & Rudd, 2005; van Viet et al., 2022). In the Ghanaian context, where students often transition from secondary education with varied academic preparedness, effective study skills are particularly crucial for navigating the demands of higher education and achieving academic success (Ahiatrogah et al., 2008; Bentil et al., 2021). According to Robbins et al. (2004), study skills are essential tools that help students organise their learning processes, adopt effective techniques, and adjust to different academic demands. They are considered transferable skills that impact not only immediate academic results but also support students' self-regulation, motivation, and lifelong learning (Mejeh & Held, 2022; Taranto & Buchanan, 2020). The ability to efficiently acquire, process, and apply knowledge is key to academic achievement, especially in higher education. These strategies, including context control, time management, and information processing, promote self-regulation and motivation, enabling students to effectively manage their learning environments and reach their academic goals (Zimmerman, 2002). Mastering these skills is vital for overcoming challenges in university and achieving academic success, as they aid understanding, retention, and application of knowledge across various disciplines (Pintrich, 2000).

The roles that study skills play in university education are multidimensional and very significant to academic performance and retention (Busato et al., 2000; Dadandı 2023; Fazal et al., 2012; Jansen & Suhre 2010; Molnár & Kocsis 2023; Shen 2024; Soares et al., 2009). Proficiency in study skills substantially affects scholastic achievement and is associated with factors such as academic self-belief, motivation, learning approaches, personality traits, and cognitive abilities. Time management and learning skills during pre-university preparation positively influence first-year study behaviour in terms of academic success (Jansen & Suhre, 2010). The relationship between academic self-efficacy and achievement is mediated by systematic and organised study habits, effective homework, and exam preparation (Dadandı, 2023); however, domain-specific knowledge and learning motivation are major predictors of academic success (Molnár & Kocsis, 2023). Academic preparation is a far more significant predictor of first-year achievement than learning strategies (Soares et al., 2009). Additionally, harmonious passion and sustainable learning, whether exploratory or exploitative, are related to academic achievement (Shen, 2024).

Despite extensive research (Ahiatrogah et al., 2008; An & Van Viet, 2025; Bentil et al., 2021; Muwonge et al., 2019; Richardson et al., 2012; Van Viet et al., 2022; Wibrowski et al., 2017), studies have examined single study strategies in isolation, with limited attention to how multiple strategies interact to support concentration. Furthermore, little is known about how these processes unfold in non-Western contexts, such as Ghana, where students are reported to often rely on rote memorisation and surface learning strategies (Aboagye et al., 2020; Amoako et al., 2020; Kamel et al., 2020). Addressing these gaps is critical for designing culturally responsive interventions that strengthen students' academic resilience. Concentration, as a fundamental cognitive process, is particularly vital for deep learning and academic achievement (Stasolla, et al., 2023), making it a critical dependent variable to investigate in the context of study skill interactions. This study adopts a theoretical framework grounded in Self-Regulated Learning (SRL) theory, which posits that effective study skills and concentration arise from cyclical processes of forethought, performance, and self-reflection, interwoven with cognitive and non-cognitive elements (Zimmerman, 2002). By employing a cross-sectional analysis, this research aims to bridge these gaps, providing empirical insights into how SRL components manifest among university students in Science Technology Engineering and Mathematics (STEM) disciplines and informing targeted pedagogical interventions to enhance academic success.

Research has identified numerous strategies that students adopt to facilitate effective learning (Lawson et al., 2021; Pressley & McCormick, 1995; Rahmat et al., 2021; Zimmerman & Schunk, 2011) These strategies can be broadly categorised into cognitive, metacognitive, and resource-management techniques. Cognitive strategies include summarising, paraphrasing, and elaborative interrogation, which enhance understanding and retention (Lawson et al., 2021; Pressley & McCormick, 1995). Metacognitive strategies involve planning, monitoring, and evaluating one's own learning process, thereby enabling students to effectively regulate their study activities (Rahmat et al., 2021; Schraw & Dennison, 1994). Resource management strategies include time management, seeking social support, and creating conducive study environments (Zimmerman & Schunk, 2011).

Empirical studies consistently demonstrate that students who combine these strategies tend to perform better. For instance, note-taking techniques have been shown to significantly boost information retention among college students (Kiewra, 1985; Kitjaroonchai et al., 2025; Salame et al., 2024). Likewise, Brown et al. (2014) discovered that self-regulated learning methods, including goal-setting and self-monitoring, are positively linked to academic success in university environments. In the Ghanaian setting, studies reveal that students often depend heavily on rote memorisation and passive listening, with limited use of metacognitive strategies (Amoako et al., 2020). This underscores the necessity for targeted interventions to promote active and strategic learning. Additionally, empirical research indicates that students employing advanced study strategies-such as improved planning, monitoring, and focus-report better performance in assessments and shorter study durations overall (Almoslamani, 2022). Similar meta-analyses combining data from diverse student groups confirm that strong study habits directly relate to higher academic achievement, with skill development interventions producing measurable gains in motivation and self-efficacy (Credé & Kuncel, 2008; Gettinger & Seibert, 2002).

These findings are reinforced by analyses of specific study skills-where concentration stands out as a key factor; students with higher focus during study sessions tend to attain superior qualitative and quantitative results, especially in demanding undergraduate courses (Van Viet et al., 2022; Abid et al., 2023). Furthermore, self-reported study habits, including focus and organisation, have been linked to exam performance, highlighting the importance of targeted training to address skill gaps (Alhassan et al., 2025; Hassanbeigi et al., 2011). Additionally, time management techniques such as goal setting, prioritising, and scheduling have been shown to reduce procrastination and enhance academic results (Akpur, 2020; Lone, 2021). Methods of note-taking like the Cornell system, mind mapping, and outlining improve information organisation and deeper cognitive processing (Buzan, 2006; Stephen, 2024). Meanwhile, behaviours associated with self-regulated learning-such as metacognitive planning, monitoring, and reflection are more common among high-achieving students (Alhameedyeen & Alhameedyeen, 2023; Caixia et al., 2025; Ha et al., 2023; Yip, 2009; Zimmerman, 1990). Active learning strategies, including summarisation, questioning, and peer teaching, further strengthen comprehension (McGuire, 2018), and retrieval-based methods such as practice testing and flashcards significantly improve retention (Fiorella & Mayer, 2015).

Meta-analytic evidence highlights the effectiveness of study skills interventions-especially when integrated within discipline-specific contexts (Hattie et al., 1996; Smith & Baik, 2021). Institutional programmes offering targeted skills training and tutoring markedly enhance student retention and performance (Eather et al., 2022). Nonetheless, the consistent application of these approaches varies according to motivation, self-efficacy, field of study, and socio-economic factors (Dahir, 2020; Shaidullina et al., 2023; Yigiter, 2025), emphasising the need for curricular integration and equitable, tailored academic support to cultivate effective, self-sustaining learning behaviours. Students' focus and academic success are influenced by cognitive preferences, memory capacity, study habits, and personal factors. Ahmad and Andini (2024) found that matching teaching methods to students' visual, auditory, and kinesthetic learning styles can increase sustained focus by up to 15%. Fadhil et al. (2022) reported a moderate positive correlation ($r = 0.48$) between memory span and attention among first-year medical students, with sleep quality and stress levels critically impacting concentration. Aljaffer et al. (2024) identified effective time management as accounting for 32% of the variation in medical students' exam results, while goal-setting, self-assessment, intrinsic motivation, emotional stability, and social support further enhanced academic performance. Shahidi et al. (2014) revealed that over 60% of newly admitted medical students displayed poor to average note-taking abilities, underused active reading techniques, and poorly managed their time, highlighting the need for early skill development efforts.

Collectively, these studies suggest that multimodal teaching, targeted memory and stress-management workshops, structured study-skills training, and proactive wellness initiatives can work together to improve students' focus and learning outcomes. By assessing individual learning preferences and study skills early on, educators can create blended curricula that reduce cognitive strain and promote sustained engagement. Early interventions-such as workshops on note-taking, active reading, time management, and sleep hygiene-can fill skill gaps, enhance memory encoding, and reduce distractions. Promoting peer mentoring and support networks can also sustain motivation and consistent study habits, reinforcing academic resilience. Combining personalised instruction, cognitive-behavioural techniques, and formative assessments demonstrates how curricula can adapt continuously to individual student profiles, ultimately boosting overall academic success. In summary, these integrated strategies foster learning environments that accommodate diverse learners and support long-term educational achievement (Ahmad & Andini, 2024; Aljaffer et al., 2024; Fadhil et al., 2022; Shahidi et al., 2014).

International research offers a broader perspective on students' use of study strategies in general. Zimmerman (2002) emphasised the importance of self-regulation and strategic planning in fostering academic success among university students globally. Studies in various countries, including the United States, the United Kingdom, and Australia, have shown that students increasingly adopt metacognitive strategies, such as self-monitoring, goal setting, and strategic reading, to enhance their learning (Mejeh & Held, 2022; Schunk & DiBenedetto, 2020; Taranto & Buchanan, 2020). For instance, a longitudinal study by Pintrich (2000) demonstrated that students who actively employ self-regulated learning strategies tend to outperform their peers in exams, retain information for longer periods, and develop more autonomous learning skills. Hassanbeigi et al. (2011) found high achievers have higher scores in all seven study skills, including time management and procrastination, when compared to low achievers. Patidar (2019) discovered a need to improve study skills regarding time management, mostly-59.5%-mostly note-taking-43%-textbook reading-

34%-concentration-23.5%-memory-20% and test preparation-15.5%. These international findings reflect a growing awareness of the importance of strategic learning, although disparities remain based on academic discipline, socioeconomic background, and institutional support.

Notably, research in Ghana has revealed notable trends and challenges regarding students' study skills. Amoako et al. (2020) investigated the study habits of university students in Ghana and found that many students predominantly use surface learning strategies such as rereading and highlighting, with minimal engagement in deep learning techniques such as critical analysis or self-testing. The study attributed this to factors such as inadequate academic guidance, limited awareness of effective study strategies, and resource constraints. Similarly, Agormedah et al. (2022) noted that Ghanaian students often lack effective time-management skills, which adversely affect their academic performance. These findings underscore the importance of integrating study skills training into the university curriculum to promote more effective learning behaviour.

There is a massive literature on techniques or approaches to study skills, but the combined effects of various study techniques and the actual methods adopted by university-level learners are still inadequate. Therefore, this study discusses some of the strategies that university students use in their studies and further establishes how six different study skill approaches interact to influence one aspect of a study strategy, which is known as concentration. Understanding these interactions is crucial, as SRL theory suggests that study skills often operate synergistically to enhance learning outcomes, necessitating an investigation into their combined effects. This study can also partially fill this gap by establishing how different study techniques interact to influence students' concentration as an integral component of learning. Such information might contribute to the formulation and adoption of an optimal academic strategy for university students through a better understanding of the interactions among various study skill approaches. The results may be used in educational practice and supporting systems to assist learners in organising more fruitful and individualised study habits that lead to success in learning tasks.

This study aimed to investigate the multidimensional study skills strategies employed by university students in the fields of Science, Mathematics, and ICT, and to examine how these strategies individually and interactively influence students' ability to concentrate during academic tasks. By employing both confirmatory factor analysis and hierarchical regression methods, this study aimed to clarify the underlying structure of study skills and identify which specific strategies most significantly contribute to sustained concentration. Ultimately, this study sought to provide empirical evidence that can inform the design of targeted educational interventions and academic support programs to enhance student learning and performance in the context of higher education. Specifically, this research hypothesised that: (1) study skills comprise a multidimensional construct with seven distinct factors; (2) Time Management, Study Aid/Note-taking, Test Strategies, Information Processing, Motivation and Attitude, and Writing Skills would significantly predict students' concentration; and (3) interactions among these study skills would account for additional variance in concentration.

METHODS

Having reviewed the relevant literature, this study aims to build on the existing knowledge by employing a cross-sectional survey design. This study used a cross-sectional survey design (Cohen et al. 2018). A cross-sectional survey was used as the researchers intended to collect one-shot data from a large group of participants; however, this design cannot establish cause-and-effect relationships because exposures and outcomes are measured simultaneously, and it is also prone to selection, participation, and recall biases that may limit the generalizability of the findings (Levin, 2006; Wang & Cheng, 2020).

Study Area

The University of Cape Coast (UCC), located in the Cape Coast Municipality of Ghana's Central Region on the Atlantic seaboard. As a prominent institution in Ghana, UCC provides a relevant context for examining student study skills within a non-Western educational system. Its main campus occupies hilly terrain overlooking the Gulf of Guinea, providing a natural sea breeze and panoramic coastal views. The climate is

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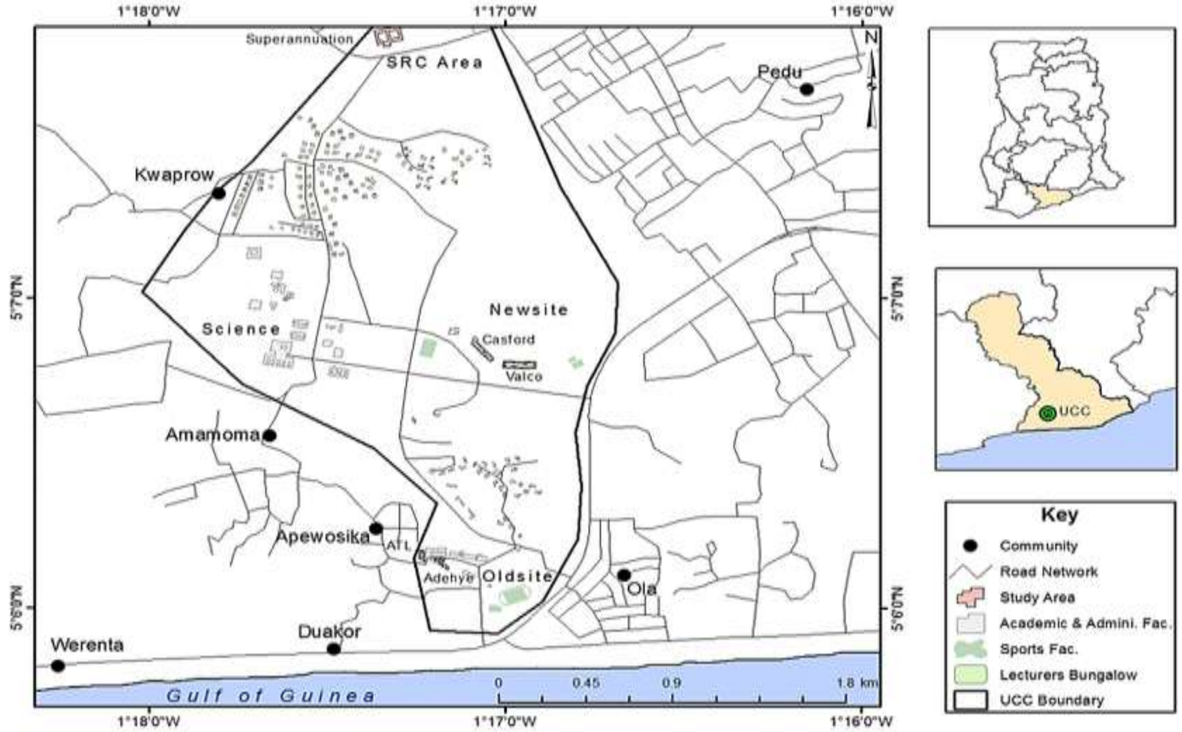
tropical maritime, characterised by two rainy seasons (March-July and September-November), moderate temperatures (24-30 °C), and mean annual rainfall of approximately 1,300 mm. The campus is bounded by the communities of Apewosika and Kokoado to the south ("Old Site") and Amamoma and Kwaprow to the north ("New Site"), with major access via the Elmina-Takoradi Highway as shown in Figure 1 below



Source: Department of Geography and Regional Development, University of Cape Coast

Sample and Sampling Procedure

A simple random sampling technique was employed to select 284 Level 400 undergraduate students enrolled in science, mathematics, and Information and Communication Technology (ICT) programmes (Creswell & Creswell, 2022). The complete roster of eligible students served as the sampling frame, with each student assigned a unique identifier and a computer-based random number generator used to draw the sample without replacement (Clark et al., 2021). The initial cohort comprised 72 males and 212 females, distributed as 99 science students, 89 mathematics students, and 96 ICT students. Returned questionnaires were screened for completeness, and 11 responses exhibiting missing or inconsistent data were expunged: 4 from the science cohort, 3 from the mathematics cohort, and 4 from the ICT cohort, yielding a final analytic sample of 273 students (science n = 95; mathematics n = 86; ICT n = 92). The sample size was justified on several grounds: first, Tabachnick and Fidell (2019) recommend a minimum of 20 observations per variable for reliable multivariate analyses, a threshold comfortably exceeded by 253 cases; second, general guidelines for parametric testing advise at least 200 participants to ensure stable estimates (Field, 2024); and third, Krejcie and Morgan's (1970) sample-size table indicates that for populations up to 500, a minimum of 217 respondents is required to achieve a 95% confidence level with a 5% margin of error-criteria more than satisfied by the final sample. While a formal power analysis was not conducted, the chosen sample size aligns with established guidelines for ensuring adequate statistical power in multivariate analyses.

Data collection instrument

To collect data to help answer the research questions, the study adapted the Study Skills Assessment Questionnaire (SSAQ) developed by the University of Houston Clear Lake's Counselling Services. The SSAQ consists of eight dimensions: concentration and memory, motivation and attitude, organising and processing information, reading and selecting main ideas, study aids and note- taking, test strategies and anxiety, time management and procrastination, and writing skills. For this study, the SSAQ was adapted to seven factors, excluding "reading and selecting main ideas", due to preliminary exploratory analysis revealing poor psychometric properties and limited cultural relevance of this dimension within the Ghanaian context. This adaptation ensured the instrument's suitability for the target population, with domain-specific Cronbach's alpha reliabilities ranging from 0.72 to 0.85 (as further detailed in the results section). All eight dimensions comprised eight items organised on a four-point Likert scale, with response options ranging from 1 (*Never*) to 4 (*Always*). The instrument was piloted and tested with 50 university students to establish reliability for the data collection. Cronbach's alpha reliability was 0.88.

Data Analysis

Data was analysed using both descriptive and inferential statistics. The descriptive statistics made use of mean, standard deviation, skewness, kurtosis and Shapiro-Wilk to assess normality of the data for further inferential statistical analysis. The inferential statistics used hierarchical multiple regression to examine the extent to which six study skill strategies and their interactions account for variance in students' concentration, and Confirmatory factor analysis to extract the subdimensions of study skills and the items that load on them. All statistical analyses were performed using IBM SPSS Statistics (Version 28.0) and IBM SPSS Amos (Version 28.0), with a significance level set at $p < .05$ for all inferential tests.

RESULTS

Descriptive Statistics

Descriptive statistics (Table 1) were calculated for the study skills strategies employed by university students majoring in Science, Mathematics, and ICT (N= 273). The analysis included seven specific domains and an overall measure of the study skills. The results indicated that Time Management had the highest mean score (M = 3.94, SD = 0.50), suggesting that it was the most frequently utilised strategy among students. Information Processing (M = 3.91, SD = 0.56) and Motivation/Attitude (M = 3.92, SD = 0.50) also showed relatively high mean scores. In contrast, Writing Strategies had the lowest mean score (M = 3.70, SD = 0.53), indicating that this skill was less frequently employed than the other strategies. The standard deviations provide insight into the variability of responses, indicating a reasonable spread around the mean for each strategy.

Table 1 Descriptive Statistics of the Sub-domains of Study Skills Strategies

			Skewness		**Kurtosis**		**Shapiro-Wilk**	
Variables	***M***	***SD***	**Skewness**	**SE**	**Kurtosis**	**SE**	**W**	**p**
Time Management	3.94	0.50	-0.67	0.15	1.26	0.29	0.97	<.001
Concentration	3.84	0.46	-0.12	0.15	-0.18	0.29	0.99	0.054
Study Aid/Note-taking	3.83	0.48	0.17	0.15	-0.20	0.29	0.99	0.011
Test Strategies	3.81	0.52	-0.11	0.15	-0.17	0.29	0.99	0.055
Information processing	3.91	0.56	-0.47	0.15	0.36	0.29	0.98	<.001
Motivation/Attitude	3.92	0.50	-0.40	0.15	0.48	0.29	0.98	<.001
Writing strategies	3.7	0.53	0.05	0.15	-0.39	0.29	0.99	0.022
Overall Study-Skills Strategies	3.85	0.37	0.05	0.15	-0.27	0.29	0.99	0.368

Note: N = 273, M= Mean, SD = Standard deviation,

From Table 1, the skewness and kurtosis values reveal variability in the distribution of the scores. Time Management displayed moderate negative skewness (-0.67) and positive kurtosis (1.26), signifying that the scores were concentrated towards higher values and slightly leptokurtic. Concentration (-0.12 skewness, -0.18 kurtosis), Study Aid/Note-taking (0.17 skewness, -0.20 kurtosis), Test Strategies (-0.11 skewness, -0.17 kurtosis), and Writing Strategies (0.05 skewness, -0.39 kurtosis) demonstrated near-normal distribution. Again, as shown in Table 1, the Shapiro-Wilk tests indicated statistically significant deviations from normality in several domains, including Time Management ($W = 0.97$, $p < .001$), Information Processing ($W = 0.98$, $p < .001$), motivation/attitude ($W = 0.98$, $p < .001$), Study Aid/Note-taking ($W = 0.99$, $p = .011$), and Writing Strategies ($W = 0.99$, $p = .022$). However, Concentration ($W = 0.99$, $p = .054$), Test Strategies ($W = 0.99$, $p = .055$), and the Overall Study-Skills Strategies score ($W = 0.99$, $p = .368$) were normally distributed. While these deviations from normality were noted, given the large sample size (N=273), the central limit theorem supports the robustness of the hierarchical regression analysis to these minor departures (Field, 2024), though cautious interpretation of specific p-values for non-normal variables is advised. These findings provide insight into the study behaviours of university students in scientific and mathematical fields, highlighting strengths in time management, motivation, and information processing strategies, alongside a potential area for development in writing strategies.

The interactive effect of the six sub-dimensions of study skills strategies on concentration

Prior to the use of hierarchical multiple regression, collinearity diagnostics were assessed. Collinearity diagnostics across Models 1–6 indicated that variance inflation factors ranged from 1.00 to 2.04 and tolerances from .49 to 1.00, suggesting that multicollinearity was not an issue. Thus, hierarchical multiple regression was conducted to examine the extent to which six study skill strategies and their interactions account for variance in students' concentration (CON). Predictor variables were entered in successive steps as follows: time management (TMP; Model 1), study aid and Note-taking (SAN; Model 2), test strategies (TST; Model 3), information processing (IFP; Model 4), motivation and attitude (MTA; Model 5), writing (WTR; Model 6), and finally all two- through six-way- interaction terms (Model 7).

Model 1 (Table 2), with TMP only, accounted for 13.6% of the variance in concentration, $R^2 = .136$, $F(1, 271) = 42.62$, $p < .001$. Adding SAN to Model 2 produced a significant increment, $\Delta R^2 = .120$, $F\Delta(1, 270) = 43.58$, $p < .001$ (total $R^2 = .256$). The inclusion of TST in Model 3 did not significantly improve the prediction, $\Delta R^2 = .002$, $F\Delta(1, 269) = 0.89$, $p = .347$. In Model 4, IFP added significant explanatory power, $\Delta R^2 = .078$, $F\Delta(1, 268) = 31.47$, $p < .001$ (total $R^2 = .336$). Subsequent entry of MTA (Model 5) and WTR (Model 6) did not yield significant changes-$\Delta R^2 = .003$, $F\Delta(1, 267) = 1.40$, $p = .239$, and $\Delta R^2 = .000$, $F\Delta(1, 266) = 0.10$, $p = .751$, respectively. Finally, the inclusion of the full block of interaction terms in Model 7 produced a small but significant increment, $\Delta R^2 = .187$, $F\Delta(57, 209) = 1.46$, $p = .031$, resulting in a final model that explained 52.8% of the variance in concentration, $R^2 = .528$, $F(63, 209) = 3.70$, $p < .001$. However, it is important to note that the adjusted R^2 for Model 7 (0.385) was considerably lower than the unadjusted R^2 (0.528), strongly indicating potential overfitting due to the large number of interaction terms and thus warranting a highly cautious interpretation of this model's overall explanatory power.

Table 2 Model Comparisons of the Sub-dimensions

Comparison							
Model		**Model**	**ΔR²**	**F**	**df1**	**df2**	**p**
1	-	2	0.12009	43.582	1	270	<.001
2	-	3	0.00244	0.886	1	269	0.347
3	-	4	0.07792	31.469	1	268	<.001
4	-	5	0.00345	1.395	1	267	0.239

5	-	6	2.50e-4	0.101	1	266	0.751
6	-	7	0.18749	1.455	57	209	0.031

The standardised regression coefficients (Table 3) for the key predictors are summarised below. In Model 1, TMP was a significant positive predictor of concentration (B = 0.340, SE = 0.052, t = 6.53, p < .001). In Model 2, both TMP (B = 0.142, SE = 0.057, t = 2.50, p = .013) and SAN (B = 0.389, SE = 0.059, t = 6.60, p < .001) were significant contributors. The effect of TST in Model 3 remained non-significant (B = 0.051, SE = 0.054, t = 0.94, p = .347), and in Model 4 only SAN (B = 0.263, SE = 0.062, t = 4.23, p < .001) and IFP (B = 0.282, SE = 0.050, t = 5.61, p < .001) were significant, whereas TMP (B = 0.039, SE = 0.058, t = 0.67, p = .505) and TST (B = 0.031, SE = 0.051, t = 0.60, p = .550) were not. Neither MTA (B = 0.073, SE = 0.062, t = 1.18, p = .239) nor WTR (B = –0.017, SE = 0.053, t = –0.32, p = .751) emerged as significant in Models 5 and 6, respectively. Although the full interaction block in Model 7 was significant, no individual interaction term attained significance (p > .302).

Table 3 Model Fit Measures of the Sub-dimensions on Concentration

					Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**	**F**	**df1**	**df2**	**p**
1	0.369	0.136	0.133	0.426	42.62	1	271	<.001
2	0.506	0.256	0.250	0.395	46.45	2	270	<.001
3	0.508	0.258	0.250	0.394	31.25	3	269	<.001
4	0.580	0.336	0.326	0.373	33.96	4	268	<.001
5	0.583	0.340	0.327	0.372	27.49	5	267	<.001
6	0.583	0.340	0.325	0.372	22.84	6	266	<.001
7	0.726	0.528	0.385	0.315	3.70	63	209	<.001

Note. Models estimated using sample size of N=273

Confirmatory factor analysis to extract the subdimensions of study skills and the items that load on them

Assumption checks indicated acceptable levels of multicollinearity (VIFs ≤ 2.04; tolerances ≥ .49) and mostly normal residual distributions (Tabachnick & Fidell, 2019). A slight deviation from normality in the final model and the presence of a few multivariate outliers did not appear to materially influence coefficients; however, these diagnostics recommend cautious interpretation of higher-order effects.

A Confirmatory Factor Analysis (CFA) was conducted to test the hypothesis that study skills strategies among university students represent a multidimensional construct comprising seven factors: Concentration, Information Processing, Motivation and Attitude, Study Aid and Note-taking, Time Management, Test Strategies, and Writing Skills. Factor loadings and inter-factor correlations were assessed based on the established threshold of 0.50 for practical significance in structural equation modelling (Hair et al., 2019).

From Table 4. The standardised regression weights demonstrated variability across the indicators. For Concentration, the loadings ranged from .067 (CON2) to .625 (CON5), with CON5 (.625) and CON8 (.502) exceeding the threshold, indicating practical significance. However, items such as CON2 (.067), CON7 (.107), CON1 (.158), CON3 (.277), CON4 (.392), and CON6 (.449) exhibited notably low loadings, falling well

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below the recommended 0.50 threshold and suggesting poor representation of the Concentration construct by these specific items. Information Processing displayed moderate loadings (.289–.565), with the strongest item being IFP7 (.565). Motivation and Attitude had consistent moderate loadings (.452–.565), suggesting a robust representation of this dimension. Study Aid and Note-taking showed variability (.174–.559), although SAN7 (.503) and SAN8 (.559) surpassed the significance threshold. Similarly, SAN2 (.174), SAN6 (.238), SAN5 (.304), SAN1 (.323), SAN4 (.360), and SAN3 (.367) demonstrated low loadings, indicating potential issues with their contribution to the Study Aid/Note-taking factor. Time Management items yielded loadings between .274 and .545, with TMP3 (.545), TMP2 (.518), and TMP7 (.515) indicating practical significance. Test Strategies had loadings from .096 (TST1) to .564 (TST8), with TST8 (.564) and TST2 (.530) significantly loading on the factor. However, TST1 (.096), TST4 (.280), TST5 (.422), TST6 (.433), TST3 (.456), and TST7 (.486) also showed low loadings, suggesting that these items may not adequately capture the Test Strategies construct. Writing Skills exhibited moderate to high loadings (.245–.597), notably WRT7 (.588) and WRT8 (.597), demonstrating practical significance. WRT3 (.245), WRT6 (.295), WRT2 (.302), WRT5 (.349), and WRT1 (.364) also had low loadings, raising questions about their fit within the Writing Skills factor.

Table 42 Standardized Regression Weights of Item Loadings on the Sub-domains of Study Skills Strategies

S/No	Indicators		Observed Variables	Estimate
1	CON2	<---	Concentration	0.067
2	CON7	<---	Concentration	0.107
3	CON1	<---	Concentration	0.158
4	CON3	<---	Concentration	0.277
5	CON4	<---	Concentration	0.392
6	CON6	<---	Concentration	0.449
7	CON8	<---	Concentration	0.502
8	CON5	<---	Concentration	0.625
9	IFP1	<---	Information processing	0.289
10	IFP6	<---	Information processing	0.456
11	IFP5	<---	Information processing	0.456
12	IFP4	<---	Information processing	0.456
13	IFP2	<---	Information processing	0.465
14	IFP8	<---	Information processing	0.484
15	IFP3	<---	Information processing	0.496
16	IFP7	<---	Information processing	0.565
17	MTA1	<---	Motivation and Attitude	0.452
18	MTA8	<---	Motivation and Attitude	0.475

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19	MTA2	<---	Motivation and Attitude	0.521
20	MTA7	<---	Motivation and Attitude	0.542
21	MTA6	<---	Motivation and Attitude	0.546
22	MTA4	<---	Motivation and Attitude	0.552
23	MTA5	<---	Motivation and Attitude	0.553
24	MTA3	<---	Motivation and Attitude	0.565
25	SAN2	<---	Study aid/Note-taking	0.174
26	SAN6	<---	Study aid/Note-taking	0.238
27	SAN5	<---	Study aid/Note-taking	0.304
28	SAN1	<---	Study aid/Note-taking	0.323
29	SAN4	<---	Study aid/Note-taking	0.360
30	SAN3	<---	Study aid/Note-taking	0.367
31	SAN7	<---	Study aid/Note-taking	0.503
32	SAN8	<---	Study aid/Note-taking	0.559
33	TMP1	<---	Time management	0.274
34	TMP6	<---	Time management	0.352
35	TMP4	<---	Time management	0.410
36	TMP8	<---	Time management	0.447
37	TMP5	<---	Time management	0.458
38	TMP7	<---	Time management	0.515
39	TMP2	<---	Time management	0.518
40	TMP3	<---	Time management	0.545
41	TST1	<---	Test strategies	0.096
42	TST4	<---	Test strategies	0.280
43	TST5	<---	Test strategies	0.422
44	TST6	<---	Test strategies	0.433
45	TST3	<---	Test strategies	0.456
46	TST7	<---	Test strategies	0.486

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47	TST2	<---	Test strategies	0.530
48	TST8	<---	Test strategies	0.564
49	WRT3	<---	Writing skills	0.245
50	WRT6	<---	Writing skills	0.295
51	WRT2	<---	Writing skills	0.302
52	WRT5	<---	Writing skills	0.349
53	WRT1	<---	Writing skills	0.364
54	WRT4	<---	Writing skills	0.547
55	WRT7	<---	Writing skills	0.588
56	WRT8	<---	Writing skills	0.597

Inter-factor correlations (Table 5) showed substantial relationships among the dimensions, supporting the multidimensional conceptualization of study skills. Particularly high correlations were observed between Concentration and Study Aid/Note-taking (.975), Study Aid/Note-taking and Information Processing (.874), and Information Processing and Motivation/Attitude (.917). Strong correlations were also found between Writing Strategies and Study Aid/Note-taking (.800), and between Time Management and Study Aid/Note-taking (.780). The path diagram (Figure 2) shows a summary of the regression weight and correlation between the subdomains of study skills strategies.

Table 3 Correlation Between the Sub-domains of Study Skills Strategies

Observed Variables		**Observed Variables**	**Estimate**
Time Management	<-->	Concentration	0.482
Time Management	<-->	Study Aid/Note-taking	0.780
Time Management	<-->	Test Strategies	0.749
Time Management	<-->	Information processing	0.710
Time Management	<-->	Motivation/Attitude	0.681
Concentration	<-->	Study Aid/Note-taking	0.975
Concentration	<-->	Test Strategies	0.546
Concentration	<-->	Information processing	0.773
Concentration	<-->	Motivation/Attitude	0.673
Writing strategies	<-->	Concentration	0.624
Study Aid/Note-taking	<-->	Test Strategies	0.857
Study Aid/Note-taking	<-->	Information processing	0.874

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Study Aid/Note-taking	<-->	Motivation/Attitude	0.761
Writing strategies	<-->	Study Aid/Note-taking	0.800
Test Strategies	<-->	Information processing	0.660
Test Strategies	<-->	Motivation/Attitude	0.683
Writing strategies	<-->	Test Strategies	0.688
Information processing	<-->	Motivation/Attitude	0.917
Writing strategies	<-->	Information processing	0.774
Writing strategies	<-->	Motivation/Attitude	0.873
Writing strategies	<-->	Time Management	0.718

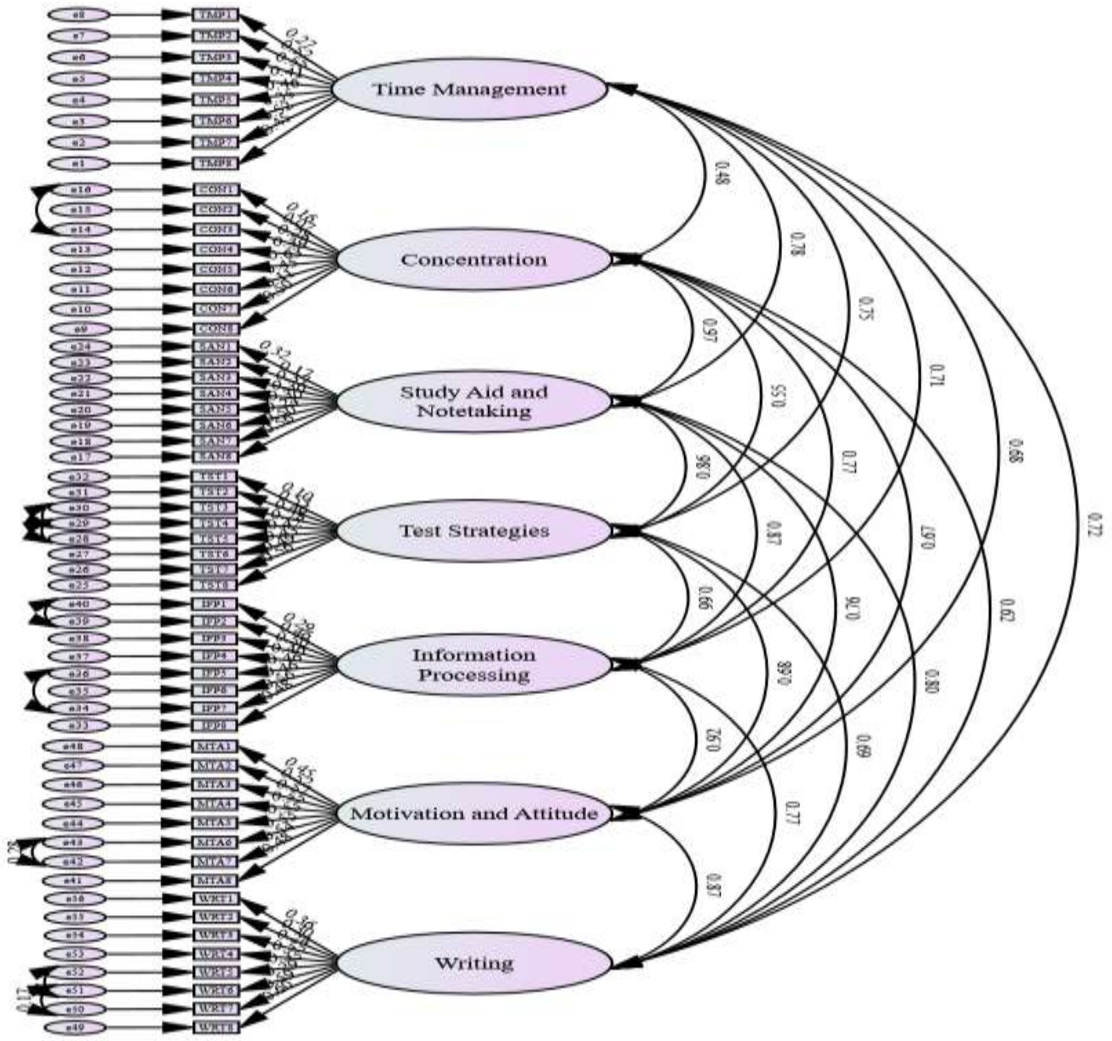

Figure 2: Path Diagram of Item Loadings and the correlation between the Sub-domains of Study Skills Strategies

DISCUSSION

This study clarified the unique and combined contributions of six study-skill strategies-time management (TMP), study aid and note-taking (SAN), test strategies (TST), information processing (IFP), motivation and attitude (MTA), and writing skills (WTR)-to university students' reported concentration (CON). The hierarchical regression analysis revealed that TMP, SAN, and IFP were significant positive predictors of concentration, underscoring the critical role of organizational and cognitive strategies in maintaining focus (Salame et al., 2024). In contrast, TST, MTA, and WTR did not contribute significantly to concentration in the final model. Moreover, although the full block of interaction terms in the final model produced a small but significant increase in explained variance, no individual interaction achieved significance, suggesting that the interplay among strategies may be complex or underpowered to detect specific effects. Notably, the adjusted R^2 in Model 7 (0.385) was lower than the unadjusted R^2 (0.528), indicating potential overfitting due to the inclusion of numerous interaction terms, which warrants cautious interpretation. Future research could address this by employing larger sample sizes or alternative analytical approaches, such as latent profile analysis, to better disentangle specific synergistic or antagonistic effects among strategies.

Consistent with extant research, TMP emerged as a robust predictor of CON, explaining 13.6% of the variance when it was entered alone (Model 1). This finding aligns with prior studies that have demonstrated that effective allocation of study time enhances focus and reduces procrastination (Britton & Tesser, 1990; Britton & Tesser, 1991). When SAN was added to Model 2, it produced the largest single-step increase ($\Delta R^2 = .120$), corroborating classic accounts that active note-taking supports encoding and attentional engagement during study sessions (Kiewra, 1985; Kitjaroonchai et al., 2025; Donaldson, 1997; Salame et al., 2024;). The persistence of TMP's effect in Model 2 further underscores its foundational role in structuring study behaviour.

Information processing strategies contributed uniquely to Model 4 ($\Delta R^2 = .078$), such that greater use of elaboration, organisation, and rehearsal was associated with higher CON (Liu et al., 2025). This finding is consistent with deep-processing frameworks that link meaningful engagement with material to sustained attention (Craik & Lockhart, 1972). In contrast, TST did not yield a significant effect at any step, suggesting that strategies geared specifically toward test performance (for example. item-specific mnemonics or self-testing) may be less directly related to moment-to-moment concentration than general organizational and encoding tactics.

Contrary to expectations based on SRL theory (Pintrich, 2000; Zimmerman, 2002), motivational and writing skills did not predict concentration. This may be due to measurement overlap with other domains, as evidenced by the high correlations between Motivation/Attitude and Information Processing (.917), and between Motivation/Attitude and Writing Strategies (.873) (Table 5), or limited variance in self-reported motivation among final-year students. It is also possible that their influence on concentration is indirect, operating through proximal behaviours such as time allocation and active note-taking. Alternatively, the nonsignificant findings may reflect overlapping variances with other skill domains. Although the full interaction block in Model 7 produced a statistically significant ΔR^2 (.187), none of the two-through six-way interactions reached significance. This pattern suggests that while combinations of strategies are collectively related to concentration, disentangling specific synergistic or antagonistic effects may require larger samples or alternative modelling approaches (for example. latent profile analysis). These findings offer a nuanced perspective on study skills in non-Western contexts like Ghana, where previous research indicated a reliance on surface learning (Agormedah et al., 2022; Amoako et al., 2020). The current study suggests that even in such contexts, specific deeper processing and organizational skills are significantly linked to concentration, potentially offering a pathway for targeted interventions to shift learning approaches.

The results from the Confirmatory Factor Analysis (CFA) supported the hypothesis that the study skills strategies of university students are best conceptualised as a multidimensional construct consisting of seven distinct but interrelated factors: Concentration, Information Processing, Motivation and Attitude, Study Aid and Note-taking, Time Management, Test Strategies, and Writing Skills. This finding aligns with prior research, indicating that effective study habits encompass a broad spectrum of skills, each contributing uniquely yet synergistically to academic performance (Gettinger & Seibert, 2002).

The varying strengths observed in the factor loadings across the seven domains suggest that not all individual skills within these domains contribute equally to the underlying constructs. Specifically, higher loadings for items such as CON5 (.625), IFP7 (.565), and WRT8 (.597) indicate that these skills may play more critical roles within their respective domains. This differential weighting of items underscores the importance of targeted interventions and educational support that prioritises stronger predictors of academic success (Credé & Kuncel, 2008).

The high correlations observed among several factors, particularly between Concentration and Study Aid/Note-taking (.975), Information Processing and Motivation/Attitude (.917), and Study Aid/Note-taking and Information Processing (.874), suggest considerable overlap and interdependency among these skill sets. These findings support the notion that improvement in one skill area is likely to positively impact other areas, emphasising the potential effectiveness of holistic approaches to enhancing students' academic performance (Hattie & Donoghue, 2016).

However, the presence of some lower-loading items (for example, CON2, TST1, and SAN2) implies the need for further refinement of the measurement instruments or reconsideration of these items within their constructs. Lower loadings suggest that these specific items may not be as representative of their intended factor or might be interpreted differently by students, necessitating revision or removal in future iterations of the SSAQ to enhance its psychometric properties and ensure greater clarity and relevance.

CONCLUSION

These results highlight the primacy of time management, note-taking, and deep processing as targets for study-skills interventions aimed at bolstering students' concentration. Educators and academic support services might prioritise discipline-specific workshops and coaching embedded within curricula that strengthen these core behaviours while recognising that motivation and writing confidence, although valuable for other outcomes, may not directly translate into enhanced momentary focus.

Collectively, the findings advance our understanding of how discrete and interactive study-skill strategies contribute to students' ability to sustain attention, guiding both theory and practice in higher education learning support. These findings support the hypothesis that study skills strategies are multidimensional, interrelated constructs with significant implications for targeted academic interventions and instructional strategies. However, the presence of several low factor loadings in the CFA suggests that while the multidimensional structure is supported, individual items within the instrument may require refinement to enhance psychometric stability and ensure greater construct validity in similar contexts. In summary, the CFA results provide empirical support for conceptualizing study skills as a multifaceted and interconnected framework. Educational practitioners should leverage these findings to design comprehensive study skills training programs that address multiple dimensions simultaneously, thereby enhancing the overall academic achievement of university students.

While the cross-sectional design precludes causal inferences and reliance on self-reports may introduce shared method variance, the robust associations identified between key study skills and concentration offer valuable insights for intervention development. Future research could employ diary methods or objective behavioural logs to capture real-time concentration and strategy use. Moreover, experimental manipulation of strategy training would help to clarify causal pathways. Finally, exploring moderating factors such as task difficulty or individual differences (for example, working memory capacity) may illuminate when and for whom specific combinations of study skills most effectively support concentration.

Implications

The findings underscore the importance of designing practical interventions that prioritise time management, structured note-taking, and information processing skills. In the Ghanaian higher education context, this could take the form of integrated workshops, peer-led note-taking groups, and curriculum-embedded training in effective cognitive strategies. Specifically, universities could implement mandatory first-year seminars focused on practical time management techniques, such as creating study schedules and prioritising tasks, and introduce active note-taking methods like the Cornell system or mind mapping within core courses. Furthermore, academic support centres could offer tailored coaching sessions on deep information processing, encouraging students to summarise, paraphrase, and elaborate on course material rather than relying on rote memorisation. These interventions would not only enhance individual student concentration but also contribute to a broader culture of effective self-regulated learning across the institution, potentially improving overall academic retention and performance.

Limitations and Future Research

Although the cross-sectional design limits causal inference, the significant associations identified provide a foundation for future longitudinal or experimental studies. The potential for overfitting in the hierarchical regression model with numerous interaction terms also suggests a need for replication with larger samples or alternative modeling techniques to confirm these complex relationships. Furthermore, the low factor loadings observed for several items in the CFA indicate that the adapted instrument may benefit from further psychometric validation and refinement, potentially through item revision or removal, to better capture the intended constructs in this specific cultural context. Further research should explore moderating factors, such as task difficulty, working memory, or gender, to better understand for whom and under what conditions study strategies most effectively enhance concentration. These factors are critical because task difficulty can influence the cognitive load required for concentration, working memory capacity affects how students process and retain information, and gender may introduce differential learning approaches or motivational patterns. Future studies could employ specific methodologies like daily diary studies to capture fluctuations in concentration and strategy use in real-time or utilise objective behavioural logs (for example, eye-tracking data or study app usage analytics) to provide less biased measures of engagement. Additionally, experimental designs could manipulate specific study strategy training to establish clearer causal links with improved concentration.

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