First Year Computing Study Behavior: Effects of Educational Design

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Abstract*— This full research paper presents a study exploring first year computing students' study behavior and the effects of educational design. Some research has indicated that the relationship between students' study behavior and their academic performance is as strong as the relationship to more common predictors such as past performance and test scores. However, knowledge about students' study behavior, how behavior develops and is influenced by program and course design, and consequently, the effect various design parameters have on learning is limited. This paper presents a model describing computing students' study behavior and how these are affected by the educational design. Through a mixed-method approach, a population of computing students was followed through their first year. Results from in-depth interviews with students throughout their first year found that the educational structure and organization of a study program conditions the students' study behavior. In order to further investigate these tendencies, two surveys (N=215) were conducted within the whole first-year student population at the beginning and end of the year. A significant difference found was in the use of surface and deep strategies at the beginning and end for the first year, indicating that students shift from deep to surface learning during the year. Even if students initially seek a deep content-driven approach to learning, the structure of the education and other organizational factors may be the cause of a more surface and task-focused approach towards the end of the first year. Students' study behavior is constrained by the educational design, which furthermore may lead to different learning outcomes than desired. Researching and developing learning goals, course content, lectures and assignments is one way to improve computing education; however, this research suggests that taking a comprehensive and integrated approach to educational design might also lead to improvements.

Keywords—Study behavior, Study habits, Computing education, Engineering education, Educational design

I. Introduction

Designing education that is suitable for all students and fulfills every learning goal is a challenging task. Within computing education (CE), the enrollment numbers into higher education are increasing; however, there is a demand for even more computing students to graduate [1], [2]. More students accepted into a program also means a more diverse group of learners, and in recent years most higher education institutions have emphasized throughput as the main metric when measuring institutional performance. Together, this creates a demanding reality where educators are required to continuously develop the quality of education with increasing student numbers, as well as improve the throughput of graduates. Unfortunately, educators and higher education institutions have a limited room for action, as teaching and organizational resources are not increasing at the same pace.

This paper describes a study looking into computing students' study behavior. Students' study skills, habits and strategies are highly important for academic performance and throughput, which is significantly influenced by program and course design. This paper contributes a new perspective that can help solve major challenges in computing and engineering higher education.

When seeking to understand the academic success and failure of students in higher education, there are many stakeholders and various factors to consider. Previous research has indicated that there is a strong relationship between academic performance and study behavior [3], [4]. In their meta-analysis from 2008, Credé and Kuncel found that study skills and habits exhibit a strong relationship to performance, even as strong as more common predictors such as prior academic performance and admission test results [3]. In other words, the way students study is central to their learning.

Therefore, the work presented in this paper aims to increase the knowledge about computing study behavior and the interaction with educational design. Additionally, the first year of higher education is said to be formative for the student and crucial for retention [5]. Hence, the research inquiry is as follows:

- What characterizes computing students' study behavior during the first year?
- How is this behavior impacted by the educational design of the study program?

II. Study Behavior

How students' study and learn can be summarized as *study behavior* and has, over the years, been the focus of many research studies, although the terms and definitions described are often inconsistent. A review by Tressel, Lajoie and Duffy from 2019 addresses this fragmented domain and proposes a hierarchal study terminology based on research from the last decades [4]. They define study behavior as "any actions students make when preparing for, or taking part in, study-based activities." This definition is broad on purpose and is the base level of all study terms. Furthermore, the study process, skills, habits, strategies and tactics are terms placed hierarchically under behavior as described in Tab. I.

There are many ways to further view these terms, and for the purpose of this paper, it is useful to differentiate between internal and explicit study behavior. The internal study behaviors are the processes and strategies on the cognitive level and inherently influences the explicit behavior. Skills, habits and tactics are the specific intentions and actions the student takes when studying. This relation is illustrated in Fig. 1.

TABLE I DEFINITION OF STUDY TERMINOLOGY.
Based on Tressel et al. (p. 121)

Term	Definition
Behavior	Any actions students make when preparing for, or taking part in, study-based activities.
Process	The cognitive level of engagement with study tasks.
Skills	The students' level of ability to maintain and succeed in study tasks.
Habits	The consistency of study behavior, including the study environment. When, where and how much students study.
Strategies	The intentional behavior where a learner chooses how to study from a variety of study tactics while considering the demands of the task.
Tactics	The individual learning tools students use. E.g., Notetaking, highlighting, self-testing, etc.

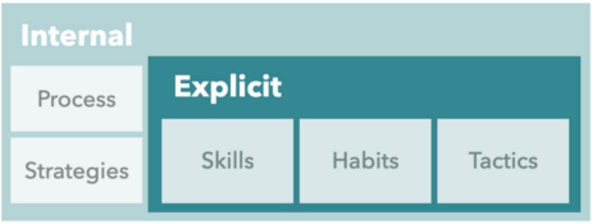

Fig. 1: Internal and explicit study behavior

When it comes to the internal aspect of study behavior the students approaches to learning (SAL) framework is an important theory developed by Marton and Säljö in 1976 and further developed by Biggs [6], [7]. According to SAL theory, students learning and studying process can be categorized into deep and surface approaches. The deep approach is an internally driven motivation and commitment to learning, where the intention to extract meaning produces active learning. Whereas the surface approach is externally driven, which concerns just coping with various tasks and is considered a much more restricted learning process. Most recently Biggs described this difference as the surface approach referring to "activities of an inappropriately low cognitive level, which yields fragmented outcomes that do not convey the meaning of the encounter" and the deep approach as "activities that are appropriate to handling the task so that an appropriate outcome is achieved" [8, p. 42]. Considering the explicit study behavior skills, habits and tactics, Credé and Kuncels work have been influential [3]. Their meta-analysis of study skill constructs is based on the study skills, habits and attitudes framework (SSHA). This framework also includes study attitudes, which refers to the students' mindset and motivation towards higher education and studying. Tressel et al. argue that attitudes are important to assess but should be placed under the broader umbrella of study skills. The remaining constructs, skills and habits, are related to the when, where and how students' study, and is similarly defined in Tressel et al.'s review.

III. EDUCATIONAL DESIGN

In general, the design of a study program and the first year varies across universities; however, there are some commonalities. Regardless of organization, higher education can be viewed as three levels: program, course and student level. The program is designed with overall learning outcomes and goals for the students. A program consists of courses, which have more specific learning outcomes, learning activities, teaching staff and assessment methods. Lastly, there is the student level, which involves the students' study behavior and interaction with the other levels.

Furthermore, each level will have certain design parameters that constitute the educational design as a whole. As described further in Tab II, these parameters pose questions about certain design aspects educators must consider. For instance, how many courses there are in a semester, 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). These parameters will affect the individual students and their behaviors, as well as the classes of students as a group.

TABLE II HIGHER EDUCATIONAL DESIGN AND PARAMETERS

Level	Description	Parameters
Program	Admission Program design Social, academic and physical learning environment	Prerequisites, enrollment structure Number of semesters Weight of a course (number of credits) Enrollment and admission regime Parallel vs. modular courses Campus layout
Course	Course structure Learning activities Educators Assessment	Open or closed enrollment Pedagogical design Number of lectures Number of assignments and/or projects Individual or group-based activities Type of assessment and exams Number of students
Student	Study behavior Demographics and background	The internal and explicit study behavior of the student, and the interaction with program and course design.

IV. COMPUTING EDUCATION

When investigating the students' study behavior, it is important to discuss the context, which, in this case, is computing study programs in Norway. For the purpose of this paper, we consistently use the term computing, with the understanding that the term includes what in Norway is often categorized as ICT: computer science, informatics, information and computer technology.

On the program level, not much directly relevant research has been done in terms of educational design. However, one can argue that the research on pedagogy is interesting in this regard. In Ben-Ari's influential discussion of constructivism in computing education (CE), the author argues that the theory is highly applicable to CE, yet not satisfactory implemented [9]. Furthermore, research investigating constructive alignment is also relevant to the program level. Biggs defines constructive alignment as formulating learning goals and synchronizing this with constructivist-based learning and teaching activities and assessment tasks likely to lead to said learning goals [10]. On the course level, there are multiple empirical studies on everything from content and curriculum to use of technology and assessment, both in computing and STEM in general.

A. *Study Behavior in Computing Education*

The 2018 ITiCSE working group on introductory programming reported that research on student behaviors had seen an increase in focus on gathering and analyzing behavior

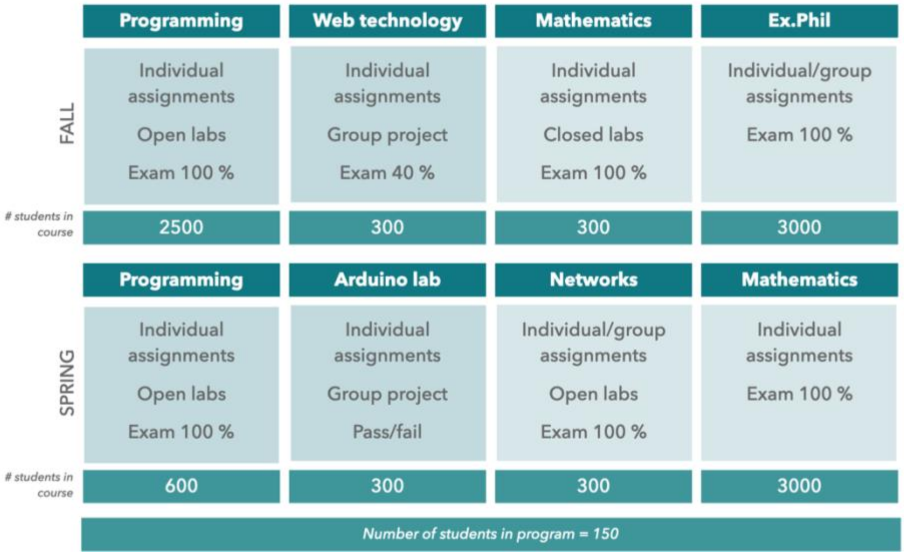

Fig. 2: Typical design of a first year computing education program in Norway.

data in order to learn about how students study and learn [11]. Furthermore, they report that predicting success, performance, identifying difficulties, encouraging change, designing interventions, and tools for these purposes to be the main value of such research to educators.

Tendencies very similar to the findings of Tressel and colleagues were observed in previous research on study behavior in CE [4]. There seem to be various perspectives and definitions being used, as well as many different research methods. Common for many studies is the data-driven approach [12],[13], meaning that behaviors and habits are defined around the data available, as compared to theoretical frameworks. As far as methodology, surveys and interviews are widely used. More recent studies have used log-file and submission data as well [12]–[14].

Many studies are focused on introductory-level courses [13], [15]–[17]. One common underlying motivation for these studies is to learn more about how computing students study and predicting performance. Previous programming experience and lecture attendance have been found to have a positive effect on exam performance while using the internet, non-lecturer instructors, working with others, and the use of tutorials and model solutions did not [15]. Furthermore, they found that classroom experience is no longer the central aspect of a student's learning behavior. Instead of lectures and teachers, students relied more on online resources and working independently [16]. More recent studies have compared behaviors of higher and lower performing students in an introductory computing course [13]. Among other factors, the results show that high performing students were better at soliciting help, seek out extra resources and take extensive course notes. In contrast, lower-performing students were more inclined to memorizing code, getting answers from others without understanding them and not continuing work on assignments post-deadline.

V. Methodology

This paper presents a mixed methods study aiming to explore computing students' study behavior and the impact of the educational design. Therefore, the study was set up with an exploratory sequential design [18]. Firstly, a qualitative interview study was done with a sample of students throughout their first year. Based on the findings from these interviews, a second quantitative survey study was done. After describing the context and participants of this design, the rest of the paper will be structured sequentially. First, the analysis and results from the interviews will be described and discussed, then the survey.

A. *Context and Participants*

Computing education (CE) at the university level in Norway is generally structured into two semesters. The fall semester lasts from August to December and the spring semester from January to mid-June. The semesters are structured into courses, usually three or four will run in parallel. Assessment is often based on a final exam, although more focus has been put on alternative and diverse assessment plans in recent years. As an example of a computing program in Norway, the structure and content of a typical computing program have been summarized in Fig 2.

The participants in this study all attended a program with a similar design. For the survey phase students from 11 different programs participated, and for the interview phase students from one of these programs were selected. Common for all these study programs is that all first year courses are mandatory and between 50-75% if the courses are in programming or computing of some sort. Generally, these courses are structured with weekly or biweekly assignments the students must complete, alone or in groups. The tasks do as a rule not count towards the final grade and are not considered forms of assessments. Instead, they are considered required work, which gives the students the qualification to take the final exam, which decides the grade. Furthermore, the number of students enrolled yearly into computing programs included in this study varies from 30-150, and the percentage of female students between 10-30% [19]. The students in these computing programs, often take courses with other computing and engineering students, increasing the total number of students in each course. For example, Fig. 2 depicts a program with 150 first year students, who in this instance take an introductory programming course with 2350 students from other programs.

Out of this student group, six students were recruited to participate in the interviews, all from the bachelor's in computing program exemplified in Fig. 2. These students agreed to meet the researcher through their whole program, or possibly follow up if they chose to switch programs or drop out. The students were recruited at a voluntary weekly study day. All attendees were invited, ten people signed up, and six were chosen on the basis of diversity and background. Out of the six interview participants, two were female, and one had a minority background. Additionally, two of the students had completed some other higher education study program before starting this one, two had done a gap year, and the remaining two started university straight from upper secondary school. Lastly, only two of the students had previous formal training in computing. When presenting the results, these details will not be linked to the various statements in order to preserve the participants' anonymity.

VI. Phase 1: Interviews

Interviews are considered a good method for gaining insight into people's attitudes, perceptions and experiences [20], [21]. As this study focused on exploring computing student's study behavior, it was essential to understand their experiences. Therefore, doing semi-structured, in-depth interviews were chosen as an approach. Three rounds of interviews were performed, one late in the first semester, one in the middle of the second, and a retrospective interview early in their third semester. This means each student was interviewed three times during their three semesters, making the total number of interviews conducted. Each interview lasted between 30-50 minutes, making the total interview time over 10 hours.

The participants consented to record the interviews, which were subsequently transcribed before analysis. The interviews were exploratory in nature but focused on certain topics. In the first interview, the focus was on previous knowledge, motivation and experiences with being a student so far. The second interview emphasized on study behavior and learning experiences, while the third was overall self-evaluation of the first year as a whole. All rounds of interviews were guided by an interview protocol; however, the researcher heavily followed the student's line of conversation. Additionally, the researcher used certain probes to make the participants comfortable and assured [21]. The researcher performing the interview had completed the study program in question and used this knowledge and experience to encourage the students to elaborate by sharing certain experiences.

A. *Interview Analysis and Results*

The interview transcriptions were analyzed with a grounded theory approach. The aim of grounded theory analysis is to reduce the data and extract theoretical ideas, explanations and understanding [21], [22]. In this case, the data was analyzed by coding in three phases, as described by Corbin and Strauss: open, axial and selective coding [22]. In open coding, all phrases and statements found interesting were initially coded, creating 36 very broad codes (e.g., study structure, study habits, learning environment, motivation, positive/negative learning experiences). In the next step, each code was inspected more closely and a set of 105 more nuanced codes emerged (e.g., factors of prioritizing work, strategies for getting unstuck, the social group as supportive, collaboration is motivating). In axial coding, these initial codes were printed and cut out, and then laid out on a big table using a constant comparative method [21]. By comparing all codes to each other, some overall categories and hierarchy emerged from the data. In the selective coding process, the research questions guided the process of identifying central themes or trends emerging from the data.

As far as the internal study behavior goes, the interview results showed how students prioritize, how they structure their study week and what underlies their study process. An example of how students talked about prioritizing is this student who described time and challenge:

> *Mostly I work on what deadline is coming up first. Either that or I work on the course, I understand the least.*

Furthermore, the students talked about how they studied, that is how they structured their independent work. It was common for all the students that the various aspects of the course design impacted their behavior. This quote describes how the student structured his/her work based on assignments:

> *It's much easier to study when I have to, rather than when I should. I have liked that about this semester. Having an assignment to do each week. It kind of forces you to study and having a study routine.*

Following these students through their first year, the learning activities provided in each course seemed to be a driving factor for the students' study behavior. As exemplified in these quotes, deadlines and assignments were fundamental to the structuring of students' study day. They also mentioned lectures and available support and resources in relation to finishing assignments. This student reflects on the benefit of morning lectures in this way:

> *Because then you get up in the morning and get to campus. And when you are there you're there, studying and working, when you're on campus anyway. So that is really just an advantage.*

When it comes to getting help, the students use a broad range of available learning recourses. Some students use the teaching assistans to get help on assignments, while others use their friends. An example of how the social and academic environment is important, is this quote:

> *I almost learn more thom my friends here. Because they just explain things easier.*

Additionally, the interview results indicated some interesting trends as to how their study behavior develops over the first year. The students all described decreased motivation and, in their own words, "worse" study habits in the second semester. They talk about taking shortcuts, impacts of social life and the increased workload as negative aspects of the second semester. They also express a motivation to change their habits and improve their study process. An example of this is a student's response when asked how the second semester as compared to the first:

> *There was something about being new. You were just so on all the time. But this semester, it's not the same.*

The final result of the coding process was the development of a model shown in Fig. 3, illustrating how the students' described their study behavior (priorities, strategies, habits, skills and motivation) and how they are constrained by the educational design, as well as how this might affect the learning outcomes.

B. *Model of Student Behavior and Educational Design*

The interview results indicated that the educational design of the first year on a program level had an impact on students' study behavior. The various aspects of a course, as well as the alignment between courses, seemed to outweigh the internal motivation or drive to learn when it came to structuring study behavior. Based on these findings, we propose a model of computing study behavior and educational design. This model illustrated in Fig. 3 describes how these elements interact and their possible impact on learning. On the one side there is the input the students bring with them, that is their behavior, here described further by prioritization, strategies, habits, skills and motivation. With this input, the educational structure and organization provide the conditions for the students' study behavior, i.e., acting as limits and constraints. The students will adapt their study behavior to fit these boundaries. Lastly, there is the outcome here described as what knowledge and skills learned.

The model describes the student perspective on and experience with the educational design. Considering the educational design parameters presented earlier, it seems like there are certain aspects students do not identify. Based on the interview results, students focus on the course design parameters, and in particular assignments and assessment. When it comes to the program level aspects, except for the social and academic learning environment, none of the parameters were mentioned by the students. Lastly, on the student level students describe their behavior and the interaction with course design parameters more often than the program parameters.

On another level, there is the educator's role. The educators have made design choices based on the parameters described in Tab. II, which will interact with the students' input, as will the planned and implemented teaching and learning activities. These will lead to the learning of skills and knowledge, which may or may not fulfill the actual planned and desired outcome. The interesting and important role of this model is how the students' input, interact with the educational design and whether or not this leads to the desired outcome. The planned and implemented teaching and learning activities may fit their learning goals; however, this model suggests that the students' priorities, strategies, habits, skills and attitudes may lead to different outcomes. In other words, if the educators' plan is based on students taking a deep approach in one course, but the students are limited by the educational design and chose a surface approach, do they learn the skills and knowledge they were supposed to?

Most educators would agree that deep learning, where the student understands the content and really learn the skills of the course, is the desired outcome [23]–[25]. However, these results have indicated that in this case, the structure and organization, together with the students' priorities and strategies, may not facilitate this. Additionally, these results indicate that the students' development over the first year is not desirable, which further suggests that there is something about the structure and organization of the education that influences them. The way the students use different words to describe their study process at the beginning and end of the year is striking. During the first interview, the students would consistently focus on the content of the courses and how interesting the various programming features were. In the second interview, on the other hand, the language used by the students was much more task-oriented. The students would consistently talk about assignments and exams instead of programming and computing constructs. This shift from a content-driven study behavior to a task-oriented one lead us

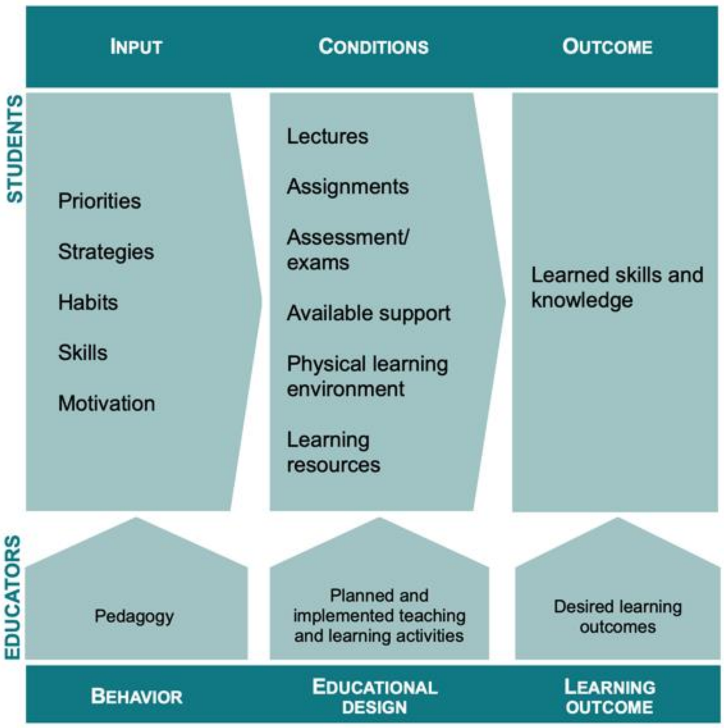

Fig. 3. Model of student behavior and educational design

to consider the possibility that students came into university with a deep approach to learning but were shifted to a surface approach in interaction with the educational organization and structure. Previous research on the SAL framework and the development over the first year has indicated that the assessment structure influences the students into a surface approach [26]. The interview results, on the other hand, suggests that incoming students were also affected by other educational factors. And that the development over the whole first year fosters this shift. To further investigate this, Phase 2 of this research was initiated.

VII. Phase 2: Survey

In addition to categorizing the characteristics of computing students' study behavior, the interviews indicated a change in study approach throughout the first year from deep to surface. The way the students changed the language when describing their study behavior from content-focused to assessment focused, indicated a switch from deep to surface strategy. This founded the motivation for the survey study. Furthermore, the survey was intended to test the hypothesis: *Computing students have a different study strategy at the end of the first year than they had in the beginning.*

In order to test this, we used the Biggs revised two-factor Study Process Questionnaire (SPQ), which can indicate whether a student has a deep or a surface approach to learning [27]. This questionnaire is commonly used to investigate students' internal study behavior, that is, the process and strategies [3], [4]. The SPQ was translated into Norwegian and sent out to the students at the beginning and end of the first year during the academic year 2018/19. All first-year students in computing programs at NTNU were invited to participate in an online questionnaire about expectations to university studies. The first iteration of this survey was sent out within two weeks of the first semester, and the second at the end of the year. Because of privacy issues, the survey did not include identifiers, so it was not possible to track the students on an individual level. However, the survey provides an overview of the student population since it was the same group of students who participated in both surveys.

A. Survey Analysis and Results

The first iteration of the survey was sent out to first year students in all NTNU computing study programs, a total of 695 students, and 215 students responded with consent. That leaves a respondent rate of 30% for the first iteration. For the second iteration, the study process questionnaire was part of a larger survey sent out to all students (in all years). Out of all the students, the number of students who responded that they were in the first year was only 96, although almost half of the respondents unfortunately did not answer this question. Therefore, the respondent rate for first year students in iteration two was 13%, while the overall respondent rate for the survey in total was 20%. For both iterations, the number of female respondents was around 30%.

The deep and surface scores were calculated following the revised two-factor method described in Biggs et al. [27]. When analyzing these results, the first step was to see if there seemed to be a difference from the beginning to the end of the semester. A Kernel density plot for respectively fall 2018 and spring 2019 was drawn using the statistical software Stata MP [28]. As seen in Fig. 4 there seems to be a visible shift. The surface approach scores seem to be the same for the fall and spring semester, whereas the deep approach scores have shifted towards the lower end of the scale.

In order to further test if the observed shift is an actual difference in study strategy, thus testing the hypothesis, the *two sample t-test* was used to evaluate the mean difference between the fall and spring scores [29]. Accordingly, the original hypothesis needed further specification:

Computing students have a different study strategy at the end of the first year than they had in the beginning.

- H1: There is a significant difference between the surface scores for the fall and spring semesters.
- H2: There is a significant difference between the deep scores for the fall and spring semesters.

B. Difference in Surface Approach

The students at the beginning of the year had a slightly higher surface score (*M= 23.5, SD=4.49*) than the end of the year (*M=22.5, SD=5.12*). The mean difference was, however, not significant within a 95% confidence interval, *t(243)=1.60, p=0.111, d=1.00*. When testing the assumptions for t-tests, it became clear that there were outliers in the data. The normality and homogeneity of variance, on the other hand, were within acceptable ranges [29]. After removing the outliers, the mean difference was significant, *t(241)=2.06, p=0.041, d=1.25.*

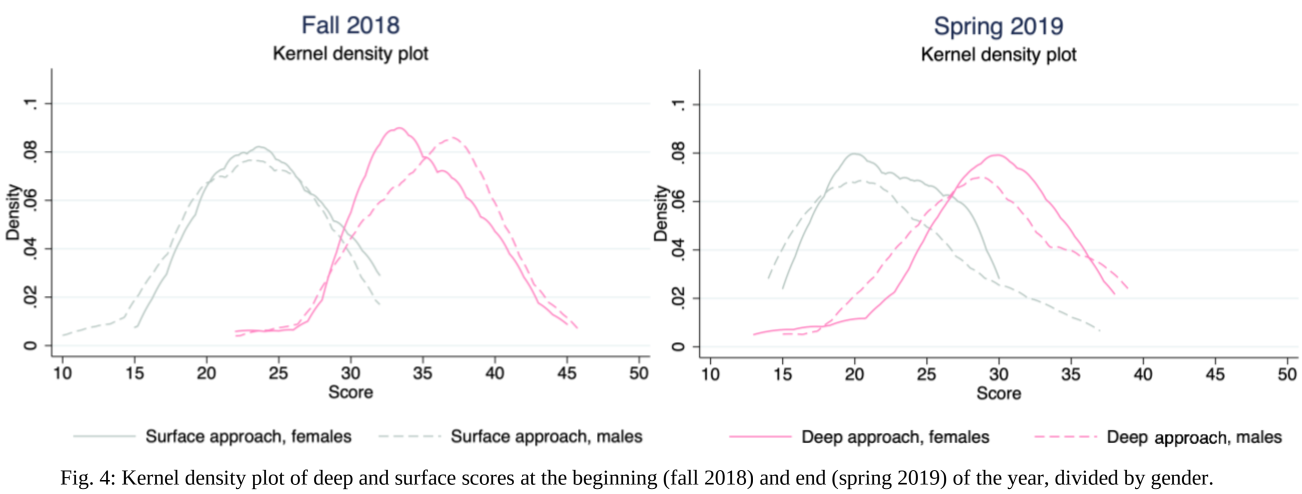

Fig. 4: Kernel density plot of deep and surface scores at the beginning (fall 2018) and end (spring 2019) of the year, divided by gender.

C. Difference in Deep Approach

The students at the beginning of the year had a considerably higher deep score (*M= 35.2, SD=4.53*) than the end of the year (*M=29.0, SD=5.47*). The mean difference was significant, *t(242)=9.54, p>0.001, d=6.16*. When testing the assumptions for t-tests, it became clear that there also were outliers in this data. The normality and homogeneity of variance, on the other hand, were again within acceptable ranges. After removing the outliers, the adjusted mean difference was still significant, *t(241)=9.16, p>0.001, d=5.68.*

D. From Deep to Surface

These results indicate that there is indeed a shift in the students' study approach at the beginning and end of the first year. However, analysis of both surface and deep scores indicate a lower score at the end of the year, which is difficult to interpret. As far as the hypothesis' goes, both H1 and H2 are confirmed. Firstly, there is a slight but significant difference in surface scores from the beginning to the end of the first year. Lastly, the change in deep scores was also significant, but considerably higher, by a factor of five.

VIII. DISCUSSION

The research goal of this study was to characterize computing students' study behavior in the first year and investigate the impact of educational design. The model of study behavior and educational design presented in this paper characterizes computing students' study behavior in the context of educational organization and structure. Furthermore, the model highlights the aspects of educational design, which typically are developed and changed by different stakeholders. For example, the fact that there are certain aspects of the design, we as course teachers can and cannot change. Students and their input into this model are aspects we cannot change; however, the design parameters which frame the students' learning are changeable. And these are aspects that were found to highly affect and influence the students' study behavior and learning outcome.

Following the framework presented in Section II, the model includes most of the mentioned dimensions [4], [7]. Considering the internal study behavior, the model addresses prioritization and strategies, which are important constructs in the students' study process and strategy. The survey results confirm that students change their internal study behavior throughout the first year. Students start the first year with a deep approach where their study behavior is content-driven and end the year with a surface and task-focused behavior. Although, this change might be due to general study fatigue during the first year, there also seems to be reason to believe that the learning activites and program design are influential.

The explicit behaviors, habits and skills, thereunder motivation, are also evident. When asked about how they plan and implement their study week, they all based their independent study time on some organizational elements, such as lectures, assignments, collaboration, or teaching assistant availability, which is in line with previous research [15], [16]. It is evident that the students are influenced and constrained by the educational design of the courses. On the program level, it is interesting to see how the students manage their computing-courses relative to their other courses. They all discuss prioritizing they study activities based on computing relevance.

As far as educational design is concerned, the results indicate that the students' study behavior is influenced by the structure and organization of the education. In other words, educational design can be viewed as an independent variable when investigating the students' study process and behavior. On the other hand, factors such as previous experience, employability concerns, expectations and social learning environments might be influential factors as well.

A. Implications and Future Work

This study has found grounds to pursue the inclusion of educational design parameters in future research and practice. As previous research has shown, there are limitations in how much insight can be gained about how students' study when only considering specific activities. In order to fully understand these processes, there is a need to broaden the theoretical discussion to include study program design elements. The current study argues that design parameters should be viewed in a holistic manner, both in theory and practice. Some concrete examples extracted from the data are listed below:

- Courses should coordinate the use of assignments and projects so that the students keep a content-driven focus throughout the program. Four weekly assignments in parallel seem to foster a task-focused approach, leading the students to surface learning.
- The use of individual and group-based activities should be balanced throughout the program, both for social and academic reasons.
- The use of formal formative assessment should be increased in a manner that keeps students in a content-driven mindset.
- The access to help and support on a program level should be increased. This should include both course-specific topics and general study support in order to scaffold first year students' study behavior over time.
- The number of students should be considered in relation to the use of open or closed courses and labs. Students report that the sense of belonging is affected by the closeness to their peers, and educators should therefore support classes as a whole. Especially in larger institutions.

Based on the results presented in the current study, we have implemented some adjustments based on these parameters in our own study programs. The Informatics Study Day initiative has shown promising results [30].

B. Generalizability and Limitations

This study examined a specific institution with one student population. Other universities with different student groups will most certainly have different inputs, conditions and, consequently, different outcomes. Nevertheless, the model presented here can be used by all educators to design better and more aligned programs and courses. Lastly, the research methodology used in this study has some limitations. The study program examined, and the students who participated were from one institution and a relatively small non-random sample. The model will need to be further validated and expanded with research on other populations. Furthermore, the constraints of qualitative research are apparent in the sense of bias, however rigorous and systematic the data gathering, and analysis was performed. The survey and interview data provided source triangulation, and during analysis, the researcher used well established and validated techniques such as thematic coding [21].

IX. Conclusion

In this paper, the theoretical perspectives on computing students' study behavior in the first year of higher education have been explored. Through analyzing in-depth student interviews, a clear link was confirmed between study behavior and educational design. Computing students' priorities, strategies, habits, skills and motivation are constrained by the educational design, which may lead to different learning outcomes than desired. Furthermore, this study found that there is a significant shift between the beginning and end of the first year when it comes to internal study behavior. The students initially have a deep, content-driven approach to studying; however, they develop a surface and task-focused approach towards the end.

Researching and developing learning goals, course content, lectures and assignments is one way to improve computing education; however, this research suggests that taking a comprehensive and integrated approach to educational design might also lead to improvements. It is important to consider what kind of learners computing students become, as well as making sure they have the required content knowledge. The model presented in this paper outlines clearly where the room for action is for educators, and the design parameters provide a concrete starting point for educational change. Developing an educational design of the first year, which aligns the curriculum, courses and teaching in such a way that students become expert learners through effective study behavior may prove useful to later courses and employers.

Acknowledgements

The work presented in this paper was conducted at the Excited Centre for Excellence in IT Education. Excited receives public funding through DIKU, Norwegian Agency for International Cooperation and Quality Enhancement in Higher Education. We would like to especially acknowledge professor emeritus Tor Stålhane for valuable feedback.

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