Study Habits of 1st Year BSCS Students: The Influence of Personal and Environmental Factors

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Abstract: *This study examined the personal and environmental factors influencing the study habits of first-year Bachelor of Science in Computer Science (BSCS) students at Surigao del Norte State University. Guided by the Desirable Difficulties framework, the study used a descriptive-quantitative research design and gathered data from 49 first-year BSCS students through a structured questionnaire. Findings revealed that 59.2% of the respondents were female, 54.5% preferred mixed learning styles, and 63.3% reported high motivation toward programming courses. In terms of environmental factors, 71.4% came from families earning below ₱10,000 monthly, 63.3% reported lacking reliable access to technology, and 61.2% lacked quiet study spaces at home. The findings indicate that both personal characteristics and environmental conditions shape the learning behaviors and study habits of first-year BSCS students. The study emphasizes the need for varied instructional methods, expanded technology access, and institutional support systems that promote self-regulated learning. Recommendations include implementing first-year seminars on study habits, extending computer laboratory access, and integrating diverse teaching approaches in programming education*

Keywords: Study habits, computer science education, first year students, environmental factors, self regulated learning, technology access.

I. INTRODUCTION

Study habits matter. For students entering a Bachelor of Science in Computer Science program, they might be more significant than anything else [1]. This transition from a senior high school to college-level computing education is challenging — and the way a student spends his or her time, practices coding, and interacts with learning resources can make the difference between being able to make it or not [2].

This is particularly with regard to students of the first year of BSCS who come from public schools of Surigao City and other surrounding municipalities since they attend Surigao del Norte State University. They come with different sets of preparedness, their home environments, and technology access. But they all have to take the same programming classes, the same deadlines, and the same expectations.

Past research has repeatedly confirmed that student achievement gaps can be attributed to more than just a difference in IQ; the difference in academic performance can most often be attributed to a difference in the quality of the students' study habits [2, 3]. It's not a matter of time spent in front of a book. It has to do with what they do in those hours. This idea is well expressed by the notion of desirable difficulties — methods that involve cognitive exertion that lead to deeper and more durable learning, like spacing out studying over time, summarizing content in own words, and self-testing as opposed to re-reading notes, tend to facilitate greater and more enduring comprehension than methods that do not require cognitive effort [1, 2]. Even when higher-achieving students and lower-achieving students had comparable backgrounds in coding, Liao et al. [3] identified meaningful differences in their study habits in Computer Science

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specifically. However, most first-year students fall back into undesirable study habits: using multi-tasking as a way to study, skimping on studying, or studying to pass the class [4, 5].

Motivation is a factor in this as well. It is not independent from study skills, it influences them [6]. Pérez-Navío et al. [6] analyzed the learning strategies and motivational profile of 436 university students and noted that intrinsic motivation was always positively correlated with good study habits and improved learning support strategies. To sum up, learners who are serious with learning study better. That's why it's important for us to take a close look at motivation as a personal factor—especially in first-year students, who are still adjusting to the rigors of the program.

In addition to the personal traits of students, the environment around the student is also not negligible [7]. In his meta-analysis of 49 studies on S.L. training programmes, Theobald [7] identified three main types of resource management strategies as essential to effective studying: Time management, effort regulation, and study environment management. This discovery leads me to believe that there is something significant here: You can't just consider the student as a person. Conditions in which they are studying are also a concern. The conditions for first year BSCS students are quite different. Some have quiet rooms and good access to the internet at home. Many do not [6, 7].

However, although there is a significant amount of research on students' study habits and academic achievement, little is known about the characteristics of the first-year BSCS students themselves [1, 2]. How old are they, what kinds of learners are they, and how motivated are they? What are the backgrounds of the families? Do they have computers in their household? Are they employed part-time employment in addition to their studies? These are not simple questions. The responses inform the types of support interventions that will effectively support this population.

This study fills this need. It reviews the personal and environmental factors such as age, gender, year level, GPA, learning style and motivation level of first year BSCS students at Surigao del Norte State University as well as type of school attended, family monthly income, parents education level, study environment, hours worked per week, and technology access. The data were collected using a structured questionnaire filled in by the students. The results provide information on the students' characteristics and learning environments, and indicate, based on literature, how these factors might be influencing students' study habits [1, 6, 7].

The aim is to be of service. Knowledge of students' personal and environmental factors can help shape targeted, realistic, and life-based interventions for first-year BSCS students that go beyond assumptions about who they are and what resources they have available to them [7].

II. OBJECTIVES OF THE STUDY

This study aims to:

- Describe the personal factors (age, gender, year level, GPA, learning style, motivation) of first year BSCS students at Surigao del Norte State University.
- Describe the environmental factors (type of school, family income, parents' education, study environment, technology access, hours working) of first year BSCS students at Surigao del Norte State University.
- Identify the most common personal factors among first year BSCS students.
- Identify the most common environmental factors among first year BSCS students.
- Discuss how these personal and environmental factors may influence the study habits of first year BSCS students based on existing literature.
- Propose evidence-based recommendations for educators and institutions to help first year BSCS students develop effective study habits.

III. REVIEW OF RELATED LITERATURE

This section summarizes studies related to personal factors, environmental factors and the impact of personal and environmental factors on student learning behavior. Literature reviewed showed that the variables studied in the research are supported by both theory and actual research findings, and formed the basis of their understanding of the personal and environmental profile of Surigao del Norte State University first year BSCS students.

A. Review if Related Studies

1) Research on personal factors and student learning.

A student's motivation, learning style, and ability to self-regulate their learning determines how they learn. This is not "just a guess. In fact, it is well documented in research.

Pérez-Navío et al. [6] analyzed the learning strategies and motivational profiles of 436 university students from different subjects. The students who were more intrinsically motivated were not only happier to be in school, they learned differently. They were more effective learners, involved more in learning and had better overall learning behaviors [6]. Motivation isn't solely a mood. It is a behaviour stimulator. For first year BSCS students that are learning programming for the first time at the college level, the difference is huge.

Theobald [7] gives valuable support to this. A meta-analysis that included 49 individual studies on university students' self-regulated learning training programs revealed that the programs had a statistically significant positive effect on students' academic outcomes, self-regulated learning strategies, and motivation overall [7]. The importance of resource management in effective studying comes from that analysis; in particular, time management, effort regulation and the management of the study environment [7]. These are not sexy skills. But it is they who distinguish those who make it to college from those who don't.

Li et al. [8] take the discussion down to the level of programming only. They explored the impact of computing students' study of programming self-efficacy, cognitive styles, and self-regulated learning on their CT. The results were quite clear that metacognition self-regulation and effort self-regulation have significant effects on learning outcomes [8]. Pupils who were able to review and reflect on their learning, adapt their strategies when they found they were misguided and persevere when they made mistakes were more successful in linking previous learning to real competence in programming. Confidence wasn't the only thing that was needed. Strategy mattered [8].

Silva et al. [9] address the issue of the same question in a qualitative manner. Students who study within the framework of SRL theory have discovered that there is a consistent pattern with high-performing students: planning, monitoring and evaluating their study [9]. Low-performing students, however, used surface level strategies, including reading, viewing but not engaging with the material. They waited for understanding to come. Often, it did not [9]. This is a disturbing discovery. It is also directly relevant to first year BSCS students who might be learning to learn programming alongside programming.

2) Studies on Environmental Factors and Student Learning

Students study with other students. They learn in a house, a dormitory, in a corner of a relative's house. They study either with or without an adequate computer. Internet enabled or not. Include or exclude a quiet area for thinking [10, 11].

It has long been established that factors like access to technology, the learning environment, family background and socioeconomic status all impact how students develop and sustain effective learning routines [10, 13]. Students with reliable computer and internet access are more likely to implement active learning strategies (practicing code, accessing the internet for resources, completing assignments on time) [13]. For those who don't have that access, it's a different story altogether. Students with a second job, in addition to their studies, are at a further disadvantage [15].

Dung [10] studied the skill of programming development in information technology students in Vietnam, and revealed that there were many problems regarding algorithmic thinking, problem solving debugging, and application. Many of these problems have been linked to poor learning routines and insufficient practice opportunities, both of which were

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linked to constraints in the environment, such as lack of access to technology and poor study environments [10]. The context is not like Surigao. But it's a pattern that's common.

Adeoye et al. [11] studied factors affecting academic achievement more generally and found similar results: A clear routine, involvement in activities and motivation to learn greatly influences learning outcomes [11]. Passive habits were always obstacles to achievement: Scrolling, half-listening, studying when one has to. Personal and environmental factors both played a role in what ways students learned, with neither one without the other [11].

From another perspective, Van Sickle [12] confirms this. The study behaviors of first-year science students and the relationship between these behaviors and their academic performance in introductory science courses was analysed by Van Sickle [12] who identified that students who used passive strategies (rereading, highlighting, reviewing without testing themselves) were ineffective at retaining knowledge in their courses and transferring skills well. Students that were ACTIVE performed better. Consistently. In various parts of the curriculum and various student contexts [12]. The results are similar to the framework of Desirable Difficulties which was used for the present study.

B. Research Gap

There is no shortage of research on study habits. The amount of research into motivation, self-regulation, technology availability, and family background is plentiful. Missing is a study that can integrate all of these together, that is, for first year BSCS students in the context of a state university in the Philippines.

Previous studies have predominantly examined the relationship between academic outcomes and a number of factors, such as personal and environmental factors. That is useful. It doesn't answer another question, however: who are these students, exactly? What ages are they? What kind of learners are they? What are their family incomes? Does your child have a computer at home? Do they need to support themselves and their household and at the same time work on passing their program courses [1, 2]?

While first-year BSCS students have received little attention as a discrete group from a combination of personal characteristics (age, gender, year level, GPA, learning style, and motivation) and environmental backgrounds (type of school, income, parents' education, learning environment, technology, and work hours) [3]. Individual studies have looked at pieces of this picture. Technology access here. Motivation there. But a full profile however? For this particular group, in this particular context? There is no such research yet [6, 7].

This study is an attempt to fill that gap "modestly" — in a descriptive, and truthful manner — to document who first year BSCS students at Surigao del Norte State University really are, and under which conditions they are really learning.

C. Synthesis of Related Literature

When combined, the literature reviewed shows a definite direction. Student's learning is influenced by personal and environmental factors. Neither operates alone [6, 7, 9].

In terms of personal, motivation and self-regulation are the most consistent influences. Pérez-Navío et al. [6] proved that there is better use of learning strategies among intrinsically motivated students. Theobald [7] demonstrated that teaching SRL to students significantly affected their academic results. Li et al. [8] and Silva et al. [9] have found that for programming, students who plan their own learning, monitor and regulate it, achieve better results than those who do not. This finding is universal in terms of country, field and research design. The pattern holds [6, 7, 8, 9].

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The picture is similar on the environmental side. Those students who have more access to technology and supportive home environment are more likely to have effective study habits [13, 14]. Families with low income or parents who have not pursued higher education might experience structural disadvantages affecting their children's learning right from the start [22]. Students who work for extended periods of time have an extra burden that directly interferes with their studies and sleep [15]. These are no excuses. They are realities. If someone does not design academic support programs for them, then academic support programs are not available for students who need it most [11, 16].

The reviewed studies all support a fundamental concept, that learning that is active and demands some mental effort results in deeper understanding and more transferable skills [1, 2]. However, the capacity for such intentional learning is a function of both the student (motivation, self-regulation, learning style) and the context in which the student learns (home environment, technology access, family's economic status [7, 8, 9, 10, 13]).
Despite this strong evidence base, the literature reveals a notable gap. No existing study comprehensively describes both categories of factors specifically for first-year BSCS students in a Philippine state university [3, 6]. This synthesis highlights precisely why such a study is needed — and what it might contribute to the design of more targeted, more equitable, and more effective academic support for students like those at Surigao del Norte State University [7, 11].

IV. METHODOLOGY

The research methodology used in this study is discussed in this chapter. It consists of the conceptual framework that was followed in the investigation, discussion of sampling techniques, research instrument developed for data collection and statistical tools applied on the collected data.

A. CONCEPTUAL FRAMEWORK

This research will be conducted within a framework of desirable difficulties as suggested by the researchers, in which the learner will be better equipped for learning if there is an active effort on the part of the learner and 'difficult' mental processes are involved [1, 2].
Personal Factors: These are factors within the student that are their own such as age, gender, year level, GPA, learning style and level of motivation.
Environmental Factors: These are factors outside of the child's control and consist of: Type of school (public/private), family monthly income, parent's education, study environment (home/dormitory/library), technology (computer and internet) and hours worked per week.

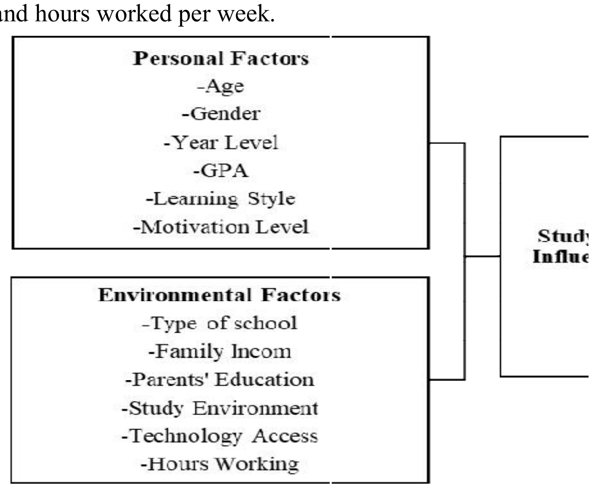

Fig. 1 Conceptual Framework of the Study

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B. Discussion of Sampling Techniques

A descriptive-quantitative research design was used in the study. The population in this study was made up of all first year students taking BSCS at Surigao del Norte State University, during the second semester of the school year in which the study was done. Official class records show that there are 93 students in this class in the first year of BSCS for this semester.

The proponent applied the total population sampling technique (also called complete enumeration). This technique was chosen due to the numbers of first-year BSCS students being manageable and accessible. A total of 93 students were officially enrolled in the data collection period and all these students were invited.

Factors like absence, partial responses and voluntary non-participation resulted in only 49 students completing and returning the questionnaire. The final sample included 49 students in the first year of BSCS or about 52.7 percent of the total population.

There were no further inclusion/exclusion criteria other than current enrollment in the first-year BSCS program. Although the intention was to survey the entire population, the respondents were a large proportion of the population, and the results were interpreted as descriptive of the respondents, but not as representative of the entire population.

C. Research Instrument – Likert Scale Discussion

The proponent developed a structured questionnaire as the main research instrument. The questionnaire was entitled "Study Habits of 1st Year BSCS Students: The Effect of Personal and Environmental Factors". It was broken down into three sections.

Part I

In Part I, the respondent's profile is collected, as well as the optional name field.

Part II

Motivation, GWA, visual/verbal/kinesthetic/mixed learning preference and age and sex were collected as part of Part II and the data was used to gain an understanding of the personal factors.

Motivation item:

"My attitude towards my programming courses is to do well in each course."

This item was measured on a 4-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = agree; 4 = strongly agree).

4 – Strongly Agree

3 – Agree

2 – Disagree

1 – Strongly Disagree

Part III

Part III collected information on environmental factors, such as the type of school attended, the father and mother's highest level of education (individually), a statement to indicate whether there is a quiet place to study, reliable access to technology, and hours worked per week.

The following statements were used in the environmental perception items:

"I have a quiet and comfortable place to study programming at home."

"I do have reliable access to a computer and internet and can practise programming with them."

The four-point Likert scale was used in both statements.

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Discussion of the Likert Scale

The items related to motivation and environmental perception were selected using a four-point Likert scale to prevent having "undecided" or "neutral" answers, as this would represent the middle range of the items.

The format used was a forced-choice, with a clear indication to agree or disagree with each statement.

The scale was treated as an ordinal scale. The proponent gave numeric values to each of the items on the Likert type items:

4 = Strongly Agree
3 = Agree
2 = Disagree
1 = Strongly Disagree

These numerical values allowed a quantitative analysis, especially calculating means.

The content of the questionnaire was content validated by the proponent's research adviser. No pilot testing was reported; however, the proponent made sure that the language of the items was suitable for first-year college students and that the items were closely related to the variables defined in the conceptual framework.

The proponent used Google Forms to meet and gather respondents' answers to the structured questionnaire, facilitating efficient and organized data collection online from respondents.

D. Statistical Tools Used

The responses were collected once and then coded into a tally sheet in Microsoft Excel by the proponent. Data collected were analysed with the following descriptive statistical tools:

1. Frequency and Percentage

The categorical variables of age group, sex, year level, learning preference, type of school, family income bracket, parents' education level and hours worked per week were summarised using these. The proponent calculated the frequencies (number) and percentages for each frequency to describe the distribution of respondents in each category.

2. Variable Conversion (Coding)

The proponent used numbers to represent each categorical answer so that it is possible to perform quantitative computations, especially with means, prior to analysis.

Variable	Original Answer	Numerical Code
Gender	Male	1
	Female	2
	Prefer not to say	3
Learning Preference	Visual (diagrams, charts, images)	1
	Auditory (listening, discussions)	2
	Kinesthetic (hands-on, practice)	3
	Mixed (combination of the above)	4
School Type	Public	1
	Private	2
Family Income		1

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	Below ₱10,000	
	₱10,001 – ₱20,000	2
	₱20,001 – ₱30,000	3
	₱30,001 – ₱50,000	4
	Above ₱50,000	5
Father's/Mother's Education	Elementary graduate	1
	High school graduate	2
	College graduate	3
	Post-graduate degree	4
Work Hours per Week	0 hours (not working)	1
	1–10 hours	2
	11–20 hours	3
	21–30 hours	4
	31+ hours	5

Table 1. Variable Conversion Table: Original Responses to Numerical Codes

Note: In the case of Likert scale items (Motivation, Study environment, Technology access), the numbers were simply assigned as:
4 = Strongly Agree
3 = Agree
2 = Disagree
1 = Strongly Disagree

3. Mean

The proponent had summarized ordinal variables, which were coded into numbers, using the arithmetic mean as the summarizing method:
The motivation item (I am motivated to do well in my programming courses)
The study environment item ("I have a quiet and comfortable place to study programming at home")
The technology access item (I have reliable access to a computer and internet to practice programming)
The proponent also calculated the mean of coded categorical variables (where applicable) for descriptive purposes, e.g., learning preference (coded 1-4) and parents' education (coded 1-4).
The mean scores are interpreted as follows:

Mean Range	Interpretation
3.50 – 4.00	Strongly Agree / Very High
2.50 – 3.49	Agree / High
1.50 – 2.49	Disagree / Low
1.00 – 1.49	Strongly Disagree / Very Low

4. Frequency Distribution Tables

The summarized data was presented in frequency distribution tables such as respondent profile by age, gender etc. (Table 2) for a clear presentation. A conversion table (Table 1) was provided in order to ensure transparency of the transformation of the categorical responses into numerical codes for analysis.

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Microsoft Excel was used for all statistical calculations. The objectives of the study were purely descriptive, to describe the personal and environmental factors of first year BSCS students, and to identify the most common factors within each group, and thus no inferential statistical test (e.g., t-test, ANOVA, correlation) was used. The discussion on the effects on the study habits was based on existing literature as mentioned in the objectives of the study.

V. RESULTS AND DISCUSSION

This chapter reports findings of the study based on the six research objectives. The researcher has provided individual insights on each of the findings, and the findings have been substantiated by existing literature. The chapter ends with suggestions for educators and institutions based on evidence.

A. Profile of the Responents

The study involved 49 first year Computer Science (1st year BSCS) students from Surigao del Norte State University. A summary of the demographic and academic profile of the respondents is given in Table 2.

Variable	Category	Frequency(n)	Percentage(%)
Age	18 years	12	24.5
	19 years	14	28.6
	20 years	7	14.3
	21 years	8	16.3
	22 years	7	14.3
	23 years	1	2.0
Gender	Female	29	59.2
	Male	20	40.8
	Prefer not to say	0	0
Learning Style	Visual	8	16.3
	Auditory	5	10.2
	Kinesthetic	5	10.2
	Mixed	24	54.5
	No response	7	14.3
Motivation Level	Strongly Agree	15	30.6
	Agree	16	32.7
	Disagree	4	8.2
	Strongly Disagree	2	4.1
	No response	12	24.5
Mean GWA		1.98 (SD=0.42)	

Table 2. Summary of Respondents' Profile (N=49)

B. Personal Factors of First-Year BSCS Students

The first purpose was to present the personal characteristics of the first year BSCS students such as age, gender, grade point average (GWA), learning style and motivating factors.The first purpose was to present the personal characteristics of the students of first year BSCS namely age, gender, grade point average (GWA), learning style, and the motivating factors.

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1) Age and Gender

As shown in Table 2, the largest age group was 19 years (n=14, 28.6%), followed by 18 years (n=12, 24.5%) and 21 years (n=8, 16.3%). The average age was around 19.7 years. It is a typical distribution among first year college students in the Philippine context, where the average age of entry into tertiary education is 18 or 19 years old.

When asked about gender, most respondents were female (n=29, 59.2%) while males made up 40.8% (n=20). The result indicates the presence of female dominated population in the BSCS program of Surigao del Norte State University. This gender balance is significant as it differs from the national and international trends in computer science education where the number of male students usually exceeds the number of female students [18].

Single case: A high number of female students in this sample may reflect a particular school's success in recruiting females to STEM courses or may suggest that there are gender differences that vary by region and/or institution.

This result supports the work of Master et al. [18] who reported gender stereotypes with respect to interests in computer science and engineering starting as early as age 6. But those authors also pointed out that it can be mitigated if young girls are exposed to computer science activities before they become "stereotyped. This relatively balanced or female dominated cohort in this study may indicate that early intervention or environmental factors may have potentially reduced stereotype effects in this population.

2) Academic Performance (GWA)

The mean of the answers for the General Weighted Average (GWA) was 1.98 (SD=0.42) on a 5-point scale (as lower scores=higher performance). This means that students' performance in the majority was in the 'Good' to 'Very Good' levels. Individual GWAs ranged from 1.5 to 2.6, however, with some variation in academic achievement.

Individual Insight: This relatively high mean GWA indicates that students in the first year of BSCS at this university are satisfactorily doing their studies. The standard deviation of 0.42, however, suggests that there is some problem for some students and can indicate that early academic interventions are necessary.

Llanos et al. [17] created a prediction model for students performance in CS1 programming courses based on grades, delivery time and number of attempts in programming labs. In their study, they determined that by the 3rd week of the course the student performance can be predicted with an accuracy of 86% by using gradient boosting classifiers. This implies that if students with lower GWAs can be identified early enough, support can be provided early enough. Moreover, Tadese et al. [20] reported that older students (25-29 years old) had lower odds for good academic performance than younger students (20-24 years old) with an adjusted odds ratio of 0.43 (95% CI: 0.22-0.91). The current study participants' age range is more limited but this suggests that maturity can provide academic benefits.

3) Learning Style

The most frequent learning style for respondents was mixed which refers to students who learned from both visual and auditory and kinesthetic type of learning (n = 24, 54.5%). There were 16.3% (n=8) visual learners, 10.2% (n=5) auditory learners, and 10.2% (n=5) kinesthetic learners.

Individual Insight: The high percentage of mixed learning styles is practically significant since it indicates that there will not be one ideal teaching strategy (pure lecture, pure hands-on coding) for all students [21]. Rather, teachers should use multiple methods of teaching to cater to different learning preferences.

This is greatly supported by Masegosa et al. [21] who did the study about the effect of learning styles on active learning methodologies in programming education. They found that students whose learning style dimensions varied perceived differently the live coding and short programming exercises using the Felder-Silverman model. For instance, the methods were rated as "very helpful" by higher percentages of active and sequential learners than by reflective or global learners. Importantly, Masegosa et al. [21] found that 'live coding' is an appropriate methodology to support all aspects of learning style, so 'live coding' is worth considering in order to achieve a balance across learning style categories. The results of the present study have been consistent with the recommendation of not using any single approach to teaching programming; of the students surveyed, more than half felt that they learned best with a mixed approach.

4) Motivation

The majority of students said that they were very motivated to succeed in their programming classes. In particular, 30.6% (n=15) agreed that they wanted to do well in the programming courses (coded "Strongly Agree") and 32.7% (n=16) agreed that they wanted to do well (coded "Agree"). 12.2% disagreed or strongly disagreed.

Individual Insight: This degree of motivation is good to see and any motivated student will have better chances to overcome the challenges involved when learning about programming [19]. Almost a third of the students (24.5%) failed to answer this question, though, which could be a result of survey fatigue or a lack of motivation, and should be explored further.

Farooq and Anwar [19] reviewed systematically 26 studies to identify the factors that influence students' motivation to learn programming and were grouped into three themes: intrinsic, extrinsic, and social cognition. They concluded that digital tools (such as robots, games) and real-world examples had a significant effect on boosting intrinsic motivation. Additionally, they were able to determine that reward, recognition and career-related incentives such as flexibility of working from home were strong extrinsic motivators. Transferring these results to the current study, the strong levels of motivation found could be maintained or even enhanced through the use of games or project-based tasks that link programming to a real-life career application. On the other hand, Farooq and Anwar [19] warn that if students are not motivated they face difficulties in attending class and have a higher risk of dropping out, even in the most motivated ones.

C. Environmental Factors of First-Year BSCS Students

This was to describe the environmental influences such as school type, family income, parents' education, study environment, technology access and hours working.

1) School Type and Family Income

100% of the 49 respondents had completed public education. As for family income, most (n=35, 71.4%) indicated that their family's monthly income is less than ₱10,000. Only 12.2% (n=6) reported incomes above ₱20,000, with 4.1% (n=2) above ₱50,000.

Individual Insight: A high concentration of students from low income families (those earning monthly income less than ₱10,000) suggests that most of the first year BSCS students have substantial economic limitations [16, 22]. This affects their technology, Internet access and even their basic needs that facilitate academic success.

2) Parents' Education

The highest level of education achieved by fathers varied, with 16.3% (n=8) reporting they have completed elementary school, 49.0% (n=24) reporting high school, 22.4% (n=11) reporting college, and 4.1% (n=2) reporting post-graduate degree. The median level of education for mothers was slightly higher with 12.2% (n=6) having completed elementary school, 28.6% (n=14) completed high school, 36.7% (n=18) completed college, and 6.1% (n=3) having higher education.

Individual Insight: A large minority of mothers (36.7%) had a college education, but the majority of parents (65.3% of fathers and 40.8% of mothers) had only a high school education or less. Many students are first-generation college students or have little firsthand experience with higher education, which indicates that many of them may be at a disadvantage [22].

The study by Ludeke et al. [22] is a study of Danish children conducted through a full-population adoption study in which they investigated the causal effect of parental education on child educational outcomes. They found that, in general, parental education showed a strong relationship with children's educational qualifications, but this relationship was significantly diminished among the adoptees, with only 17% of the relationship with education being explained by parental education in a biological family. Furthermore, the non-genetic effect of parental education on child enrollment in advanced education was not significant after controlling for childhood academic achievement. Ludeke et al. [22] have therefore found that the fundamental non-genetic processes through which education is passed down from generation to generation might have an impact on children in early stages of schooling. In the current research, this implies that although many students are from families with rather limited educational backgrounds, these families do not necessarily mean that they will have limited educational outcomes. Factors that are more proximal to academic success than parental education might be early academic success and conscientiousness.

3) Study environment and technology access.

When asked about the study environment, 38.8% agreed or strongly agreed they have a quiet and comfortable study environment at home where they can program. Likewise, 36.7% agree or strongly agree that they have a reliable access to a computer and internet for programming practice. Meanwhile, 42.9% of respondents disagreed or strongly disagreed that they had a quiet study space, and 46.9% disagreed or strongly disagreed that they had access to reliable technology.

Individual Insight: These are troubling numbers. Almost 2/3 of students do not have proper study space at home and nearly 1/2 of students do not have access to reliable technology at home [13, 14]. The lack of sustained concentration, a functional computer and internet connectivity for research or assignments submission may directly affect learning when involved in programming [10].

LiYing and Ahmad [13] employed a quantitative correlational design to examine the correlation between technology access and academic performance in digital art among students in undergraduate programs in China. They found that the academic performance was moderately positively correlated with access to technology ($r=0.412$, $p<0.01$). In particular, hardware ($r=0.412$) and software for learning ($r=0.412$) were positively related to GPA with $p<0.05$. Furthermore, the usefulness of technology in studies showed the slight correlation with academic results. LiYing and Ahmad [13] found that "students, who have stable internet connections, access to high-performance computers and industry standard software, tend to do better academically. The 46.9% of students indicating a lack of technology access in this context may be at a higher risk for poorer academic achievement if the university can provide a solution that helps make up for this lack, like increased computer lab time or loaned laptops.

Using a one-to-one (1:1) computer program, Hall and Lundin [14] studied students' performance in primary schools in Sweden. They analyzed student test scores in math, Swedish, and English for 55,972 students and concluded that, on average, the use of 1:1 technology had no significant impact on student test scores in those three subjects. But Hall and Lundin [14] observed that investments in ICTs that are geared only towards access to technology and do not have a

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clearly defined educational purpose have limited impacts on learning outcomes. This is a key point that needs to be highlighted – it is not enough to give computers. The present study's conclusion that the access to technology is limited is an important first step, but interventions must also provide opportunities for technology to be used with clear pedagogical goals, teacher preparation, and organized programming activities.

4) Hours Working per Week

Most students (69.4%, n=34) said that they didn't work at all. Among those who worked, 22.4% (n=11) worked 1-10 hours weekly, 6.1% (n=3) worked 11-20 hours, and one student (2.0%) worked 21-30 hours.

Individual Insight: The number of working students (30.6%) is lower than would be expected because families tend to have low incomes [15]. This could suggest that students use alternative means of financial support (such as scholarships, government grants or financial support from family) rather than formal jobs. Or students might be doing something other than their survey work that is also a type of work, but not formally reported or paid.

Hulla [15] carried out a wide-ranging dissertation study on working college students that focused on the relationship between work demands, psychosocial factors, and health outcomes and academic performance. Hulla [15] used a sample of 207 working students at the University of Texas at Arlington and found work-school conflict to be a significant predictor of perceived stress (4.84% variance accounted for) and job satisfaction to be a significant predictor of sleep quality (4.84% variance accounted for). Perhaps most importantly, Hulla [15] was able to show that students who worked 20 hours or more per week were 1.45 times more likely to report bouts of shorter sleep. While none of the students in the current study work, a small number of students (8.2%) work 11+ hours per week, which is a risk factor for poor sleep quality, higher stress levels, and reduced academic involvement. Students who think that their job interferes with school performance unfairly might experience a health impact that is more severe than others who feel the same way, as Hulla [15] found that perceived injustice partially mediated the relationship between job satisfaction and sleep quality.

D. Most Common Personal Factors

Amongst the first year BSCS students, the most common personal factors were:
Female gender (59.2%)
Age 19 years (28.6%)
Mixed learning style (54.5%)
Motivation (Agree/Strongly Agree): 63.3% of valid responses

One thing that is most pedagogically important is Individual Insight, the percentage of mixed learning styles. It suggests that no single modality is sufficient for effective instruction in programming. Rather, instructors need to mix up the modalities of demonstration (e.g., live coding), explanation (e.g., talk), and activity (e.g., hands-on).

Masegosa et al. [21] offered specific suggestions given the results of their empirical study on live coding. Students responded that the 3+1 format, which is three hours of lecturing/live coding/short exercises and one hour of group work, was the most preferred session structure by 47% of students, followed by the 3+2 format, with 13% preferred. The traditional 2+2 format, with 13 hours of lecture and 13 hours of live coding and group work, was the least preferred format by 16% of students. Furthermore, they discovered that the rate at which active learners and sequential learners perceived live coding as being "very helpful" was greater than that for reflective learners. Students in the present study whose learning styles were mixed (54.5%) would be most likely to be engaged when a diverse approach to teaching (a combination of live coding, short exercises, and learning in groups) was used.

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E. This is the most common list of the factors that affect the environment.
The most common environmental factors were:
Public school attendance (100%)
Family income below ₱10,000 (71.4%)
49.0% of fathers had obtained a high school diploma or less.
Mother's education: College graduate (36.7%)
Having a quiet place to study (61.2% did not agree or strongly agree)
Not having reliable access to technology (63.3% disagreed or strongly disagreed)
Zero work hours (69.4%)

Multiple Disadvantages: Low income, low level of parental education and poor home study resources may indicate that students have multiple overlapping disadvantages. But, these students have taken part in and stayed through their first year of a challenging BSCS program, which shows some level of resilience. This resilience can be a tool that could be utilized by teachers.

Stavrulaki et al. [16] studied the relationship between perceived parenting styles, motivation orientation, life satisfaction and GPA among college students. With the 432 students, they revealed that authoritative parenting (high demandingness and responsiveness) was positively related to intrinsic motivation and life satisfaction, and authoritarian parenting (high demandingness, low responsiveness) was positively related to amotivation. Parents play an important role in college students' wellbeing and performance, both directly and indirectly through motivation orientation, is the critical finding by Stavrulaki et al. [16]. For participants with low educated parents in the present study, this implies that parenting style (autonomy support and warmth) could be more important than the level of education attained by parents, so to speak. Teachers could have a positive impact on students without altering their parents' educational attainment by teaching supportive involvement to parents.

F. Discussion of How Personal and Environmental Factors May Influence Study Habits
This section collates the results of literature search and reports the understanding of the researcher on how personal and environmental factors listed in the previous sections can affect BSCS first-year students' study habits.

1) Influence of Learning Styles on Study Habits
The Felder-Silverman learning styles model, as implemented by Masegosa et al. [21] is useful. They found that live coding and brief sections of programming are valuable tools for the active learner, since actual coding is engaging and gives instant feedback. Reflective learners, on the other hand, like to think about the information before they act on it, and might not learn as quickly from live coding. The mixed learner (54.5% of the students in this study) would find a study strategy that would alternate between active and reflective learning activities effective: for example, writing code and debugging, or reading notes and manually tracing code. If students do not adjust their study strategies to their learning style, they may suffer from unnecessary cognitive overload, loss in motivation or learning retention.

2) Influence of Motivation on Study Habits
Farooq and Anwar [19] compiled evidence that intrinsically motivated students are more likely to process the information at a deeper level, last longer on difficult tasks and enjoy programming more. Students who are extrinsically motivated can do well but may be more interested in getting a good grade than learning the concepts. In the present study, for the 63.3% of students who said that they are highly motivated, there is a high probability that they practice them regularly, seek assistance if they get blocked, and complete the optional exercises. But, Farooq and Anwar [19] warn of the volatility of motivation, that is, it is not constant and gradually decreases during the semester if not

reinforced. Thus, studying skills need to be actively sustained by setting up learning goals, self monitoring, and regular rewards.

3) Influence of Technology Access on Study Habits

Lying and Ahmad [13] showed that there is a correlation between the students' GPAs and their reliable hardware and software access. It is probably implemented in reality through study habits; students who have computers at home can practice coding every day, watch online videos to help with their work and have the flexibility to complete their assignments when they want to. However, access to unreliable computers means that students without reliable access will need to use the school computer labs during limited time periods, potentially reducing practice frequency and making it easier to procrastinate. However, an important caveat was added by Hall and Lundin [14] that the access to technology is not enough. Schools with no intentional use of technology for learning and education in their L1 programs experienced no improvement. Therefore, when access is improved, students need to be guided in their effective study practices that will utilize technology (self-assess using online judges, join coding forums, streamline lectures at 1.5 speed, etc.).

4) Influence of Work Hours on Study Habits

Hulla [15] reported that work-school conflict was directly related to perceived stress and indirectly related to sleep quality via perceived injustice. Students who worked 20+ hours per week had less time to study, fewer classes and reported lower engagement. Only 8.2% of students are working more than 11 hours per week in the present study, and consequently these students' study habits may be negatively affected. They might have limited attention spans, may not be able to sit through lengthy lessons, may not be able to focus, or may not attend school to study because of work commitments. The most common way that employment-related issues had an impact on the students' academic work that Hulla discussed in his qualitative thematic analysis was through "vitality factors" (e.g., being tired, not getting enough sleep).

5) Influence of Parental Education and Family Income on Study Habits

In the adoption design, Ludeke and colleagues [22] very rigorously showed that this was the case. One of their main conclusions was that non-genetic influences of parental education on educational outcomes "get baked in" to the initial outcomes (grade 2) and are not themselves associated with later outcomes, such as high school enrollment or graduation. This means that when students go to university, parental education is mainly shaping their study habits through the way they have already learned to work.When students go to university, they have been brought up to work in a certain way, so that the main channel through which parents' education affects their study habits is already laid. Students from lower-education families might not have received as many books, educational games, parental support in studying, etc., during early childhood, which might have adversely affected their self-regulation and study skills. But Ludeke et al. [22] also showed that conscientiousness, a personality trait strongly associated with academic achievement, was not environmentally transmitted by parents, either: the relationship between conscientiousness and parental education was purely genetic. This implies that a student from a less educated family can form good study habits if he or she is responsible to his or her own work and the university makes a point of teaching the techniques of studying.

6) Influence of Gender on Study Habits

Master et al. [18] identified that gender-interest stereotypes (the belief that girls are less interested in computer science than boys) are held by children as young as age 6 and are associated with girls' lower sense of belonging and interest in computer science. By the time of adolescence, these stereotypes have been reinforced by racial/ethnic subgroups alike. More than half of the students in the present study are female (59.2%), indicating either a lack of strength of these stereotypes in this context or that previous experiences have counteracted them. However, Master et al. [18] have recently found that 8- to 9-year-old girls actually showed decreased interest in a gender-typed activity that was labelled "boy" when it was done in the context of a stereotype that was biased toward boys. In the current study, feelings of belonging with computer science might be related to study habits for female students, as they are more likely to engage in study groups, office hours, and are more likely to persevere when facing challenges. Institutions should thus be vigilant and take steps to detect and correct any implicit stereotype cues in the learning environment.

G. Evidence-Based Recommendations for Educators and Institutions

The following recommendations are presented based, as outlined above, on the results of this study and the literature review.

Recommendation 1: Use a variety of teaching strategies to support diverse learning styles.

Finding: 54.5% of students are of a mixed learning style.

Evidence: Masegosa et al. [21] identified that active and sequential learners have a significant advantage from the live coding and from programming exercises of a short duration, whereas reflective learners have an advantage in working alone. The most preferred 3+1 session structure (3 hours mixed instructions, one hour of group work) was chosen.

Recommendation: Instructors should use live coding to demonstrate, individual short exercises, pair programming and reflective individual exercises during each class period. Don't just have lecture-based content and just have hands-on coding.

Recommendation 2: Maintain Intrinsic Motivation through Authentic, Real-World Projects.

Finding: 63.3% of students said that they were highly motivated to learn English, but their motivation may fade over time.

Evidence: Farooq and Anwar [19] found that the use of digital tools (such as robots, games) and real world examples successfully boosted intrinsic motivation. Extrinsic rewards (grades, recognition) are also effective but need to be felt as personally relevant.

Recommendation: Develop programming projects to address a real-world problem that has local significance (e.g., data management for small businesses, simple mobile applications for local use). Use game based learning platforms (e.g., CodeCombat, Scratch) to keep it engaging!

Recommendation 3: Increase Equitable Technology Access via Institution Resources

Finding: 63.3% of students do not have reliable technology access at home; 61.2% of students do not have a quiet study place.

Evidence: They discovered a moderate positive correlation between technology access and GPA (r=0.412) between LiYing and Ahmad [13]. Hall and Lundin [14] determined that access to technology is not enough, pedagogical integration is essential.

Recommendation: The university should increase lab time (evenings, weekends, etc.), provide a loan program for low-income students with laptops, and ensure that the programming software used on all the computers in the lab is industry-standard software such as VS Code, PyCharm, Java SDK, etc. Also, set up a designated quiet area in the computer science department for programming practice.

Recommendation 4: Keep track of Work-School Conflict and offer flexible academic accommodations

Finding: 30.6% of students are in some kind of work; 8.2% work 11+ hours per week.

Evidence: Hulla [15] reports that work-school conflict directly influences perceived stress which is then related to lower GPA and less engagement. The quality of sleep plays a mediating role between job satisfaction and academic outcomes.

Recommendation: Have lecturers record their lessons and post them online so that students who miss class because of work can view the recorded lectures. Extend the deadlines on assignments where possible. Working students should be identified as a subject of a mid-semester academic advising. The university should consider evening or weekend classes in the core programming courses.

Recommendation 5: Inform Parents about Autonomy-Supportive Involvement
Finding: Many parents have little formal education, but parenting style may be more significant than level of education.

Evidence: Authoritative parenting (high demands/low warmth) is associated with higher life satisfaction and intrinsic motivation and authoritarian parenting (low demands/high warmth) is associated with amotivation [16]. Ludeke et al. [22] have shown that non-genetic influences of parental education occur very early in a child's development.

Recommendation: Parents should be given the opportunity to attend one-hour workshops at the university during freshman orientation or at family weekend. These workshops should include knowledge of principles of autonomy support; understanding the child's emotions, providing choices in behaviour, explaining why rules are necessary, and not using techniques that can be too controlling. These strategies can be done by parents who lack formal education.

Recommendation 6: Explicitly Challenge Gender Stereotypes in Course Materials and in Classroom Culture
Finding: Gender stereotypes about interest in computer science are still common in the larger society although the sample is largely female.

Evidence: Evidence shows that children as young as six endorse gender-interest stereotypes, which leads to a decrease in their sense of belonging and interest in computer science activities [18]. Stereotype cues were experimentally removed and no gender gaps in interest were found.

Recommendation: Computer science course syllabus should contain statements that reflect the fact that computer science is for everyone regardless of gender. The selection of names and scenarios for instructional examples should be varied—or not male coded. Depict women and non-binary people in a programming role in posters, other forms of classroom visuals, etc. Language that suggests programming is "masculine" (e.g., "hacker culture") should be avoided by the instructor.

Recommendation 7: Develop First-Year Seminars on Study Habits and Self-Regulated Learning
Finding: Students are exposed to several environmental disadvantages and resilient.

Evidence: It was shown by Llanos et al. [17] that prediction of student performance based on student grades, delivery time and number of attempts is possible and reliable as early as week 3 (F1 score of 86%). Early intervention can then be aimed. Motivation has to be maintained and if it is, students will persist longer, as explained by Farooq and Anwar [19].

Recommendation: Recommendation: require all BSCS students to take a first year seminar that will explicitly include instruction on evidence-based study habits, spaced practice, self-testing, error analysis (debugging logs), and time management. Assign low stakes programming quizzes each week to monitor students that may be at risk early (by week

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3-5) and offer peer tutoring or office hours specifically for these identified students. This seminar should also include discussing growth mindset (intelligence is malleable) to overcome any fixed mindsets on programming skills.

VI. CONCLUSION

The findings of this study are presented in this Chapter with the conclusions drawn along the six objectives of the study. The conclusions are treated in detail, drawing on, and incorporating the outcomes, findings and existing literature.

A. Objective 1: Personal Factors of First Year BSCS Students

The first was the description of personal factors of first year BSCS student of Surigao del Norte State University.The first was to describe the personal factors of Surigao del Norte State University's first year BSCS students. The results indicated that females (59.2%) outnumbered males, the age group of 19 years was the most frequently found age group (28.6%), mixed learning styles were the most common (54.5%) and the respondents were highly motivated, with 63.3% agreeing and strongly agreeing that they are motivated to perform well in their programming course. The overall General Weighted Average (GWA) was 1.98 (SD=0.42) which represents overall satisfactory academic performance.

Interpretation: The typical first-year BSCS student in this study is a young female, who learns best by multi-modal learning and has a real interest in achieving success [19, 21]. In this case, the majority of learners belong to mixed types (visual, auditory or kinesthetic), meaning that they do not follow a single style of learning but require a synthesis of the three styles [21]. This result is consistent with the work of Masegosa et al. [21] who found that learning through a mixed presentation of learning channels is the preferred choice of computing students because the learning tasks in the program are cognitive tasks that require both abstract thinking (visual /logical learning) and concrete application (kinesthetic learning).

This is significant since the high percentage of female students is opposite to that reported nationally and internationally by Master et al. [18] which reported that gender interest stereotypes favoring boys in computer science are found as early as age 6 and continue through adolescence. However, the fact that this study is conducted with a female-dominated sample of students indicates that perhaps some local measures, such as targeted recruitment, inclusive classroom practices, or community support, have been effective in challenging such stereotypes. Female learners must not be considered a minority who need special provision, but are a majority whose learning needs must be at the centre of course design. Although there is high motivation levels, keeping these high is important according to Farooq and Anwar [19] since, intrinsic motivation can drop after a semester if it is not reinforced.

B. Objectives 2 Environmental Factors of First-Year BSCS Students

The second goal was to provide a description of the environmental factors of BSCS first-year students. They found that 49 of the respondents (100%) went to public schools. The majority of families earned minimal income, 71.4% of which was below ₱10,000 per month. Fathers' education centered on the high school level (49.0%), and the education of the mothers was somewhat higher with 36.7% holding college degrees. Importantly, none of the students agreed or strongly agreed that they have a quiet and comfortable home environment in which to study programming, and none agreed or strongly agreed that they can have reliable access to a computer and Internet at home to practice programming. In terms of work hours, 69.4% of students indicated that they do not work at all.

Interpretation: BSCS first year students have a lack of advantages in environment. The majority are from low-income households, a significant number are first-generation college students (as only 36.7% of mothers have gone to college), and most do not have sufficient study environments and reliable technology at home [13, 22]. The combination of disadvantages is alarming because both access to hardware (r=0.412) and use of software for learning (r=0.412) are moderately positively correlated with academic performance as shown by LiYing and Ahmad [13]. Students who don't have a home computer or reliable Internet connection will have to use the school computer labs at limited times, lessening the frequency, flexibility and opportunities for self-directed learning.

Implication: However, Ludeke et al. [22] have a more complex view. They discovered in their adoption study that effects of parental education (beyond the unique genetic contribution) are "baked in," to early academic performance, by grade 2, and do not have an independent impact on later educational outcomes. This implies that by the time students enter college their approach to education and academic careers are well on their way to being influenced by their early experiences. This is not to say that being a student from a low-income family is a sign of poor performance; instead, it suggests that the university has the charge of delivering compensatory resources (such as computer labs, quiet study areas, academic advising) to help offset early disadvantages of 71.4% of students. This is protective since 69.4% of the students are not working, and Hulla [15] found that work-school conflict was directly related to perceived stress, which was directly related to lower GPA and student engagement.

C. Objective 3: Most Common Personal Factors

The third goal was to determine what the most prevalent personal factors were among the students in the first year of BSCS. The results revealed the following four factors: (a) female gender (59.2%), (b) age 19 years (28.6%), (c) mixed learning style (54.5%) and (d) high motivation (63.3% Agree/Strongly Agree).

Interpretation: The most pedagogically relevant result to come out of this is the high proportion of mixed learning styles. This implies that no one method of instruction from pure lecture to pure hands-on coding, to pure visual demonstration will be best for most students. Masegosa et al. [21] identified that the active and sequential learners saw live coding and short programming exercises as "very helpful" more frequently than the reflective learners. Deliberate variation is required for effective teaching of students with mixed learning styles. The high motivation levels suggest that students enter the program with positive attitudes, but the training programs in self-regulated learning could further increase the motivation and academic performance as Theobald [7] proved in a meta-analysis of 49 studies.

Implication: Teachers should not take for granted that students have good study skills when they are motivated. If students put in effort, but fail to gain much, they become frustrated and demoralized, which leads to a lack of motivation.Without a strategy, students can put in effort, but not get much out of it, that results in frustration and demoralization and in turn a lack of motivation. Based upon the most common personal factors, the first-year BSCS students are learners who are motivated and diverse in their learning styles, but who may not have a clear idea about how to translate such motivation into good habits of programming.

D. Objective 4: Most Common Environmental Factors

The fourth goal was to discover what are the most frequent environmental factors in first year BSCS students. Results showed that every student are enrolled in public school, 71.4% of whose fathers earn income of less than ₱10,000, 36.7% of whose mothers completed college and, most importantly, 61.2% of whom did not have a quiet study place or 63.3% of whom did not have reliable access to technology at home. Most students do not work (69.4%).

Interpretation: First-year BSCS students' environmental profile is one of economic constraint and resource limitation. This is especially concerning for programming education, where long periods of focus are required, frequent practice, and access to development environments and online resources. One to one computer programs in schools did not have any significant effects on average test scores, Hall and Lundin [14] cautioned, but "investments in ICT that merely improve access to technology without having a distinct educational purpose have limited effects". This means giving

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computers is not enough; technology has to be combined with good pedagogical goals, training and a controlled structure of programming activities.

Implication: University does not want to assume students have an adequate home environment for learning. Computer labs, library study spaces, even isolated quiet spaces in the Computer Science department are considered "infrastructure". Stavrulaki et al. [16] found that authoritative parenting (warm engagement and appropriate demands) is related to higher intrinsic motivation, whereas appropriate demands are related to higher life satisfaction, but the structure and support it provides might be lacking in the university for students whose parents do not have high levels of formal education.

E. Objective 5: Influence of Personal and Environmental Factors on Study Habits

The fifth goal was to talk about if personal and environmental aspects have an impact on the study habits of first-year BSCS students, according to literature. The results from the literature synthesis show that personal factors like mixed learning styles require different study methods, high motivation for study encourages persistence, but without some help or guidance, and environmental factors like the lack of technology make up for restricted practice opportunities, while few hours of work make for protected study time.

Interpretation: The Desirable Difficulties is a framework that indicates that learning that asks a great deal of cognition will result in deeper learning. If you are going to use this framework, however, you need to be ready, or motivated, and you need to set up the environment, in terms of technology, study space, or time. Mixed learners might have to make an effort to switch between active coding (kinesthetic), looking at diagrams and code examples (visual), and verbalizing concepts or in study groups (auditory). Consistent planning, monitoring and evaluation of learning behaviours were observed with high performing students whereas low performing students demonstrated less regulation and used surface-level learning strategies, as Silva et al. [9] found.

Implication: There is not necessarily a direct link between personal factors and study habits. Students who are highly motivated, but have poor self-regulation, can still experience problems, while students who are not high motivated, but have high self-regulation may do well. Li et al. [8] found that the programming self-efficacy and self-regulated learning strategies have a significant impact on the outcomes of computational thinking. This implies that all students may benefit from explicit instruction in planning, monitoring and regulating their efforts toward learning, as an intervention to study habits.

F. Objective 6: Evidence-Based Recommendations

The sixth goal was to make recommendations for educators and institutions that are backed by evidence. The results from the study, in conjunction with the literature reviewed, carry a number of practical recommendations, both personal and environmental.

Interpretation: The findings of this study do not introduce speculations but were directly based on the profiles of the first year BS chemistry students of Surigao del Norte State University. Since most students are mixed learning style, they lack reliable technologies, and they are from low income families with limited parental education, interventions must be practical, affordable and supported by institutions. The need for systematic routines, motivation and active use of learning materials to promote learning outcomes has been stressed by Adeoye et al. [11] which supports the need to train study skills explicitly.

Implication: The greatest need is the technology and study environment deficiency—it is necessary for effective programming practice. Students will not be able to do their homework, watch tutorial videos, or use any coding platforms online without reliable computers and Internet [13, 14]. Good concentration is hard to maintain when there are no quiet areas for study [10]. Thus pedagogical innovations should follow or be made in parallel with institutional investments in infrastructure.

VII. RECOMMENDATIONS

The following recommendations are provided for teachers, schools/institutions, and future researchers based on the findings of this study.

A. Recommendations for Educators

Use diverse teaching strategies per class period. Since 54.5% of students are mixed learners, teachers need to use a mix of live coding demonstrations (visual/auditory), short individual programming tasks (kinesthetic), pair programming (social/active) and reflective individual tasks (reflective). Masegosa et al. [21] determined that the 3+1 session model (three hours of mixed teaching and one hour of group work) is the most preferred session model by the students. Don't use only lectures and don't do all the coding.

Create meaningful, meaningful programs that will maintain student motivation. When asked about their motivation, 63.3% of students stated their high motivation, but Farooq and Anwar [19] state that without reinforcement, students' motivation will diminish over the course of the semester. Assignments which have a purpose as part of a real problem in the students' community (such as data management for the local sari-sari shop, or simple mobile applications for school functions) are more likely to be of intrinsic interest than textbook problems. As a supplement, game-based learning platforms such as CodeCombat and Scratch can be used.

Explicitly teach study skills, not learned skills. There are many students who come to a university without effective self-regulated learning strategies. According to Theobald [7], the programs of self-regulated learning training have a significant effect on academic achievement. Teachers of programming should spend a minimum of 10-15 minutes in certain programming courses to explicitly teach study strategies, such as spaced practice, self-testing, debugging logs, and time management. Silva et al. [9] proved that the planning, monitoring and evaluating skills that the students need to be good programmers can be taught.

B. Recommendations for Institutions

Increase access to technology in an equitable way through institutional resources. 63.3% of students do not have a reliable technology at home and 61.2% do not have a quiet study spot, which means that the university has to compensate for these shortcomings by offering adequate infrastructure. Specifically:
Increase computer lab time (evenings and weekends)
Implement a laptop loan program for low-income students, with emphasis on students at BSCS requiring to practice programming outside class time.
Provide industry standard programming software (VS Code, PyCharm, Java SDK, Python, etc.) on all lab computers.
Provide quiet areas in the Computer Science department for programming practice, distinct from regular library study areas.

Create an evidence-based first-year course in study skills & SRL. If many of the students in the class are first-generation college students (indicated by the parents' levels of education) and they have other environmental disadvantages, a one credit course in the first semester of the course could cover: spaced practice, self-testing, error analysis (debugging logs), time management for programming projects, and effective use of university resources (tutoring centers, office hours, computer labs). Li et al. [8] concluded that metacognitive self-regulation and effort regulation are important factors for learning outcomes. The growth mindset should also be discussed during this seminar to overcome the fixed mindset about programming.

Provide parent training sessions on autonomy supportive involvement during freshman orientation. Although parental education is relatively low, parenting style (authoritative parenting: high warmth and appropriate demands) is a better predictor of intrinsic motivation than parenting education is. [16] The one hour workshop for families might have included teaching how the student feels when having difficulty learning, provide choices instead of instructions, provide explanations for expectations, and avoid controlling approaches. Parents with low levels of formal education can put these strategies into practice.

Use available data to monitor students and keep track of them at an early stage if they are at risk. Llanos et al. [17] found that prediction models based on the number of attempts, delivery time and grades in programming labs could achieve 86% accuracy at week 3 of a course to predict at-risk students. The college should establish a rudimentary mechanism for first-year programming classes for students who are not "on track" and provide a tool to assist in proactively engaging in peer tutoring or check-ins with the instructor: students with low scores on the first two labs, students who miss assignments, and students who submit work late.

C. Recommendations for Future Researchers

Follow a cohort over time in the BSCS program. The present study is descriptive, cross-sectional, which describes students at a certain moment. A longitudinal study could look at the changes in study habits over the next three years, at predicting students' long-term success in retention and graduation as a function of early exposure to technology, and at the compensatory strategies (or lack thereof) that students acquire over time or that they lose interest in acquiring.

Explore the reasons why there is a high proportion of females. The proportion of female respondents (59.2%) is unusual considering the national and international trends. Qualitative interviews with female BSCS students might be able to uncover protective factors: Did targeted recruitment occur? Inclusive teaching practices? Role models? Family support? The lessons learned in this context could help in interventions at other institutions where there are ongoing gender disparities, as Master et al. [18] showed that gender-interest stereotypes were a source of disparities but could be counteracted.

Analyze how programming is related to specific environmental factors. The current study identified environmental factors, but did not statistically examine (e.g., correlation or regression) the effects of technology access and/or study environment on GWA. A subsequent quantitative study might allow these relationships to be quantified, whilst holding prior academic attainment constant, to identify the most important environmental factors when implementing intervention.

Assess interventions recommended. The recommendations made here should be implemented and thoroughly tested in future studies. For instance, using a quasi-experimental research design (pre-post design), the changes in the self-regulated learning strategies, motivation, and programming performance of the study groups, as well as the control groups, could be measured. Likewise, a randomized controlled trial of a laptop loan program could evaluate the effect on assignment completion rates, GWA and retention.

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