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ASSOCIATIONS OF SLEEP PATTERNS, TECHNOLOGY USE AND EATING HABITS WITH SELF-REPORTED COGNITIVE FUNCTION AMONG MALAYSIAN UNDERGRADUATES

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Abstract: *University students' cognitive functioning may be associated with modifiable lifestyle behaviours, but sleep, technology use, and eating habits are often examined separately. This cross-sectional study investigated their bivariate and adjusted associations with self-reported cognitive function among 85 Malaysian undergraduate students at Universiti Teknologi MARA Cawangan Kelantan, Kampus Kota Bharu. Data were collected using a bilingual questionnaire containing six items per construct and analysed using reliability analysis, Pearson correlation, and multiple linear regression. Higher sleep, eating-habits, and cognitive-function scores represented healthier sleep, healthier eating, and better perceived cognition after reverse coding the specified negative items. Technology items were retained in their original direction, so higher scores represented more intensive or problematic use. Sleep pattern was positively correlated with cognitive function, $r = .322$, 95% CI [.117, .501], $p = .003$; technology use, $r = .160$, 95% CI [-.055, .361], $p = .143$, and eating habits, $r = .205$, 95% CI [-.008, .401], $p = .060$, were not statistically significant. The regression model was significant, $F(3, 81) = 6.724$, $p < .001$, R-squared = .199. Sleep pattern and technology use had significant adjusted coefficients, whereas eating habits did not. The positive adjusted technology coefficient was counterintuitive under the retained coding and is compatible with a suppression-type pattern. The findings are associational and require replication with fully documented scoring, participant profiles, and objective measures.*

Keywords: *cognitive function, eating habits, multiple linear regression, sleep pattern, technology use, Malaysian undergraduates*

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Introduction

Cognitive function comprises the mental processes used to sustain attention, retain and retrieve information, exercise executive control, reason analytically, and solve problems. These processes are central to learning because undergraduate students must attend to lectures, integrate new information, plan academic work, and respond effectively to complex tasks. Cognitive performance is therefore shaped not only by formal instruction but also by daily behaviours that influence alertness and mental efficiency. Recent evidence indicates that sleep quality and duration are associated with working memory, attention regulation, cognitive failure, and academic functioning among university students (Hershner, 2020; Jaffri et al., 2024; Xu et al., 2025).

The transition to university life creates a distinctive behavioural environment in which cognitive demands increase while daily routines often become less structured. Students may face irregular timetables, assessment deadlines, commuting demands, employment responsibilities, and greater independence in deciding when to sleep, eat, and use digital devices. These conditions make lifestyle behaviours especially relevant to cognitive functioning. Attention and memory are not fixed personal attributes; they fluctuate with fatigue, emotional condition, environmental distraction, and physiological regulation. Consequently, an analysis of cognition among university students should consider the behavioural context within which learning occurs rather than attributing performance solely to ability or motivation. The present study focuses on three modifiable domains because sleep, technology engagement, and nutrition are common parts of everyday student life and are theoretically capable of operating both independently and in combination.

Sleep is especially important during university because academic demands, social schedules, and evening screen exposure can disrupt both sleep duration and regularity. Variations in sleep patterns have been linked with differences in memory retention, while digital media use shortly before bedtime has been associated with poorer sleep outcomes (Dahat et al., 2023; Orzech et al., 2016). Technology may also affect cognition more directly by interrupting sustained attention and more indirectly by delaying sleep or increasing bedtime procrastination (Caninsti & Rahayu, 2024; Lin & Zhou, 2022; Rosen et al., 2016). At the same time, meal irregularity, breakfast skipping, low diet quality, and reliance on processed food may affect psychological well-being, sleep, and cognitive performance (Almoraie et al., 2025; Faris et al., 2022; Solomou et al., 2023).

These lifestyle behaviours do not occur independently. A student who uses a smartphone late at night may sleep later, experience daytime fatigue, and adopt irregular eating schedules. Longitudinal evidence has demonstrated reciprocal associations among internet addiction, insomnia, resilience, and healthy eating habits, while research on breakfast frequency has shown that sleep chronotype and depressive symptoms can form part of the pathway connecting diet and sleep (Xian et al., 2023; Yao et al., 2024). In Malaysia, technology use, sleep patterns, and eating habits have been identified as relevant correlates of cognitive skills among university students (Jamal & Hasan, 2025). Nevertheless, evidence remains limited on their simultaneous association with cognitive function within a single multivariable model in a specific Malaysian undergraduate population.

The central problem addressed by this study is therefore both substantive and methodological. University students commonly experience irregular sleep, intensive technology exposure, and inconsistent eating practices, yet previous work has frequently examined these factors separately or used academic performance as a proxy for cognitive function. Separate analyses

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cannot determine whether an observed association remains after related behaviours are controlled. Furthermore, evidence derived from other settings may not represent students at Universiti Teknologi MARA Cawangan Kelantan, Kampus Kota Bharu. A locally grounded multivariable analysis is required to estimate the independent statistical contribution of each lifestyle factor while recognising that a cross-sectional survey can establish association, but not causation.

An additional problem concerns the conceptual distinction between academic achievement and cognitive function. Grade point average is shaped by prior preparation, assessment structure, attendance, motivation, course difficulty, and institutional practices. It is therefore an imperfect substitute for cognitive processes such as concentration, alertness, recall, and information processing. Conversely, a self-report cognitive scale captures students' perceptions of these processes rather than their performance on standardised neuropsychological tasks. The distinction matters because lifestyle factors may affect perceived mental efficiency without producing an immediately observable change in grades. By treating self-reported cognitive function as the outcome, the study addresses a more proximal psychological construct, although the interpretation must remain limited to subjective functioning and should not be presented as an objective clinical assessment.

Accordingly, this study examined the relationships of sleep patterns, technology use, and eating habits with self-reported cognitive function among Malaysian undergraduate students at UiTM Cawangan Kelantan, Kampus Kota Bharu. The first objective was to determine whether each lifestyle factor was significantly correlated with cognitive function. The second objective was to determine which factors remained significant predictors when all three were entered simultaneously into a multiple linear regression model. Three predictor-specific hypotheses were evaluated: sleep pattern, technology use, and eating habits would each be associated with cognitive function. An additional omnibus hypothesis stated that the three-predictor regression model would explain a statistically significant proportion of variation in cognitive function. This formulation avoids treating a partially supported collection of predictors as a single indivisible hypothesis.

The contribution of the study lies in its simultaneous treatment of the three behavioural domains. A bivariate correlation describes the total linear association between two variables, whereas a regression coefficient estimates the association that remains after the other predictors have been statistically controlled. Comparing these two forms of evidence can reveal whether apparently weak relationships are masked by shared variance among lifestyle behaviours. This is particularly important when technology use is related to sleep timing and when eating habits are associated with sleep quality. The analysis therefore contributes not only a set of significance tests but also a clearer account of how correlated predictors behave within the same statistical model.

Literature Review

Cognitive Function Among Undergraduate Students

Cognitive function is multidimensional and includes attention, memory, processing speed, executive functioning, and problem-solving ability. In undergraduate education, these capacities support comprehension, knowledge retention, task completion, and adaptive decision-making. Sleep-related cognitive failure has been observed even among young adults, challenging the assumption that university students are resilient to short or disrupted sleep (Jaffri et al., 2024). Sensor-based research has also linked sleep quality with variation in

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objective cognitive performance, reinforcing the relevance of behavioural conditions outside the classroom (Visuri et al., 2025). Because the present study used a questionnaire rather than performance-based cognitive tests, its outcome should be interpreted specifically as self-perceived cognitive functioning.

Self-perceived cognition remains meaningful because students make day-to-day academic decisions on the basis of whether they feel attentive, mentally alert, able to remember information, and capable of completing demanding tasks. Repeated difficulty in these areas can affect study persistence and the selection of learning strategies even when objective ability is unchanged. Nevertheless, self-report measures are vulnerable to mood, expectations, social desirability, and common-method variance. A respondent who generally evaluates personal health positively may provide favourable ratings across sleep, diet, and cognition, thereby increasing observed correlations. When predictors and outcomes are collected from the same respondent using the same response format at the same time, method-related covariance can contribute to the observed relationships (Podsakoff et al., 2003). Objective tests and behavioural records would address a different aspect of cognition and might produce different effect sizes.

Sleep Patterns and Cognitive Function

A sleep pattern incorporates duration, quality, continuity, regularity, and daytime consequences. These components are interrelated but not interchangeable. A student may obtain an adequate number of hours yet experience fragmented sleep, or may report good sleep quality despite an irregular schedule. A systematic review found that different patterns of sleep were associated with different forms of memory retention (Dahat et al., 2023). Broader evidence similarly indicates that inadequate sleep is related to poorer concentration, executive functioning, and academic performance (Hershner, 2020).

Among university students, the relationship is particularly plausible because late-night study, social commitments, and digital engagement compete with sleep. Recent studies have associated sleep quality with cognitive failure and multimodal cognitive outcomes, including attention and working memory (Jaffri et al., 2024; Xu et al., 2025). Wearable and mobile sensor data provide complementary support by reducing exclusive reliance on retrospective self-report (Visuri et al., 2025). Taken together, this literature supports the expectation that healthier sleep patterns will be positively associated with cognitive function.

Several mechanisms may explain the association. Adequate and continuous sleep supports memory consolidation, while sleep loss increases daytime sleepiness and reduces the capacity to sustain attention. Irregular timing may further disturb circadian alignment, causing students to undertake cognitively demanding work when alertness is low. These mechanisms suggest that sleep duration alone is insufficient as a measure of healthy sleep. The questionnaire used in this study included duration, schedule consistency, difficulty falling asleep, waking refreshed, night-time disturbance, and daytime sleepiness. This breadth is conceptually useful, but it also requires correct reverse coding because difficulty sleeping, disturbance, and sleepiness represent poorer rather than better sleep. A composite score is interpretable only when all items point toward a common underlying direction.

Technology Use and Cognitive Function

Technology use is not a single exposure. Its cognitive implications depend on duration, timing, purpose, multitasking, and the degree to which use is compulsive or displaces sleep. Digital media use during the two hours before bedtime has been associated with poorer sleep variables among university students (Orzech et al., 2016). Bedtime smartphone use may also affect

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academic performance through stress and sleep-related pathways rather than through a simple direct mechanism (Lin & Zhou, 2022). Research on sleeping with technology further suggests that patterns of device use and cognitive-affective characteristics jointly predict sleep problems (Rosen et al., 2016).

More recent evidence indicates that smartphone addiction can contribute to bedtime procrastination, while digital interventions can improve sleep outcomes when technology is used deliberately for behavioural support (Caninsti & Rahayu, 2024; Lu et al., 2025). Technology should therefore not be interpreted as uniformly harmful. A scale consisting of statements about excessive screen time, bedtime device use, difficulty reducing screen time, phone checking, lecture-time use, and sleep interference is better understood as problematic or intensive technology use. The direction of any statistical association depends on whether these negatively worded items are retained as scored or reverse-coded to represent responsible use.
The timing and function of device use also complicate interpretation. Four hours of smartphone use may reflect social media browsing, but it may also include digital textbooks, statistical software, recorded lectures, communication with lecturers, or employment. The same duration can therefore represent either distraction or academically productive engagement. Similarly, bedtime use may affect sleep through light exposure, emotional stimulation, time displacement, or an inability to disengage, and these pathways cannot be distinguished by a general agreement scale. The literature supports a move away from treating total screen time as a homogeneous risk factor. Measures that separate educational use, social communication, entertainment, compulsive checking, and night-time exposure would yield more precise conclusions about which aspects of technology are associated with cognition (Lin & Zhou, 2022; Orzech et al., 2016).

Eating Habits and Cognitive Function

Eating habits include meal regularity, breakfast consumption, dietary variety, fruit and vegetable intake, fast-food consumption, and reliance on processed food. University students may experience disrupted eating patterns because of time constraints, academic workload, financial limitations, and increased autonomy. A narrative review identified nutritional concerns and unhealthy eating behaviours as common issues within university populations (Almoraie et al., 2025). Diet quality has also been associated with mental health among university students, providing a plausible indirect pathway to cognitive functioning (Solomou et al., 2023).

Diet and sleep may reinforce one another. Unhealthy eating habits have been associated with poorer subjective sleep quality, and breakfast frequency has been related to sleep quality through chronotype and depressive symptoms (Faris et al., 2022; Xian et al., 2023). Nutrition may also operate alongside physical activity to influence psychological well-being, cognitive performance, and quality of life (Vasco et al., 2025). The anticipated association between eating habits and cognition is consequently plausible, although its independent effect may be modest after correlated lifestyle behaviours are controlled.

Measurement breadth is again important. Eating breakfast, consuming fruit and vegetables, avoiding fast food, maintaining regular meal times, and limiting processed food describe related but distinct practices. A student may eat breakfast every day while relying on nutritionally poor food, or may consume a balanced diet despite irregular meal timing. Combining heterogeneous behaviours into a six-item score can lower internal consistency because the items do not necessarily change together. This provides a substantive explanation for the weaker reliability observed for the eating-habits scale in the final sample. A low-to-moderate alpha does not

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automatically invalidate the construct, but it indicates that the composite contains greater measurement error and may underestimate its relationship with cognition.

Integrated Conceptual Basis

The literature supports an integrated model in which sleep, technology use, and eating habits are correlated behaviours with both direct and indirect links to cognition. Malaysian research provides contextual support for considering all three factors together (Jamal & Hasan, 2025), while cross-lagged evidence illustrates how insomnia, internet addiction, and healthy eating may influence one another over time (Yao et al., 2024). Multiple linear regression is therefore appropriate for estimating the unique association of each predictor with cognitive function while holding the other predictors constant. However, the model should be viewed as explanatory rather than causal because temporal ordering cannot be established from one-time observations.

This integrated perspective also clarifies what the regression model does not test. Entering three predictors in one additive model does not demonstrate that they interact in the statistical sense. An interaction would require a product term, such as sleep pattern multiplied by technology use, and would test whether the association of one predictor changes across levels of another. The fitted model instead estimates three adjusted main effects. It can show whether sleep contributes information beyond technology and eating habits, but it cannot establish mediation, moderation, reciprocal influence, or a behavioural pathway. The distinction is essential because the literature proposes several indirect mechanisms, particularly from technology use to cognition through sleep. Testing those mechanisms would require longitudinal data or an appropriately specified mediation model.

Methodology

Research Design and Setting

The study adopted a quantitative cross-sectional survey design. Data were collected at one point in time from undergraduate students enrolled at UiTM Cawangan Kelantan, Kampus Kota Bharu during the 2025/2026 academic session. The target population comprised 1,030 students from the College of Computing, Informatics and Mathematics and the Faculty of Business and Management. A cross-sectional design was suitable for estimating contemporaneous associations efficiently, although it does not permit conclusions about temporal sequence or causal effects. Reporting was strengthened with reference to the STROBE recommendations for observational studies, particularly the need to distinguish design, participants, variables, statistical methods, results, limitations, and generalisability (von Elm et al., 2007).

The unit of analysis was the individual undergraduate student. Sleep pattern, technology use, eating habits, and cognitive function were treated as continuous composite variables derived from Likert-type items. This treatment is common when several ordered-response items are combined into a scale with sufficient range, but it assumes that the resulting scores approximate interval-level measurement. The design did not manipulate exposure, assign participants to conditions, or follow changes over time. Terms such as effect, influence, and improvement must therefore be interpreted as statistical prediction within the observed sample rather than as evidence that one variable produced a change in another.

Sample Size and Sampling

The planned sample size was calculated using the Raosoft Sample Size Calculator with a population of 1,030, a 95% confidence level, a 50% response distribution, and a 10% margin

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of error, resulting in a target of 88 respondents. Sample-size decisions should be aligned with the intended statistical analysis and the precision required for inference (Adhikari, 2021). The final analytical sample comprised 85 complete responses, three fewer than the planned target. The value 85/88 (96.6%) describes target attainment, not a response rate, because the number of invitations and refusals was not retained. The study reported simple random selection from the student sampling frame using random values generated in Microsoft Excel.

Although the achieved sample was close to the survey target, the Raosoft calculation is based primarily on estimating a population proportion and does not directly evaluate power for a three-predictor regression. A sensitivity calculation for N = 85, three predictors, alpha = .05, and 80% power indicated a minimum detectable effect of approximately f-squared = .135 (equivalent R-squared approximately .119). The observed model effect was f-squared = .248. The study was therefore reasonably sensitive to moderate model-level effects but remained less informative for small individual associations. Nonsignificant results, particularly the correlation between eating habits and cognition (p = .060), should be interpreted with their confidence intervals rather than as evidence of no association (Lakens, 2022).

Instrument and Measurement

Table 1 summarises the structure and measurement scale of the questionnaire used in the study.

Table 1: Summary of the Research Instrument

Section	Construct	Items	Scale and scoring
A	Demographic profile	3	Gender, age, and semester
B	Sleep pattern	6	1-7; B3, B5, and B6 reversed; higher = healthier sleep
C	Technology use	6	1-7; no reversal; higher = more intensive/problematic use
D	Eating habits	6	1-7; D2, D4, and D6 reversed; higher = healthier eating
E	Cognitive function	6	1-7; E3 and E5 reversed; higher = better perceived cognition

Data were collected using a bilingual, self-administered questionnaire adapted from Jamal and Hasan (2025). Section A recorded gender, age, and semester of study. Sections B to E contained six items each for sleep pattern, technology use, eating habits, and cognitive function. Responses ranged from 1, strongly disagree, to 7, strongly agree. Before forming mean composite scores, sleep items B3, B5, and B6, eating-habits items D2, D4, and D6, and cognitive-function items E3 and E5 were reverse-coded as 8 minus the original response. Thus, higher scores represented healthier sleep, healthier eating, and better self-reported cognitive function. The six technology items were retained in their original direction because each described intensive or problematic behaviour; higher technology scores therefore represented more problematic use. This coding definition governs all interpretations in the article.

Adaptation of an existing questionnaire should preserve construct meaning while ensuring linguistic and cultural suitability. The bilingual presentation improved accessibility, yet translation quality cannot be assumed merely because equivalent statements appear side by side.

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Ideally, the adaptation process would include expert review, forward and backward translation, cognitive interviewing, and documentation of all changes to the original items. Content validity concerns whether the items adequately represent the domain, whereas internal consistency concerns whether they respond coherently. Cronbach's alpha alone cannot demonstrate that a scale is valid or unidimensional. These distinctions are important because a statistically reliable score may still omit relevant aspects of sleep, technology behaviour, diet, or cognition.

Pilot Study Data Collection and Ethics

A pilot study involving 40 students with characteristics similar to the target respondents evaluated internal consistency and item clarity. Cronbach's alpha values were interpreted in relation to the number of items, construct breadth, and intended use (Tavakol & Dennick, 2011). The final questionnaire was distributed through Google Forms. The institutional ethics application recorded that external Research Ethics Committee review was not required. Participants received information about the study purpose, voluntary participation, confidentiality, academic use of the data, and the right to withdraw, and provided informed consent before responding. Completed responses were screened for incompleteness, duplication, and missing values before analysis in IBM SPSS Statistics Version 29.

For the sampling procedure to qualify as simple random sampling in practice, every member of the population must appear once in the sampling frame, selection probabilities must be equal, and nonresponse must be documented. The report did not retain the number invited, refusals, replacements, or gender, age, and semester frequency tables. Accordingly, a response rate and the demographic representativeness of the final sample cannot be calculated. The available sample and data-completeness information is summarised in Table 2; unavailable distributions are identified explicitly rather than estimated.

Table 2: Available Participant and Data-Completeness Information

Characteristic	Available information
Analytical sample	85 complete responses
Planned target	88 respondents; three more than the achieved sample
Population frame	1,030 undergraduates
Study site	UiTM Cawangan Kelantan, Kampus Kota Bharu
Academic units	College of Computing, Informatics and Mathematics; Faculty of Business and Management
Complete cases in correlations/regression	85 for all four composite variables

Statistical Analysis

Internal consistency was assessed separately for the four six-item constructs using Cronbach's alpha. Pearson correlations were used to estimate the strength and direction of the bivariate linear association between each predictor and cognitive function. Correlation magnitudes were interpreted cautiously rather than as fixed categories because their practical meaning depends on context (Cohen, 1988; Schober et al., 2018). Multiple linear regression was then used to estimate the unique association of sleep pattern, technology use, and eating habits with cognitive function. Statistical significance was evaluated at an alpha level of .05, while effect

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estimates and confidence intervals were used to retain information about magnitude and uncertainty.

Regression diagnostics addressed independence of errors using the Durbin-Watson statistic, multicollinearity using tolerance and variance inflation factors, normality of residuals using a normal probability plot, and homoscedasticity using a plot of standardised residuals against predicted values. Appropriate regression interpretation also requires linearity and an assessment of influential observations (Field, 2018). The model was summarised using R, R-squared, adjusted R-squared, the standard error of estimate, the omnibus F test, unstandardised coefficients, standardised beta coefficients, t tests, and p values.

Composite scores were formed only after applying the coding rules in Table 1. The retained SPSS output reported N = 85 for every pairwise correlation and for the regression model, indicating complete model data. It did not contain the predictor means, standard deviations, skewness, or observed ranges, and the item-level dataset was not available for reconstruction. These descriptive statistics therefore cannot be reported without invention and remain a limitation of the archived analysis. Model evaluation used scatterplots and residual plots where available; standardised residuals, leverage, Cook's distance, and casewise diagnostics were considered the appropriate influence checks, although only the standardised-residual range was retained.

Results and Analysis

Reliability of the Measures

All four scales reached alpha values above .70 in the pilot study. In the final sample, sleep pattern and technology use retained acceptable to good internal consistency, cognitive function was at the conventional threshold, and eating habits declined to .661. The item-total analysis reported corrected item-total correlations from .306 to .461 for the eating-habits items, and deletion of any single item did not increase the overall alpha. Retaining the six items was therefore defensible for exploratory analysis, although estimates involving eating habits should be interpreted with additional caution because measurement error can attenuate associations.

The contrast between pilot and final reliability estimates also deserves attention. Technology use remained the most internally consistent construct, although alpha decreased from .920 to .870. Sleep pattern was highly stable across the two samples, whereas cognitive function declined to exactly .700 and eating habits declined more noticeably. Sampling variation can produce these differences, especially in modest samples, but variation in respondent interpretation may also be involved. Reliability is a property of scores in a particular sample, not a permanent characteristic of a questionnaire. Accordingly, the pilot result cannot substitute for reporting reliability in the analytical sample, and the final-sample coefficients are the most relevant values for evaluating attenuation and measurement quality.

Table 3: Internal Consistency of the Study Measures

Construct	Pilot alpha (n = 40)	Final alpha (n = 85)	Final interpretation
Sleep pattern	.782	.783	Acceptable
Technology use	.920	.870	Good
Eating habits	.733	.661	Questionable
Cognitive function	.747	.700	Acceptable

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Bivariate Relationships

Sleep pattern was positively and significantly correlated with cognitive function, r = .322, p = .003. Under the stated coding, students with healthier sleep scores tended to report better cognitive functioning. Technology use showed a weak, nonsignificant positive zero-order correlation with cognitive function, r = .160, p = .143; because higher technology scores represented more intensive or problematic use, this direction should not be interpreted as evidence of benefit. Eating habits also showed a positive but nonsignificant relationship, r = .205, p = .060. Thus, only sleep pattern met the .05 criterion in the bivariate analysis.

The correlations among the predictors were substantively relevant. Sleep pattern correlated negatively with technology use, r = -.338, p = .002, and positively with eating habits, r = .590, p < .001. Technology use correlated negatively with eating habits, r = -.450, p < .001. These relationships explain why a predictor may be nonsignificant by itself but significant after the other behaviours are controlled: the regression coefficient represents the predictor's unique component rather than its raw bivariate association.

The p value of .060 for the correlation between eating habits and cognitive function lies close to, but remains above, the predetermined .05 threshold. It should not be redescribed as marginally significant or interpreted as proof of no relationship. A p value does not measure effect size or the probability that the null hypothesis is true, and scientific interpretation should not depend on a significance threshold alone (Wasserstein & Lazar, 2016). The estimate r = .205 and its confidence interval indicate a small positive sample relationship with appreciable uncertainty. This pattern is compatible with effects ranging from approximately zero to a moderate positive association and should be treated as inconclusive rather than absent.

Table 4: Pearson Correlations With Cognitive Function

Predictor	r	95% CI	p	Inference
Sleep pattern	.322	[.117, .501]	.003	Statistically significant
Technology use	.160	[-.055, .361]	.143	Inconclusive
Eating habits	.205	[-.008, .401]	.060	Inconclusive

Note. Confidence intervals for Pearson correlations were calculated using Fisher's z transformation with n = 85. The intervals quantify sampling uncertainty and were not available in the original narrative tables.

Regression Diagnostics

The Durbin-Watson statistic was 1.768, providing no indication of problematic residual autocorrelation. Tolerance values ranged from .581 to .790 and variance inflation factors ranged from 1.266 to 1.720, which did not indicate severe multicollinearity. The normal probability plot showed residuals tracking the diagonal reasonably closely, and the residual-versus-predicted plot did not display a pronounced funnel or systematic curve. Standardised residuals ranged from -2.563 to 2.112, so none exceeded an absolute value of 3. The retained output did not include leverage or Cook's distance; influential observations therefore could not be ruled out independently, and this limits claims about model stability.

The absence of severe multicollinearity does not imply that the predictors were unrelated. A correlation of .590 between sleep and eating habits is substantial enough to alter adjusted coefficients, yet not high enough to make the regression estimates unusable. Tolerance and variance inflation factors assess whether shared predictor variance inflates standard errors to a

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problematic degree; they do not test whether statistical suppression or conceptual overlap exists (Vatcheva et al., 2016). The model can therefore satisfy conventional collinearity thresholds while still producing an adjusted technology coefficient that differs markedly from its zero-order correlation. Interpretation requires examination of both the correlation matrix and the regression table rather than reliance on diagnostic cut-offs alone.

Multiple Linear Regression

The regression model containing the three lifestyle measures was statistically significant, F(3, 81) = 6.724, p < .001. The multiple correlation was R = .447. The predictors jointly explained 19.9% of the observed variance in cognitive function, R-squared = .199, with adjusted R-squared = .170 and a standard error of estimate of .870. The corresponding observed model effect was f-squared = .248. The ANOVA components were regression sum of squares = 15.257, residual sum of squares = 61.264, total sum of squares = 76.521, regression mean square = 5.086, and residual mean square = .756. Approximately four-fifths of the observed variance remained unexplained.

The omnibus F test evaluates the null hypothesis that all three population slopes are simultaneously zero. Its significance establishes that the predictor set improved prediction relative to an intercept-only model, but it does not establish that every predictor was significant or that the model was practically strong. The adjusted R-squared was lower than the unadjusted value because it penalises the addition of predictors relative to the available sample size. The difference of .029 was not extreme, yet the adjusted estimate of .170 is the more conservative description of expected explanatory performance. Neither statistic should be interpreted as the percentage of cognition caused by lifestyle, because the variance decomposition is observational and depends on the measurement scales and sample.

Sleep pattern made a significant positive unique contribution, B = .266, beta = .347, t = 2.803, p = .006. Technology use also made a significant positive unique contribution after sleep and eating habits were controlled, B = .292, beta = .348, t = 3.109, p = .003. Eating habits did not make a statistically significant unique contribution, B = .134, beta = .157, t = 1.201, p = .233. The standardised coefficients for sleep and technology were almost identical, so it is more accurate to regard them as similarly influential within this sample than to claim that one was clearly the strongest predictor.

Table 5: Multiple Linear Regression Predicting Cognitive Function

Predictor	B	SE	95% CI for B	Beta	t	p
Constant	1.351	.797	[-.236, 2.937]	-	1.694	.094
Sleep pattern	.266	.095	[.077, .455]	.347	2.803	.006
Technology use	.292	.094	[.105, .479]	.348	3.109	.003
Eating habits	.134	.112	[-.088, .356]	.157	1.201	.233

The fitted equation was: cognitive function = 1.351 + .266(sleep pattern) + .292(technology use) + .134(eating habits). Each slope is the expected change in cognitive-function score for a one-unit increase in that predictor while the other two predictors remain constant. The estimates in Table 5 reproduce the primary SPSS coefficient output, including standard errors and 95% confidence intervals.

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The positive technology coefficient requires careful interpretation because all six technology statements were retained in their original direction and higher scores represented more intensive or problematic use. The adjusted estimate therefore indicates that greater problematic technology use was associated with higher self-reported cognition after sleep and eating habits were controlled. This counterintuitive result should not be translated into a recommendation for greater technology exposure. It may reflect statistical suppression, residual confounding, the mixture of educational and non-educational device use, or limitations in the construct score.
This adjusted pattern is compatible with statistical suppression at the descriptive level. Technology use had a zero-order correlation of .160 with cognition, but its partial correlation increased to .326 after the other predictors were controlled. Suppression is suggested when adjustment strengthens or reverses a predictor-outcome relationship, but its substantive meaning must be established conceptually rather than from coefficients alone (MacKinnon et al., 2000). Here, technology was negatively correlated with sleep (r = -.338) and eating habits (r = -.450), while sleep and eating habits were positively correlated (r = .590). The positive adjusted technology coefficient therefore represents residual technology variation after this shared behavioural variance is removed, not a total beneficial effect of technology use.

Discussion

The results provide the clearest support for sleep pattern. Its significant bivariate and adjusted associations are consistent with evidence connecting sleep quality and duration to memory, attention, cognitive failure, and academic functioning (Dahat et al., 2023; Hershner, 2020; Jaffri et al., 2024; Xu et al., 2025). The finding is also plausible within the university context, where late schedules and digital engagement can reduce sleep regularity. Although the effect was not large, sleep remained significant after technology use and eating habits were controlled, suggesting that it contained information about perceived cognition beyond the other lifestyle measures.

Technology use illustrates the distinction between zero-order and adjusted associations. Its bivariate correlation with cognition was weak and nonsignificant, but its regression coefficient was positive and significant after sleep and eating habits were held constant. Because the technology scale was scored so that higher values represented more problematic use, the adjusted direction is counterintuitive. The negative correlations of technology with sleep and eating habits make a suppression-type pattern plausible. Prior research indicates that timing, purpose, bedtime exposure, and compulsive use matter more than technology exposure in the abstract (Lin & Zhou, 2022; Lu et al., 2025; Orzech et al., 2016; Rosen et al., 2016). Replication with separate educational, recreational, compulsive, and night-time technology measures is required before drawing a behavioural conclusion.

The comparison with previous research is not a simple confirmation or contradiction. Studies linking technology with poorer sleep and academic outcomes often examine bedtime exposure, addiction, or time displacement, whereas the present model combined several behaviours into one score and adjusted for sleep directly. If sleep lies on the pathway from technology use to cognition, controlling for sleep removes part of the association that is theoretically meaningful. Conversely, if sleep is a confounder, adjustment is necessary. Cross-sectional data cannot determine which causal structure is correct. A longitudinal design with separate measurement occasions would be better suited to distinguishing direct, indirect, and reciprocal relationships. Eating habits were not statistically significant at the bivariate or adjusted level. This does not establish that nutrition is irrelevant to cognition. The eating-habits scale had the lowest reliability, and the small sample reduced precision for detecting modest effects. Dietary effects may also operate indirectly through sleep, mental health, or physical activity, which were not

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modelled (Faris et al., 2022; Solomou et al., 2023; Vasco et al., 2025). The result is best stated as an absence of sufficient evidence for an independent association in this sample, rather than evidence of no relationship in the wider population.

Several limitations constrain interpretation. The cross-sectional design precludes causal statements; all constructs were self-reported; the final sample was limited to one campus; and the model omitted plausible confounders such as stress, mental health, physical activity, academic workload, socioeconomic background, and programme of study. The achieved sample of 85 was three below the planned target, the number invited was not retained, and a response rate could not be calculated. Gender, age, and semester distributions and predictor descriptive statistics were not available in the retained output. The eating-habits scale had comparatively low reliability. Finally, item-level data, Cook's distance, and leverage statistics were unavailable for independent verification and influence analysis.

Despite these constraints, the study has useful features. It examined several modifiable behaviours within one model, reported reliability for both pilot and analytical samples, and included primary SPSS output that allowed key estimates to be checked. The diagnostic statistics did not indicate severe violations of independence, normality, homoscedasticity, or multicollinearity. The study also addressed a defined population within a Malaysian university setting, adding local evidence to a literature that is often dominated by other educational contexts. Its principal value is exploratory: it identifies patterns that can guide better-specified studies rather than providing a final causal explanation of student cognition.

Conclusion

This study examined sleep patterns, technology use, and eating habits as simultaneous predictors of self-reported cognitive function among 85 Malaysian undergraduate students at UiTM Cawangan Kelantan, Kampus Kota Bharu. Sleep pattern was significantly related to cognitive function in both the Pearson correlation and multiple regression analyses. Technology use was nonsignificant at the bivariate level but significant after adjustment for sleep and eating habits, while eating habits did not achieve statistical significance. Collectively, the three predictors explained 19.9% of the variance in cognitive function.

The findings support the practical importance of healthy sleep and justify further investigation of the conditions under which technology use relates to cognition. They do not demonstrate that changing any behaviour will cause cognitive improvement. Under the documented scoring, the positive adjusted technology coefficient links more problematic use with higher self-reported cognition after adjustment; its counterintuitive direction and suppression-type pattern preclude a beneficial interpretation. Universities may promote sleep hygiene, mindful technology practices, and balanced nutrition as general student-wellness measures, but claims about cognitive benefits should remain proportional to the observational evidence.

Future research should use a larger probability sample across multiple campuses, conduct an a priori regression power analysis, report full participant and construct descriptives, and preserve item-level data and scoring syntax for reproducibility. Longitudinal designs would improve temporal inference, while objective measures of sleep, screen exposure, dietary intake, and cognitive performance would reduce common-method bias. Models should distinguish educational from problematic technology use, evaluate influential observations, and include stress, mental health, physical activity, academic workload, and socioeconomic conditions.

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