Characteristics of the Student-Driven Learning Environment in Computing Education

A case study on the interaction between educational design and study behavior

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ABSTRACT

Important learning happens outside organized lectures and labs, but much of the interaction between these educational design constructs and the study behavior of computing students is unknown. In this study, we follow a group of computing students through their first semester in order to explore these dependencies. Through weekly reports, students tracked their study behaviors in a CS1 course. An exploratory cluster analysis was performed, mapping the students' organization, independent study, planning and priorities, time engagement, and use of different study environments. By comparing these aspects of student behavior to design parameters at both the program and course levels we get a holistic understanding of the student-driven learning environment. The results of this analysis confirm that there are close relationships between the educational design and when, where, and how students study. Three characteristics were identified: the home alone tendency, the executive action factor and the organized activities component. These results were used to outline the room for action, which can support computing educators to identify the adjustable educational design parameters that will most significantly affect the students' study behaviors.

CCS CONCEPTS

• **Social and professional topics → Computing education**; **Computer science education**.

KEYWORDS

computing education, learning environments, study behavior, educational design

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1 INTRODUCTION

Students' individual study behaviors are closely intertwined with the educational design of courses and study programs. Educators can explicitly adjust certain aspects of this ecosystem of learning, but not others. For example, we can change educational design parameters such as the number of courses, learning activities, and assessment regime. On the other hand, students' tacit study behaviors are not as easily altered, especially when, where, and how students study. It is where study behavior meets educational design that we find the *student-driven learning environment*, further defined here as the study activities that students engage in on their own, and the relation of these activities to the organized teaching and learning activities. Recently there has been increased interest in gathering and analyzing behavior data in order to learn about how students study and learn [19], but few contributions have focused on the holistic student experience. Therefore this paper aims to examine what characterizes the student-driven learning environment for first year computing students, and specifically the interaction between educational design parameters (lectures, labs, assignments) and study behavior (when, where and how).

By understanding what drives students' study behavior, educators can implement more effective designs and innovations, and it is essential that the computing discipline be investigated in this manner. Computing education has its own specific challenges along with the general issues highlighted by the learning sciences [1, 21]. From previous research on computing students' study behavior, we know that the classroom experience is not always the central aspect of a student's study day [25]. Instead of lectures and teachers, students tend to rely more on online resources and their own independent work. The behaviors of higher-performing students are characterized by soliciting help, seeking out extra resources, taking extensive course notes [16], starting assignments early, working incrementally [10], attending lectures [5], keeping to an average workweek [30], and applying consistent behaviors throughout the semester [11]. In contrast, lower-performing students are more inclined to memorizing code, getting answers from others without understanding them, not working on assignments post-deadline [16], using the internet, working with others, and relying on tutorials and model solutions [5]. In general, many researchers agree that study behaviors and non-cognitive factors contribute strongly to students' performance and achievement [7, 24, 29].

When it comes to the learning environment, research has found that students benefit from being part of a learning community [4], and that a holistic focus on all aspects of the learning process and environment is valuable for students and educators [27]. There seems to be a strong connection between the way that students study and certain educational design parameters, such as mandatory assignments [13] and individual assignments [12]. For example, assessment practices have been found to drive individual learning even when peer learning is advocated to students [12]. Also, mandatory tutorials have been found to increase submissions and early starts on assignments [30]. The structure and teaching of a course defines the learning environment, and educators should consider the implicit message that these factors convey to students [28].

1.1 Computing Education Design

The current research examines students in the first semester of several similar programs at one specific university. We use the word 'program' to describe the organization of students into a specific field of study, otherwise commonly referred to as major or school. Regardless of how the first year of a computing program is designed, there are some common elements. There will be organized teaching activities, such as lectures and labs, where an educator is present. In addition, there will be some forms of organized learning activity, such as assignments, project work or deliverables, often related to a form of assessment. Students also have access to resources, such as books, websites, teaching assistants (TAs) or other tools, as well as physical areas in which to study and meet peers. The way that students act when preparing for or taking part in these activities constitutes the students' study behavior [29].

General higher education can be viewed at three levels: program, course, and student level. The program level includes courses with specific learning outcomes, learning activities, teaching staff, and assessment methods, as well as overall learning outcomes and goals for the students within the program. The course level includes the teaching and learning activities for a specific course, and the student level includes the student body and student life. The program and course level will have certain design parameters that constitute the educational design as a whole. These parameters pose questions about design aspects that educators must consider. For instance, how many courses there are in a semester (program level), the use of assignments and assessment in a course, and if the course open to all students or reserved for one study program (open or closed enrollment).

2 THE STUDENT-DRIVEN LEARNING ENVIRONMENT

Learning environments are essential to student learning, but they are tricky to define and measure [9, 26]. Educational psychologist John B. Biggs described learning environments in his seminal work on student learning processes in the 1980s. In his 3P model of learning in higher education – presage, process, and product – he describes how "students undertake, or avoid, learning for a variety of reasons; those reasons determine how they go about their learning, and how they go about their learning will determine the quality of the outcome" [3, p.5]. An important part of the presage is the teaching context. In addition to the learning environment, presage includes the curriculum, assessment, and teaching methods. Common for these factors is that the institution controls them, whereas the other aspect of presage, the student characteristics, exists prior to the learning and relates to the student. The final two parts of the model, process and product, are related to the students' approaches to learning and the learning outcome. The current study focuses on one of the presage factors, namely the learning environment. How a student learns is influenced not just by the teaching context but by the student's perceptions of the learning environment [17]. Thus, the quality if the learning can be altered by changing the educational design parameters and importantly the student perceptions of the learning environment [9, 22].

As the 3P model suggests, there will be learning environments present within each course, as well as the at the program level. It is in these interactions that we have the *student-driven learning environment* (SDLE), which is based on the individual students' perspective and describes how they navigate and interact with the educational design constructs across courses within a program. It is student-driven because it is the student who has to navigate between organized activities and independent study, prioritizing and balancing the course load, managing their time, and using physical study spaces. The authors' previous work on the relation between computing students' study behaviors and educational design further divides the SDLE into the following five dimensions [18]:

Table 1: The five dimensions of the SDLE

Dimension	Description
Organization	How students interact with organized learning activities and manage their independent study.
Independent study	What tactics the student employs outside of organized learning activities.
Planning and priorities	Management of the course load.
Time engagement	When the students study: what days and what times of the day.
The study environment	Where the students study.

3 METHODOLOGY

The current study is designed as a case study [6, 31] aimed at describing and explaining aspects of how first-year computing students study. The case can be viewed as the first semester of a computing program, where the phenomenon of *studying* is researched holistically [2] by following a group of students throughout their studies.

To characterize the student-driven learning environment, we need to know what the students do when studying computing, what educational design parameters they interact with, and how this progresses over time. The research involves two main data sources: weekly learning reports handed in by the students along with their assignments, and the educational design parameters in the investigated study programs. It is important to note that the first author was part of the teaching staff, thus gaining essential insight into the educational design; however, that author was not involved in the assessment of the students. Ethical approval was granted by the Norwegian Centre for Research Data (841439).

3.1 The Case

The research was carried out at a large university in Norway during the 2019/20 academic year. Students follow a set plan, taking four equally weighted courses each semester. The courses in the first year vary somewhat from program to program, but all the programs involved in this study included some mathematics courses as well as a course in scientific philosophy in the first semester. Common to all programs are an introductory programming course using Python (CS1).

The current study aimed to investigate the students' journey through their first semester. The students begin the semester in mid-August with a two-week social and academic introduction program. After that, the 'regular' semester lasts for ten weeks, followed by an exam period of four weeks. This study is based on the common introductory programming course, but the research perspective is on the whole semester, including the other courses taken. The course is taught with theoretical, programming, and exercise lectures, as well as weekly assignments. Two of the ten assignments are 'mock exams', where instead of having a whole week to work on it, students must complete the assignment within a two-hour session in an auditorium. The assignments were assessed by TAs on a pass/fail basis but did not count towards the final grade. In order to qualify for the final exam, which accounts for the whole grade, the students must have completed eight out of ten weekly assignments, including at least one mock exam.

The students participating in this study were all enrolled in a computing study program: computing engineering, informatics, technology management, engineering and ICT, communication technology, or teaching and computing. There was a total of 544 students, of whom 203 (37%) consented to take part in the research study. The gender distribution in the course is approximately 70/30 male to female, and in the participation group, 60/40. The students' age and ethnicity were homogeneous, with an average age of 20 and no international students.

3.2 Data Collection and Variables

Along with the weekly assignments, participants handed in a learning report in which they recorded when, where, and how they had worked on the assignments. From these weekly reports, students' study behaviors were modeled and tracked. Organization was measured by students indicating how much time they spent on the following activities: lectures, sessions with TAs, collaboration, working alone in proximity to peers, or working alone. Independent study was measured by students indicating to what extent (very often – never) they used the following tactics: doing the assignment, examples from lectures, reading the book, taking notes, working self-made examples, using the internet, videos, or memorizing. Planning and prioritizing was measured by having students compare how much time they spent on other courses, such as mathematics or scientific philosophy, to their effort in CS1 (a lot more – a lot less). Time engagement was measured by tracking what days (Monday – Sunday) they were working on the assignment, as well as an indication of what times (morning, afternoon, evening, or all day). The study environment was measured by students reporting to what extent (very often – never) they used the following areas to work on the assignment: the open computing labs, the general study areas, the library, the cafeteria, their home, or somewhere else off-campus. The wording of the questions in the learning reports was created by combining various study behavior surveys and questionnaires [14, 15] and revising them for the current educational context.

3.3 Threats to Validity and Limitations

This study is based on self-reported data, which poses a threat to the validity of the research. Students could have been dishonest in their reporting or unmotivated to answer, or they might have had trouble remembering exactly what they did that week. These are always concerns when basing research on surveys and questionnaires; however, efforts were made to ensure that students felt comfortable reporting 'bad' behaviors. They were informed on several occasions that the researcher was not involved in the grading of assignments or the exam and that the reports were confidential. Examining the data, it is clear that many students were not afraid to be honest; however, that does not mean everyone was. On the other hand, the large number of observations (2035 in total) might offset an occasionally flawed report. In addition, there are some limitations to the case study methodology, especially with only one institution being involved [2]. Future research is needed to further explore the results from this study in other educational context.

Table 2: Cluster analysis of the SDLE dimensions

Study behavior	**Clusters**		
	k	Description	Freq.
Organization	1	Lectures	313
	3	Alone and lectures	286
	2	Alone	265
Independent study	1	Assignment	324
	4	Assignment and lecture examples	190
	5	Assignment and internet	179
	2	Internet and book	90
	3	Assignment and book	81
Planning and priorities	2	Spent more time on mathematics	188
	3	Spent more time on CS1	111
	1	Spent more time on non-CS	60
Time engagement	6	Late, weekends	177
	5	Late, work week	165
	1	Afternoon	148
	3	Late, towards deadline	134
	4	Work week	120
	2	Early	105
Study environment	3	Home	469
	4	Study area	107
	1	Home and lab	196
	2	Lab	92

4 ANALYSIS AND RESULTS

The analysis of the learning reports consists of two parts: a descriptive analysis and a cluster analysis. In order to explore the SDLE, and specifically how study behaviors interact with the educational design parameters, we examine how the five dimensions described in Table 1 developed over the semester. This was done by graphing the various study behavior variables by week. Note that mock exams were in weeks 4 and 8, and that week 11 was the first week of the exam period and had no lectures or assignments.

In addition, we wanted to examine the interconnections between the various elements of the dimensions. A cluster analysis was performed in Stata on the different study behavior variables. K-median clustering with random initial group centers was run until a fitting model was found, exploring the number of clusters from 1-20 as described by Makles [20]. Frequency tables of the best fitting clustering were used to describe the clusters. The results of the clustering analysis are presented in Table 2, sorted by the size of the cluster for each dimension. These clusters depict tendencies in when, where, and how the students study, and will be described in detail in the following subsections, along with the results from the descriptive analysis.

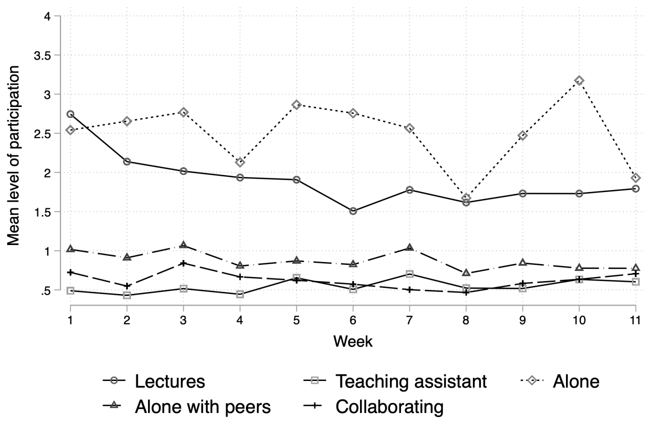


Figure 1: Organization over the first semester

4.1 Organization

For the organization dimension, we see from Figure 1 that time spent in lectures and studying alone are the most predominant characteristics. Lecture participation seems to go down after the first two weeks, while time working alone fluctuates according to the exams in weeks 4, 8 and 11. The remaining parameters, time with TAs, collaboration, and working with other students, were stably low.

The cluster analysis produced three clusters. The first cluster consists of students who spent most time in lectures but also working alone. The third cluster describes students who mostly worked alone, and the second was a combination of working alone and in lectures. All groups spent little time on collaboration, but some time with TAs and other students.

4.2 Independent Study

Three parameters stand out in the examination of independent study as shown in Figure 2: doing the assignments, using the internet, and working on examples from the lectures. Where the first two seem to dip in use in the weeks with exams, the use of lecture examples goes up.

Under independent study, five clusters were formed. Four clusters were related to doing the assignment (1) or doing the assignment along with either reading the book (3), doing lecture examples (4), or using the internet (5). The last cluster (2) was made up of students who preferred using the book and the internet. Common to all clusters was that self-made examples, videos, and memorizing were unpopular tactics.

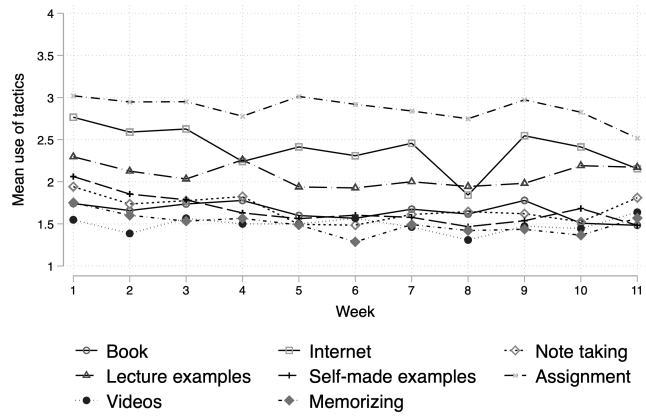


Figure 2: Independent study over the first semester

4.3 Planning and Priorities

The descriptive analysis of the planning and priorities dimension (Figure 3) indicates that mathematics courses have a higher priority than the introductory programming course, while the scientific philosophy course is consistently lower. The cluster analysis further explores this, finding three clusters. Cluster 1 describes students who, in general, spent more or the same time on calculus, discrete mathematics and philosophy, compared to CS1. Students who spent more time on mathematics (both calculus and discrete), but less on philosophy, were placed in the second cluster. The third cluster describes the students who spent the same or less time on all other courses, hence spent the most time on CS1.

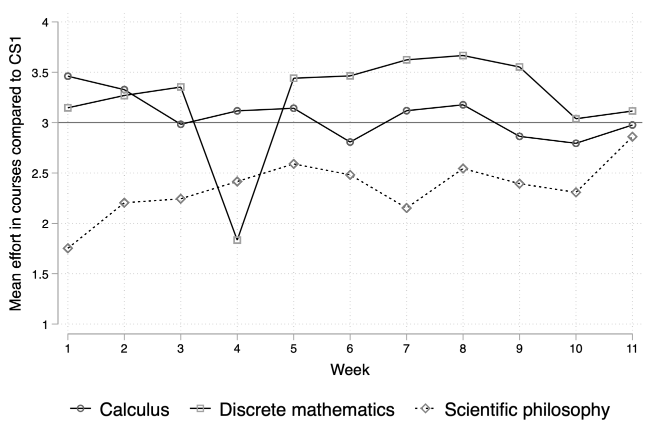
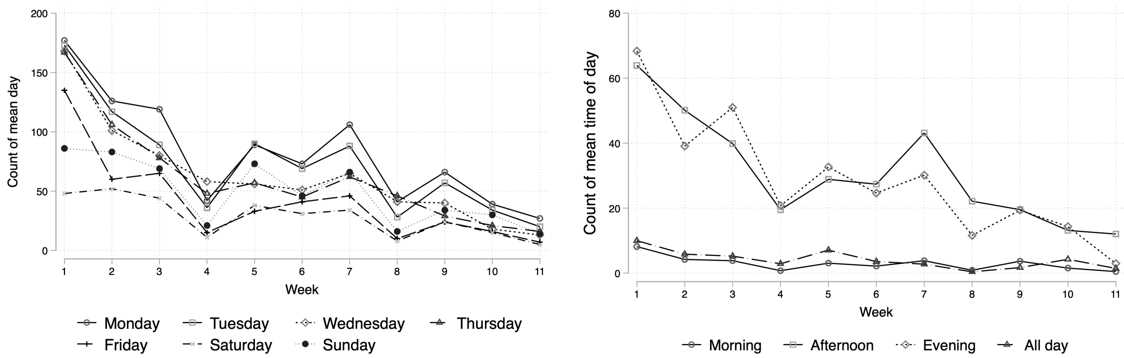


Figure 3: Priorities over the first semester, with CS1 presented as a uniform 3



(a) (b)

Figure 4: Time engagement over the first semester

4.4 Time engagement

To examine students' time engagement, we look at *what days* they studied as well as what *time segment of the day*. The descriptive results in Figure 4 seem to indicate that the total time use goes down towards the end of the semester; however, this is probably due to using frequency instead of mean. All days of the week seem to be used for studying; however, weekdays are slightly above weekends. Furthermore, students seem to be studying more in the afternoon and evening than during the morning.

The cluster analysis of students' time engagement and found that students can be divided into six clusters. The first two clusters describe students who prefer to study in the afternoon (1) or early in the day (2) but tend to use all days of the week. The third cluster describes students who tend to study late in the day and more on the days before the deadline. Cluster four is for students who study according to a regular workweek. The last two clusters describe students who prefer studying later in the day during either the workweek (5) or the weekend (6).

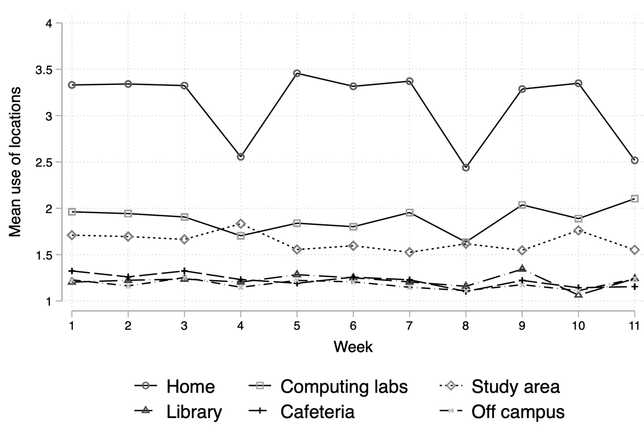


Figure 5: The study environment over the first semester

4.5 The Study Environment

When exploring where students are studying, two characteristics emerge from the descriptive results in Figure 5. The home environment seems to be the preferred place to study for these computing students. Next in line are areas on campus intended for studying: the computing labs or general study areas. Libraries, cafeterias, and off-campus sites were, to a large extent, not used. The cluster analysis found four clusters. Students tended to divide their time between home and the open computing labs (1), or mostly the lab (2), home (3), or the general study area (4). These three locations are popular across the clusters, while the library, cafeteria, and off-campus sites are equally unpopular for all groups.

5 DISCUSSION

Examining the results of the descriptive and cluster analysis collectively, we identify three main findings, which together constitute the characteristics of the SDLE for these computing students. The characteristics must be viewed in relation to the design parameters of the courses and programs in this case.

5.1 The Home Alone Tendency

Looking at organization and the study environment together, there seems to be a strong tendency for computing students to study at home and to study alone. Although we have not checked whether these are the same students, this is still a striking tendency. Previous research on the effect of the study environment is not clear on whether the home is an advantageous place to study; however, some studies have shown that studying in peace and quiet is preferred by most students [23]. On the other hand, we know that learning computing is a collaborative process and that students benefit from learning communities [4]. Another concern regarding the home alone tendency is that access to help and support is valuable [16], and for these computing students, help is found mainly on campus.

Possible explanations for the home alone tendency can be found in the educational design parameters. During this semester, all assignments in CS1 were individual, and very few of the other courses employed any form of collaborative activity. Furthermore, the computing labs and the general study areas on campus are known to be crowded. It can often be difficult to find a place to study, especially as these are new students.

5.2 The Executive Action Factor

When students manage their time and handle their course load, they are constantly making executive decisions, although in many cases these might be more reactive than proactive. This group of computing students seems to have a preference to avoid working in the morning and on weekends; no other clear trends can be found. Previous work has found that high performing students are likely to follow a regular workweek and not to work at nights and on weekends [30].

Considering the balance and priorities, the results suggest that mathematics was largely prioritized above CS1. It is important to note that all courses had equal credit, and that participation in lectures and labs was not mandatory and did not count towards the grade in any way. It is reasonable to assume that the students' executive actions would be affected if one or more courses implemented mandatory participation, perhaps guiding all students towards a more structured study week [8].

5.3 The Organized Activities Component

The results further indicate that the learning activities, in this case assignments, were even more of a driving factor for student behavior than lectures. The analysis of how students study independently shows a clear assignment-based approach, which is not unexpected [25]. The assignments are the backbone of this course, and when learning programming, it has been established many times that students must do programming in order to master it. This perception that the assignments drive student behavior is in line with previous research [13]. Across all behavior dimensions, it is evident that students study differently during weeks where there are mock exams (4 and 8) or after the assignments are finished (11). This indicates that the way students are assessed largely impacts when, where, and how they study. During mock exams, they spend less time at home and more in the study areas, use the internet less, and focus more on lecture examples, note-taking, and reading the book. Similarly, during the exam preparation week they spend more time on campus, memorizing and note-taking more, and make more use of videos.

5.4 Implications

The current study represents one case at one institution with one set of design parameters, but it does offer some generalizable features and areas for future research. First, we must consider the room for action within the SDLE, that is, what we can and cannot change. One dimension for consideration is time: what can be changed quickly and with short term effects, and what is more of a long-term change? All parameters at the program level are long-term because there are many other stakeholders involved, which brings us to the next dimension: control. The question of who controls the various parameters and can make decisions and implement change varies from institution to institution. Most parameters are managed by the responsible professor and are, therefore, department controlled at the course level. On the other hand, campus layout, scheduling, and semester design are controlled by the institution. Finally there is the dimension of resources: time and finances. The best example of this is in the course dimension, where making changes to the learning activities and assessment will often imply more educators or increased time commitments from the existing educators.

The role of the current study is to help computing educators find the educational design parameters that can be changed and that have the greatest impact on the students' study behavior. Considering the dimensions of the room for action and the findings from this study, we have some examples of changes to the design parameters that should be considered and researched further:

- Increased use of group activities is a learning activity that will decrease the time students spend alone, and perhaps encourage more time on campus. This is a short-term, low-resource change that can be implemented by the educator, with a potentially high impact.
- Scheduling of lectures and lab in a more coherent and holistic manner across courses can help students structure their studies better. This is a long-term, low-resource change at the program level, with potentially high impact.
- Changing the assignment structure or including the assignments in the formal assessment will change the students' time use and activity planning. This is a short-term, medium-resource change at the program level with potentially high impact.

6 CONCLUSIONS AND FUTURE WORK

This paper has investigated the relationship between study behavior and educational design parameters encompassed in the student-driven learning environment. By examining weekly reports from the student participants, we have found close relationships between the educational design and when, where, and how students study. Results from a cluster analysis indicate that students are studying all days of the week, and mostly later in the day. This might indicate that students are working evenly, but it might also be a symptom of a heavy timetable and fragmented study behavior. Furthermore, a majority of the students tend to prefer working from home, or to a lesser extent using the computing labs or study areas. Exactly what drives these choices, beyond the assignment structure, is not clear from this data and should be a question for future research.

For the programs studied in this research the educational design scope and course structure are strictly controlled at the department level or above. Nevertheless, the dimensions of the SDLE applied in this study can serve as a tool for other researchers and educators, and can help to identify the local room for action. Computing education is experiencing a surge of students while at the same time being urged to increase throughput without additional resources. Understanding when, where, and how first-year computing students are learning can inform educational design decisions and provide insight for innovations.

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REFERENCES

[1] Vicki L. Almstrum, Orit Hazzan, Mark Guzdial, and Marian Petre. 2005. Challenges to Computer Science Education Research. In *Proceedings of the 36th SIGCSE Technical Symposium on Computer Science Education (SIGCSE '05)*. ACM, New York, NY, USA, 191–192. https://doi.org/10.1145/1047344.1047415

[2] Michael Bassey. 1999. *Case Study Research In Educational Settings.* Open University Press, Buckingham.

[3] John B. Biggs. 1989. Approaches to the Enhancement of Tertiary Teaching. *Higher Education Research & Development* 8, 1 (Jan. 1989), 7–25. https://doi.org/10.1080/0729436890080102

[4] Candido Cabo and Ashwin Satyanarayana. 2018. Promoting students' social interactions results in an improvement in performance, class attendance and retention in first year computing courses. In *2018 IEEE FRONTIERS IN EDUCATION CONFERENCE (FIE) (Frontiers in education conference)*. 1–8. https://doi.org/10.1109/FIE.2018.8658548

[5] Donald Chinn, Judy Sheard, Angela Carbone, and Mikko-Jussi Laakso. 2010. Study Habits of CS1 Students: What Do They Do Outside the Classroom?. In *Proceedings of the Twelfth Australasian Conference on Computing Education - Volume 103 (ACE '10)*. Australian Computer Society, Inc., Darlinghurst, Australia, Australia, 53–62.

[6] Louis Cohen, Lawrence Manion, and Keith Morrison. 2002. *Research Methods in Education* (5 ed.). Routledge, London, UK.

[7] Marcus Credé and Nathan R. Kuncel. 2008. Study Habits, Skills, and Attitudes: The Third Pillar Supporting Collegiate Academic Performance. *Perspectives on Psychological Science* 3, 6 (Nov. 2008), 425–453. https://doi.org/10.1111/j.1745-6924.2008.00089.x

[8] Marcus Credé, Sylvia G. Roch, and Urszula M. Kieszczynka. 2010. Class Attendance in College: A Meta-Analytic Review of the Relationship of Class Attendance With Grades and Student Characteristics. *Review of Educational Research* 80, 2 (June 2010), 272–295. https://doi.org/10.3102/0034654310362998

[9] Noel J. Entwistle. 1991. Approaches to Learning and Perceptions of the Learning Environment: Introduction to the Special Issue. *Higher Education* 22, 3 (1991), 201–4.

[10] James B. Fenwick, Jr., Cindy Norris, Frank E. Barry, Josh Rountree, Cole J. Spicer, and Scott D. Cheek. 2009. Another Look at the Behaviors of Novice Programmers. In *Proceedings of the 40th ACM Technical Symposium on Computer Science Education (SIGCSE '09)*. ACM, New York, NY, USA, 296–300. https://doi.org/10.1145/1508865.1508973

[11] Seth Copen Goldstein, Hongyi Zhang, Majd Sakr, Haokang An, and Cameron Dashti. 2019. Understanding How Work Habits Influence Student Performance. In *Proceedings of the 2019 ACM Conference on Innovation and Technology in Computer Science Education (ITiCSE '19)*. ACM, New York, NY, USA, 154–160. https://doi.org/10.1145/3304221.3319757

[12] Sheryl Guloy, Farimah Salimi, Diana Cukierman, and Donna McGee Thompson. 2017. Insights on supporting learning during computing science and engineering students' transition to university: a design-oriented, mixed methods exploration of instructor and student perspectives. *Higher Education* 73, 3 (March 2017), 479–497. https://doi.org/10.1007/s10734-016-0097-6

[13] Vegard Hellem and Madeleine Lorås. 2020. The Effect of Mandatory Assignments on Students Learning Outcome and Performance in Introductory Programming Courses. In *2020 IEEE Global Engineering Education Conference (EDUCON)*. 704–712. https://doi.org/10.1109/EDUCON45650.2020.9125198

[14] Wayne H. Holtzman, William F. Brown, and W.G. Farquhar. 1954. The Survey of Study Habits and Attitudes: a New Instrument for the Prediction of Academic Success. *Educational and Psychological Measurement* 14, 4 (Dec. 1954), 726–732. https://doi.org/10.1177/001316445401400420

[15] Caesar R. Jackson. 2018. Validating and Adapting the Motivated Strategies for Learning Questionnaire (MSLQ) for STEM Courses at an HBCU. *AERA Open* 4, 4 (Oct. 2018), 2332858418809346. https://doi.org/10.1177/2332858418809346

[16] Soohyun Nam Liao, Sander Valstar, Kevin Thai, Christine Alvarado, Daniel Zingaro, William G. Griswold, and Leo Porter. 2019. Behaviors of higher and lower performing students in CS1. In *Proceedings of the 2019 ACM conference on innovation and technology in computer science education (ITiCSE '19)*. Association for Computing Machinery, New York, NY, USA, 196–202. https://doi.org/10.1145/3304221.3319740

[17] Alf Lizzio, Keithia Wilson, and Roland Simons. 2002. University Students' Perceptions of the Learning Environment and Academic Outcomes: Implications for theory and practice. *Studies in Higher Education* 27, 1 (Feb. 2002), 27–52. https://doi.org/10.1080/03075070120099359

[18] M. Lorås and T. Aalberg. 2020. First Year Computing Study Behavior: Effects of Educational Design. In *2020 IEEE Frontiers in Education Conference (FIE)*. 1–9. https://doi.org/10.1109/FIE44824.2020.9274285

[19] Andrew Luxton-Reilly, Simon, Ibrahim Albluwi, Brett A. Becker, Michail Giannakos, Amruth N. Kumar, Linda Ott, James Paterson, Michael James Scott, Judy Sheard, and Claudia Szabo. 2018. A Review of Introductory Programming Research 2003–2017. In *Proceedings of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education (ITiCSE 2018)*. ACM, New York, NY, USA, 342–343. https://doi.org/10.1145/3197091.3205841

[20] Anna Makles. 2012. Stata Tip 110: How to Get the Optimal K-Means Cluster Solution. *The Stata Journal* 12, 2 (June 2012), 347–351. https://doi.org/10.1177/1536867X1201200213

[21] Lauren E. Margulieux, Brian Dorn, and Kristin A. Searle. 2019. Learning Sciences for Computing Education. In *The Cambridge Handbook of Computing Education Research*, Sally A. Fincher and Anthony V.Editors Robins (Eds.). Cambridge University Press, 208–230. https://doi.org/10.1017/9781108654555.009

[22] J. H. F. Meyer and M. W. Muller. 1990. Evaluating the quality of student learning. I—An unfolding analysis of the association between perceptions of learning context and approaches to studying at an individual level. *Studies in Higher Education* 15, 2 (Jan. 1990), 131–154. https://doi.org/10.1080/03075079012331377471

[23] E. Ashby Plant, K. Anders Ericsson, Len Hill, and Kia Asberg. 2005. Why study time does not predict grade point average across college students: Implications of deliberate practice for academic performance. *Contemporary Educational Psychology* 30, 1 (Jan. 2005), 96–116. https://doi.org/10.1016/j.cedpsych.2004.06.001

[24] Matthew Scheidt, Ryan Senkpeil, John Chen, Allison Godwin, and Edward Berger. 2019. SAT Does Not Spell Success: How Non-Cognitive Factors Can Explain Variance in the GPA of Undergraduate Engineering and Computer Science Students, Vol. 2018-October. https://doi.org/10.1109/FIE.2018.8658989

[25] Judy Sheard, Angela Carbone, Donald Chinn, and Mikko-Jussi Laakso. 2013. Study Habits of CS 1 Students: What Do They Say They Do?. In *2013 Learning and Teaching in Computing and Engineering*. 122–129. https://doi.org/10.1109/LaTiCE.2013.46

[26] Katrien Struyven, Filip Dochy, Steven Janssens, and Sarah Gielen. 2006. On the dynamics of students' approaches to learning: The effects of the teaching/learning environment. *Learning and Instruction* 16, 4 (Aug. 2006), 279–294. https://doi.org/10.1016/j.learninstruc.2006.07.001

[27] Neena Thota. 2011. Repertory grid: Investigating personal constructs of novice programmers. In *Proceedings of the 11th koli calling international conference on computing education research (Koli calling '11)*. Association for Computing Machinery, New York, NY, USA, 23–32. https://doi.org/10.1145/2094131.2094137

[28] Denise Tolhurst. 2004. The influence of web-supported independent activities and small group work on students' epistemological beliefs. In *Proceedings of the sixth australasian conference on computing education - volume 30 (ACE '04)*. Australian Computer Society, Inc., AUS, 311–316.

[29] Tara Tressel, Susanne P. Lajoie, and Melissa C. Duffy. 2019. A guide for study terminology: Reviewing a fragmented domain. *Canadian Psychology/Psychologie canadienne* 60, 2 (2019), 115. https://doi.org/10.1037/cap0000138

[30] Salla Willman, Rolf Lindén, Erkki Kaila, Teemu Rajala, Mikko-Jussi Laakso, and Tapio Salakoski. 2015. On study habits on an introductory course on programming. *Computer Science Education* 25, 3 (July 2015), 276–291. https://doi.org/10.1080/08993408.2015.1073829

[31] Robert K. Yin. 2009. *Case Study Research: Design and Methods* (4 ed.). Applied social research methods, Vol. 5. SAGE Publications, California.