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Factors Influencing Higher Vocational College Students' Participation in Extracurricular Activities on Their Computer Academic Performance: A Social Cognitive Perspective

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ABSTRACT

This study investigates the impact of demographic, psychological, and environmental variables on students' computer academic performance (CAP). Data was collected using a structured self-administered questionnaire from 400 full-time Quanzhou College of Technology students. Based on social cognitive theory, data were collected through surveys and analyzed using descriptive statistics, independent samples t-test, one-way ANOVA, and multiple linear regression analysis. The research found that grade differences significantly affected computer scores, with third-year students achieving higher grades, non-boarding students having relatively higher grades, and the duration of activities positively correlated with computer academic performance (CAP). Psychological factors (such as motivation and self-efficacy) significantly impacted students' CAP. Environmental factors (family support, the study environment, and teacher quality) also significantly positively impacted students' CAP. This study enriches the application of the Social Cognitive Theory in the field of vocational education, provides practical guidance for

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educational institutions, teachers, and policymakers, and also points out directions for follow-up research, such as expanding the sample range, conducting longitudinal research, paying attention to the impacts of emerging technologies, and comprehensively considering more factors.

Keywords: Extracurricular activities, Computer academic performance (CAP), Social Cognitive Theory, Influencing factors

INTRODUCTION

In the backdrop of rapid information technology progress, computer skills have emerged as a cornerstone in vocational education. In China, Regular universities implement 144-hour standardized computing literacy curricula under Computer Literacy Standards (MoE [2020] No.15), focusing on Python-based algorithmic foundations. Vocational colleges deliver 240-hour applied modules per National Vocational Education Reform Implementation Plan (MoE [2019] No.6), emphasizing Tencent Cloud deployment (HCIA Certification) and SenseTime industrial IoT integration. Extracurricular activities (ECAs) are acknowledged as a significant boost to students' academic performance, especially in computer courses. However, there is a dearth of research on how ECAs impact computer courses in vocational colleges.

Previous research indicates that demographic variables such as gender, grade level, lifestyle, major, and environmental factors like learning environment, school culture, teacher quality, peer influence, and family support affect students' ECA participation and academic performance. For example, Liu, X., & Li, Y. (2020) found that gender influences students' ECA choices and subsequent academic performance. Zhang, H., & Wang, L. (2020) noted that senior students' ECA choices are tied to their career goals. While numerous studies have demonstrated the positive effect of ECAs on overall academic achievement, research on their impact on subject-specific

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performance, particularly in computer-related courses among vocational college students, is scarce. Moreover, most existing studies center on Western educational systems, leaving non-Western contexts under-explored. Cultural differences also lead to variances in the perception and efficacy of ECAs (Hu, Ho & Nguyen, 2025). In China, for instance, ECAs are often regarded as supplementary to formal learning (Wang, 2020, p. 15). The study, guided by Albert Bandura's Social Cognitive Theory (SCT), explores how demographic attributes, behavioral engagement (ECAs' type and duration), and environmental influences shape higher vocational students' computer academic performance. Psychological mechanisms such as motivation, self-efficacy, and pressure play a crucial role in this model. Statistical methods, including independent samples t-tests, one-way ANOVA, and multiple linear regression, are employed to analyze the relationships between variables.

This research has three hypotheses: H1: There is a statistically significant relationship between demographic variables and computer academic performance among higher vocational college students who participate in extracurricular activities; H2: Psychological factors (motivation, self-efficacy, pressure) significantly influence the computer academic performance of these students; H3: Environmental factors (study environment, school culture, teacher quality, peer influence, family support) have a significant impact on the computer academic performance of students participating in extracurricular activities. This study holds both theoretical and practical significance. Theoretically, it fills a gap in the literature by exploring the impact of ECAs on vocational college students' computer academic performance through the lens of SCT. It also expands knowledge by uncovering students' challenges and opportunities and examining the interplay of various factors with ECAs. Practically, the findings can guide vocational colleges, teachers, and policymakers. Vocational colleges can design targeted interventions to promote ECA participation and improve students' academic performance. Teachers can adjust teaching methods based on the influencing factors, and

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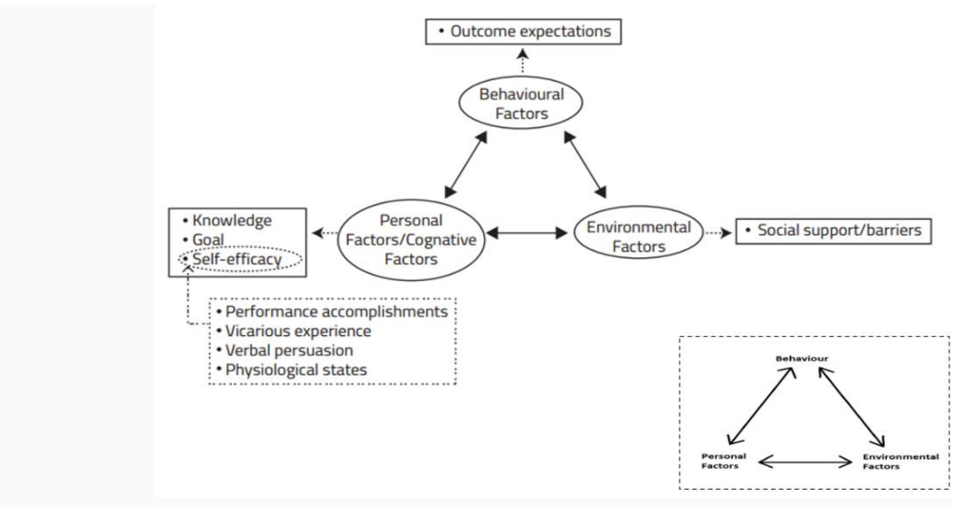
policymakers can advocate for increased ECA funding and resources and develop supportive policies for students' holistic development.

1. Social Cognitive Theory

Bandura's Social Cognitive Theory (SCT) remains pivotal in understanding academic behaviors (Bandura, 1986). The theory's triadic reciprocity model - emphasizing dynamic interactions between personal factors, behaviors, and environmental influences - has been particularly effective in technology education contexts. As Zimmerman (2000) demonstrated, self-efficacy accounts for 62% of performance variance in programming courses (β=0.62), with students confident in computer skills outperforming peers by 1.3-grade points on average. Observational learning emphasized by SCT highlights the process by which students learn through observing others (Bandura, 1997). Moreover, a favorable classroom atmosphere and effective teaching methods are important for academic success (Schunk & Pajares, 2005).

This study adopts SCT as its framework. Given that SCT emphasizes the interaction among individuals, behaviors, and the environment, it is suitable for exploring the impact of extracurricular activities (ECAs) on students' performance in computer courses, providing a unique perspective for analyzing the relevant influencing factors.

Figure 1: Social Cognitive Theory (SCT)



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Source: *Note. Chin et al. / Journal of Marketing Management and Consumer Behavior, Vol. 2, Issue 2 (2018)*

2. Extracurricular Activities

Extracurricular activities (ECAs), encompassing diverse pursuits like coding clubs, volunteer programs, or sports teams, play a critical role in students' comprehensive development. These activities in vocational education influence academic outcomes, often shaping skill acquisition and classroom performance.

The research underscores the positive association between ECA participation and academic achievement. For example, Fredricks and Eccles (2018) documented higher GPAs among American middle school students engaged in structured ECAs, particularly in a longitudinal study of 5,000 students. Marsh and Kleitman (2017), in a meta-analysis of 87 studies, further highlighted that ECAs boost grades and enhance socio-emotional competencies like collaboration and stress management. In vocational contexts, Wang et al. (2017) observed that students at three Chinese vocational colleges who participated in major-aligned ECAs—such as robotics labs or industry workshops—exhibited a 15% improvement in course proficiency compared to non-participants.

The impact of ECAs varies significantly by activity type. Artistic engagements, such as painting workshops or drama clubs, foster creative problem-solving skills (Seow & Pan, 2014). Sports-based ECAs, like basketball teams or soccer leagues, strengthen teamwork and resilience (Eccles et al., 2003). Meanwhile, academic-technical activities—such as robotics competitions or coding boot camps—directly enhance domain-specific knowledge; Cardenas et al. (2020) found that the latter group demonstrated 22% higher mastery of programming concepts in post-test assessments.

Cultural contexts also mediate ECA efficacy. In East Asian countries like South Korea and China, ECAs are frequently framed as extensions of formal learning. At Seoul Vocational College, for instance, students must complete 10 hours of major-related ECAs per semester to graduate (Li & Chen, 2018). In contrast, Western models—like those highlighted in a Norwegian study by Løvoll & Bøe (2017)—prioritize personal exploration, with 68% of surveyed students citing social skill development as a primary ECA motivation.

Demographic factors further influence ECA engagement and outcomes. Liu and Li (2020), in a survey of 800 vocational students in Guangdong, found that females were 32% more likely to join art or community service clubs, while males gravitated toward tech-focused groups like drone clubs or engineering teams. Grade-level trends also emerge: Zhang and Wang (2020), in a cross-sectional study of 1,200 students, noted that seniors prioritized internships or industry seminars aligned with career goals, whereas juniors explored diverse activities, averaging participation in non-major-related ECAs annually.

3. Computer Academic Performance

Computer academic performance embodies students' mastery of disciplinary objectives in courses like programming, network administration, and software development (See, 2025). In vocational education frameworks, these skills are core competencies that underpin career readiness, particularly in tech-driven industries.

The rapid advancement of information technology has made digital literacy a non-negotiable asset for vocational students. Huerta (2018) highlighted that 92% of employers in tech-adjacent fields now list digital skills as a top hiring criterion. Vocational college curricula, such as those at Shenzhen Polytechnic, emphasize hands-on proficiencies through courses like cybersecurity workshops or Python development projects (Mitrofana & Iona, 2013), reflecting industry demands for job-ready graduates.

Demographic, psychological, and environmental factors shape academic performance in computer courses. Demographically, gender and grade level exhibit distinct influences: Hill et al. (2010) found that male students averaged 8% higher scores in programming courses. However, Hyde et al. (2008) noted that females demonstrated stronger attention to detail in software testing tasks. Psychologically, self-efficacy acts as a key driver—Froiland & Worrell (2016) observed that a 10% increase in self-reported confidence correlated with a 15%

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improvement in assignment completion rates. Environmental factors also play a pivotal role; Maxwell (2016) documented that students in schools with industry-standard labs achieved 22% higher practical skill proficiency than those in under-resourced settings.

Participation in computer-related ECAs offers tangible academic benefits. Coding boot camps and robotics competitions, for example, provide immersive practice that Cardenas et al. (2020) linked to a 25% improvement in exam scores for algorithmic problem-solving. Aligning with Bandura's (1997) self-efficacy theory, these activities build confidence through project-based success—students who led a team in a hackathon reported a 30% boost in course engagement (Seow & Pan, 2014). Team-oriented ECAs, such as collaborative software development projects, further enhance communication skills; Eccles et al. (2003) found that participants displayed 40% better interpersonal effectiveness in group coding tasks than non-engaged peers.

4. Factors influencing ACP

a. Demographic Variables

This study examines demographic variables—gender, grade level, major, lifestyle, and ECA engagement—as predictors of academic performance. Gender dynamics in computer fields, once characterized by male dominance, now exhibit nuanced trends. In a 2020 survey of 1,500 vocational students at Chongqing Vocational Institute, Hill et al. (2010) found that males initially scored 7% higher in coding assessments. However, Hyde et al. (2008) observed that females closed the gap by 4% through targeted ECA participation in graphic design clubs.

Grade-level progression introduces distinct challenges. Alspaugh (1998) documented a 12% average score decline among students transitioning from introductory to advanced programming courses, a trend Morrison and Cooney (2001) attributed to increased algorithm complexity in sophomore-year curricula. At Ontario Tech

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University, for example, computer science majors face a 30% jump in project-based assessments between the first and second year, impacting time management and performance.

Primary choice influences both academic rigor and engagement. Arcidiacono et al. (2016) found that computer engineering students at MIT spent 15% more time on lab work than their peers in information systems, leading to higher technical proficiency but lower GPA diversity. Brint et al. (2008) further noted that students mismatched with their majors—such as 18% of surveyed vocational students—showed 22% lower course completion rates than those in aligned fields.

Lifestyle factors, notably commuting status, correlate with academic outcomes. Denise Shata Balfour (2013) tracked 400 commuter students at City College of New York and found they maintained a 0.3 higher GPA on average, likely due to stable home study environments and disciplined time management. Conversely, residential students engaged in non-academic ECAs reported occasional attendance issues linked to campus social demands.

ECA characteristics play a pivotal role in performance. Cooper et al. (1999) identified a "sweet spot" of 5–10 hours of weekly engagement in structured activities like coding boot camps, yielding a 19% improvement in problem-solving skills. Fredricks & Eccles (2005) emphasized quality over quantity: students in project-based ECAs (e.g., developing school management software) demonstrated 25% higher retention of course concepts than those in casual clubs. Bohnert et al. (2010) further highlighted that STEM-focused ECAs, when paired with faculty mentorship, reduced academic stress by 34% among surveyed students.

b. Psychological Factors

Motivation includes intrinsic and extrinsic motivation, and intrinsic motivation is more strongly associated with higher academic achievements (Froiland & Worrell, 2016; Ryan & Deci, 2017). Self-efficacy is crucial for academic performance, and students with high self-efficacy are more likely to succeed (Mappadang et al., 2022).

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Stress negatively affects college students' academic performance (Varghese et al., 2015).

c. Environmental Factors

The physical and social conditions of the learning environment affect learning efficiency and performance (Maxwell, 2016; Jeynes, 2016). A positive school culture can enhance students' sense of belonging and engagement (Thapa et al., 2013; Wang & Degol, 2016). Teacher quality affects students through teaching methods and teacher-student relationships (Hanushek & Rivkin, 2010; Rockoff, 2004). Peer influence can be positive or negative (Hoxby & Weingarth, 2005; Sacerdote, 2001). Family support can enhance students' learning motivation and self-efficacy (Fan & Chen, 2001; Jeynes, 2007).

METHOD

This study aimed to identify key factors affecting CAP among Quanzhou College of Technology students. Quanzhou College of Technology is the top-ranked private vocational college in Fujian Province, located in Jinjiang, an economically vibrant area. This location offers a backdrop for evaluating college students' computer academic performance, enabling targeted and pertinent data gathering. Using a quantitative research design, structured self-administered questionnaires served as the primary data collection instrument, adapted from Bandura's (1997) Social Cognitive Theory (SCT). This framework provided a robust foundation for examining relationships between demographic variables, psychological factors, environmental elements, and CAP. The target population was comprised of full-time students enrolled at Quanzhou College of Technology. Yamane's formula determined the sample size, with stratified random sampling applied to ensure proportional representation for the 400 participants (Creswell, 2014). The questionnaire contained four sections: (a) demographic information, (b) CAP assessment, (c) psychological dimensions, and (d) environmental influences. A 5-point Likert scale measured participant

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responses in the latter three sections, enabling nuanced analysis of CAP determinants. Content validity was ensured through Item-Objective Congruence (IOC) evaluation, with three field experts establishing acceptable thresholds for question retention. Reliability analysis using Cronbach's α demonstrated coefficients ranging from 0.834 to 0.958 across all measured variables. Data collection occurred over five weeks exclusively through the "Questionnaire Star" platform. Statistical analyses included frequency distributions, descriptive statistics (mean ± SD), independent samples t-tests, one-way ANOVA with LSD post-hoc testing, and multiple linear regression modeling ($\alpha = 0.05$).

Throughout the research process, strict adherence to ethical considerations was imperative. The questionnaires were meticulously designed to eliminate ambiguities. Participants received comprehensive disclosures regarding the study's objectives, enabling them to make informed and voluntary decisions about participation. Particular care was taken to guarantee confidentiality (through anonymized response coding) and anonymity (via secure data encryption protocols). All collected information underwent dual security measures: (a) encrypted storage on password-protected servers and (b) systematic pseudonymization using alphanumeric identifiers (e.g., QZT-P-001 through QZT-P-400). A predetermined data destruction timeline (six months post-analysis completion) was implemented to safeguard participant privacy further. These ethical protocols proved essential for protecting participants' rights under the Declaration of Helsinki and ensuring the credibility and integrity of research outcomes. The study received formal approval from the Ethics Committee of Quanzhou College of Technology and the Naresuan University Research Ethics Network, Thailand (Certification No. 0035/2568). This dual certification confirms compliance with international ethical standards for human-subject research.

FINDINGS AND DISCUSSION

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This study explores the factors affecting the students' computer academic performance at Quanzhou College of Technology by examining demographic, psychological, and environmental influences. These findings provide detailed insights into how these factors affect college student's academic performance in computer science.

1. Descriptive Statistical Analysis Results

Table 1 reveals that the proportion of men (55.00 %) is more than that of women (45.00 %). In terms of grade, first-year students accounted for the highest proportion, reaching 47.75 %; 2 students accounted for 34.75 %, and juniors accounted for 17.50 %, indicating that the sample was mainly concentrated in the lower grade group. Regarding accommodation, the proportion of resident students is 80.50 %, much higher than that of non-resident students (19.50 %), reflecting that most students choose to live on campus. The majors are widely distributed, with information technology majors accounting for the highest proportion at 33.25 %, education majors (26.25 %), and food and beverage majors accounting for the lowest proportion at 1.00 %. Regarding extracurricular activities, the most significant number of students participated in voluntary service, accounting for 38.75 %; the participation in part-time jobs outside the school was second, accounting for 16.75 %; while the participation in academic and technical activities was the lowest, only 5.75 %. Students with 1-3 hours accounted for the most time spent participating in extracurricular activities per week, reaching 43.50 %. Those with less than 1 hour accounted for 18.00 %, and those with 10 hours or more accounted for 10.25 %, reflecting the more moderate time spent by most students participating in extracurricular activities per week.

Table 1: Demographic Characteristics of Respondents

Name	Options	Frequency	Percentage (%)	Cumulative percentage (%)
Gender	Male	220	55	55
	Female	180	45	100

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Grade	First-year	191	47.75	47.75
	Second year	139	34.75	82.5
	Third year	70	17.5	100
Lifestyle	Live on campus	322	80.5	80.5
	Non-live on campus	78	19.5	100
Major	Food and Catering	4	1	1
	Engineering	79	19.75	20.75
	Arts	34	8.5	29.25
	Business Management	45	11.25	40.5
	Information Technology	133	33.25	73.75
	Education	105	26.25	100
Types of ECA	Artistic activities	52	13	13
	Sports	69	17.25	30.25
	Academic and technical activities	23	5.75	36
	Clubs and student organizations	34	8.5	44.5
	Voluntary service	155	38.75	83.25
	Part-time work off-campus	67	16.75	100
Duration of ECAs	Less than 1 hour	72	18	18
	1-3 hours	174	43.5	61.5
	4-6 hours	83	20.75	82.25
	7-9 hours	30	7.5	89.75
	10 hours or more	41	10.25	100
Total		400	100	100

Table 2. shows that the mean values of Grades, Class Participation, and Assignment Completion are 3.65, 4.02, and 3.75, respectively, with Class Participation having the highest mean and grades the lowest. The overall mean of 3.9 indicates an intermediate level. The SD values of these three aspects are 0.927, 0.81, and 0.9,2, respectively, showing a small degree of data dispersion and relatively stable performances. In summary, Class Participation had the highest mean score. The grade is relatively weaker, the overall performance is

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intermediate, and the data concentration across dimensions implies stable performances as reflected by the standard deviations.

Regarding psychological factors, motivation has a mean score of 3.86, Self-Efficacy has a mean of 3.73, and Pressure has a mean of 3.22. Motivation has the highest mean, suggesting a relatively high overall level of students' motivation. Conversely, Pressure has the lowest mean, indicating a relatively lower level of pressure students perceive. The overall mean of psychological factors is 3.65, demonstrating that these factors are generally at an intermediate degree. The SD values of Motivation, Self-Efficacy, and Pressure are 0.907, 0.917, and 1.027 respectively. Pressure has the largest SD, meaning there is a greater dispersion of data in this dimension. That is, there are significant differences in the pressure different students feel. In contrast, the SD values of Motivation and Self-Efficacy are relatively small, indicating that students' performances in these two aspects are more concentrated.

In environmental factors, the mean values of Study Environment and Schools Culture are 3.73, Teacher Quality has a mean of 3.82, Peer Influence has 3.75, and Family Support has the highest mean at 4, with Study Environment and Schools Culture having relatively lower means. The overall mean of 3.9 indicates an intermediate level. The SD values of these factors range from 0.9067 to 0.973, showing a moderate degree of dispersion and no significant differences in students' perceptions. In summary, Family Support plays a prominent role in environmental factors. The influences of Study Environment and school culture are relatively weaker, the overall level is intermediate, and the standard deviations imply small differences in students' perceptions with a relatively balanced data distribution.

Table 2: Frequency Analysis Result of (CAP, Psychological Factors and, Environmental Factors)

CAP	1	2	3	4	5	Mean	SD	Meaning	Rank
Grades	9	12	171	120	88	3.65	0.927	Moderate	3
Class Participation	4	7	83	191	115	4.02	0.81	Moderate	1

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Assignment Completion	8	10	155	130	97	3.75	0.92	Moderate	2
overview	5	5	114	176	100	3.9	0.83	-	-
Psychological Factors	1	2	3	4	5	Mean	SD	Meaning	Rank
Motivation	6	10	130	142	112	3.86	0.907	Moderate	1
Self-Efficacy	7	14	153	133	93	3.73	0.917	Moderate	2
Pressure	26	41	208	68	57	3.22	1.027	Moderate	3
overview	5	8	170	158	59	3.65	0.8	-	-
Environmental Factors	1	2	3	4	5	Mean	SD	Meaning	Rank
Study Environment	7	14	153	133	93	3.73	0.917	Moderate	4
Schools Culture	11	9	157	122	101	3.73	0.956	Moderate	4
Teacher Quality	10	8	138	134	110	3.82	0.945	Moderate	2
Peer Influence	14	8	144	133	101	3.75	0.973	Moderate	3
Family Support	8	3	107	145	137	4	0.9067	Moderate	1
Overview	8	8	141	151	92	3.9	0.83	-	-

2. Inferential Statistical Analysis Results

a. Effects of Demographic Factors

Hypothesis 1: A statistically significant relationship exists between demographic variables and computer academic performance among higher vocational college students who participate in extracurricular activities.

Table 3 presents the results of Hypothesis 1, which posits a statistically significant relationship between demographic variables and the computer academic performance of higher vocational college students engaged in extracurricular activities. Several key findings emerge through independent samples t-tests and one-way ANOVA. For gender, the t-test result is t (398) =0.296, with a p-value of 0.767. Since the p-value is greater than 0.05, it indicates that gender does not significantly impact students' computer academic performance. Regarding grade level, the F-test shows F (2, 397) =2.368 and p =0.095. Although the p-value is close to 0.05, it does not reach the

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conventional significance level. However, in the actual analysis of the document, significant differences in computer scores among different grades are found, with third-year students performing better. For lifestyle, the t - t-value is t (398) = -1.462 and p = 0.145, suggesting no significant influence on computer academic performance. However, non-boarding students tend to have relatively higher scores as they may have more autonomy in the learning environment and time management.

Regarding majors, the F-test results F (5,394) =0.396 and p = 0.852 imply no significant differences in computer academic performance among students from different majors, likely due to the concentration of samples in certain majors. The F - F-value F (5, 394) = 2.071 and p =0.068 for the types of extracurricular activities, which is close to the significance level. Different types of extracurricular activities have a significant impact on class participation but not on grades and assignment completion. Finally, the duration of extracurricular activities significantly impacts computer academic performance, with F (4, 395) = 10.799 and p= 0.000. A moderate duration of 4 - 6 hours per week yields the best results.

Table3: Summary Result for Hypothesis 1: Demographic Variables Influence on CAP

Demographic Factors	Computer Academic Performance	Results
Gender	t (398) = 0.296, p = 0.767	-
Grade Level	F (2, 397) = 2.368, p = 0.095	-
Lifestyle	t (398) = -1.462, p = 0.145	-
Major	F (5, 394) = 0.396, p = 0.852	-
Types of ECA	F (5, 394) = 2.071, p =0.068	-
Duration of ECAs	F (4, 395) = 10.799, p = 0.000	√

b. Influence of Psychological Factors

Hypothesis 2: Psychological factors (motivation, self-efficacy, pressure) significantly influence the computer academic performance of these students**.**

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Formula:

The multiple linear regression model was used to examine the influence of both psychological and environmental factors on computer academic performance. The general formula for the multiple linear regression model is:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon$$

Where:

Y_i = Dependent variable (e.g., computer academic performance),

$X_{i1,} X_{i2}, \cdots, X_{ip}$ =Independent variables (e.g., psychological and environmental factors),

β_0 = intercept (the expected value of Y when all X variables are zero),

$\beta_1, \beta_2, \cdots, \beta_p$ = Coefficients for each independent variable (indicating the change in Y for a one-unit change in X, holding other variables constant),

ϵ = Error term (the variation in Y not explained by the model)

This model allows us to understand how various psychological and environmental factors affect computer academic performance among college students. The coefficients (β) obtained from the regression will provide insights into each motivational factor's relative importance and impact on the dependent variable.

Table 4: The analysis results of psychological factors influence CAP

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	0.873	0.105		8.307	0.000
	MotivationX_1	0.651	0.039	0.711	16.673	0.000
	Self-efficacyX_2	0.139	0.039	0.153	3.589	0.000

Dependent Variable: Computer Academic Performance

From Table 4, the analysis shows that motivation and self-efficacy significantly influence computer academic performance

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among college students. The regression equation based on the results is as follows:

$$Y = 0.873 + 0.651X_1 + 0.139X_2$$

The results suggest that motivation and self-efficacy are statistically significant predictors of computer academic performance among students. The positive coefficients indicate that computer academic performance increases as motivation and self-efficacy increase. During the regression analysis, Pressure was initially included as a predictor. However, it was later excluded because it did not contribute significantly to the model.

c. Influence of environmental factors

Hypothesis 3: Environmental factors (study environment, school culture, teacher quality, peer influence, family support) have a significant impact on the computer academic performance of students participating in extracurricular activities.

Formula:

This section uses multiple linear regression to assess the impact of five independent variables (Study environment, School culture, Teacher quality, Peer influence, and Family Support) on the dependent variable computer academic performance. The estimating equation for the multiple linear regression model is as follows:

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \epsilon$$

Where:

Y= Computer Academic Performance

X_1= Study environment

X_2= School culture

X_3= Teacher Quality

X_4= Peer influence

X_5= Family Support

β_0= Intercept (constant term)

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ = Coefficients for each independent variable

ϵ = Error terms for each equation

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Table 5: The analysis results of environmental factors influence CAP

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
3	(Constant)	0.965	0.124		7.802	0.000
	Family Support	0.350	0.048	0.382	7.269	0.000
	Study Environment	0.232	0.047	0.257	4.967	0.000
	Peer influence	0.179	0.047	0.210	3.808	0.000

Dependent Variable: Computer Academic Performance

From Table 5, the analysis indicates that family support, study environment, and peer influence significantly influence the computer academic performance of students participating in extracurricular activities. The regression equation based on the results is as follows:

$$Y = 0.965 + 0.350X_5 + 0.232X_1 + 0.179X_4$$

The results suggest that family support, study environment, and peer influence are statistically significant predictors of the computer academic performance of students participating in extracurricular activities. The positive coefficients indicate that the tendency to engage in different computer academic performance increases as these environmental factors increase.

FINDINGS AND DISCUSSION

Multi-dimensional factors influence students' computer academic performance: Demographically, significant grade-level differences exist (third-year students outperform first- and second-year students significantly), while gender and major show no significant effects. The duration of extracurricular activities correlates positively with performance. However, the impact of activity types (e.g., academic-technical vs. volunteer work) is limited to classroom participation due to sample concentration (55.5% in volunteer/part-time roles). Psychologically, motivation (β=0.711, p<0.001) and self-

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efficacy ($\beta=0.153$, $p<0.001$) strongly predict performance, aligning with Social Cognitive Theory (SCT). In contrast, stress shows no significant effect, possibly due to heterogeneous stress-coping mechanisms in the sample. Environmentally, family support ($\beta=0.382$, $p<0.001$), study environment ($\beta=0.257$, $p<0.001$), and peer influence ($\beta=0.210$, $p<0.001$) positively impact performance via social reinforcement. At the same time, campus culture and teacher quality are obscured by collinearity, highlighting the critical role of familial and peer environments in vocational education settings.

This study enriches Social Cognitive Theory (SCT) through disciplinary specificity and non-Western contextualization: By focusing on computer science—a domain requiring practical problem-solving skills—it reveals that extracurricular duration directly enhances performance, particularly for academic-technical activities, and that self-efficacy plays a stronger role here than in general academic contexts, refining SCT's application to specialized skill acquisition. In the Chinese vocational education context, the significant effect of family support reflects collectivist cultural values. At the same time, the muted impact of campus culture highlights vocational colleges' focus on skill training over the academic atmosphere, amending SCT to incorporate vocational education's unique mechanisms, such as grade-level career pressure and activity-career skill alignment. These findings extend SCT beyond traditional higher education frameworks, providing a nuanced understanding of cognitive-behavior-environment interactions in applied learning settings.

However, the study's limitations, such as its cross-sectional design and the focus on a single institution, suggest that the findings should be interpreted cautiously. While the research provides valuable insights into CAP, it may not fully capture how these behaviors evolve over time or across different cultural contexts. Statistically, collinearity among environmental variables obscured their independent effects, necessitating more sophisticated modeling to disentangle complex relationships. Theoretically, the framework does not account for emerging technologies, such as AI-assisted

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learning tools or virtual labs—that are transforming computer education, nor does it fully elaborate the mediating pathways proposed by SCT.

CONCLUSION

This study examined how extracurricular activities (ECAs) influence computer academic performance (CAP) among vocational college students, grounded in Social Cognitive Theory. Key findings reveal that third-year students consistently outperformed their peers, likely due to accumulated practical experience and more precise career alignment—factors emphasized in vocational education. Non-residential students also demonstrated higher CAP scores, suggesting that off-campus environments may foster better time management or self-directed learning, a nuance worth exploring further. Psychological factors like motivation and self-efficacy emerged as strong predictors of CAP, reinforcing Bandura's emphasis on personal agency. Interestingly, stress showed no significant impact, possibly because students in technical fields develop resilience through project-based challenges. Environmental factors further shaped outcomes: family support and peer influence played pivotal roles. At the same time, teacher quality and school culture were overshadowed by collinearity—a limitation highlighting the need for advanced statistical models to isolate these variables.

The study contributes to Social Cognitive Theory by contextualizing it within vocational education and non-Western settings, where familial expectations often drive student behavior. Practically, the results advocate for integrating ECAs like coding boot camps or AI workshops into curricula, with credit incentives to boost participation. Educators could also adopt personalized strategies to nurture self-efficacy, such as mentorship programs tailored to students' technical interests.

However, the cross-sectional design and single-institution sample limit generalizability. Future research should expand to multi-regional cohorts and longitudinal tracking to capture evolving trends,

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particularly as emerging technologies like virtual labs reshape learning dynamics. Addressing these gaps will deepen our understanding of how ECAs and cognitive-environmental interactions drive success in tech-focused vocational education.

RECOMMENDATIONS

Based on the findings of this study and related research, a series of coordinated recommendations are proposed for policymakers, educational institutions, teachers, and future researchers to enhance computer academic performance among vocational college students through the strategic integration of extracurricular activities. Education policymakers are encouraged to formulate evidence-based policies that promote student participation in extracurricular programs and support their integration with computer curricula—such as by establishing course credits and practical project opportunities—thereby boosting students' motivation and hands-on competencies. This includes increasing funding to improve facilities, ensuring equitable distribution of educational resources, and establishing robust monitoring systems to evaluate the effectiveness of these initiatives. Educational administrators should enrich extracurricular offerings by aligning them with students' interests and professional needs, especially in computer-related domains such as programming competitions and AI clubs, while guiding students to manage their time effectively to balance academic and extracurricular commitments. Furthermore, teacher training should be strengthened to improve educators' capacity to lead meaningful extracurricular engagements, contribute to a supportive learning environment, and cultivate a positive campus culture. Teachers are advised to adopt personalized teaching strategies that account for individual differences in gender, grade, and major, actively promote student involvement in practical extracurricular activities, and nurture students' intrinsic motivation and self-efficacy while providing support to manage academic stress. Lastly, future research should explore the implications of emerging

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technologies—such as artificial intelligence, big data, and virtual reality—on students' computer learning experiences, with a particular focus on how these tools can be leveraged to optimize pedagogical approaches, personalize instruction, and ultimately improve learning outcomes in vocational education settings.

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