Why Students Drop Computing Science: Using Models of Motivation to Understand Student Attrition and Retention

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Computing science (CS) classrooms, whether at school or university level, provide a useful context for examining disparities in participation: particular groups – especially females – remain under-represented. Among the factors that influence retention in CS are those associated with motivation. In this study, we investigate why students drop CS by drawing on two motivation models: the expectancy–value model developed by Eccles, Wigfield, and colleagues, and Marsh's internal/external frame of reference model. Through a survey of 32 undergraduate students who dropped CS, we identify and discuss the factors that affected their decision to do so. We highlight the interplay between components of both models, revealing how utility value, cost, and students' internal/external comparisons influenced their decision to drop the subject. We find that comparisons with peers, social concerns, perceived subject difficulty, and issues of attainment associated with self-concept all play a more significant role in female students' decision to drop CS.

CCS Concepts: • **Social and professional topics → Software engineering education**.

Additional Key Words and Phrases: higher education, participation, gender balance, motivation, self-concept

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1 INTRODUCTION

Concerns about participation in CS fields continue to rise [26] despite initiatives to improve diversity. In the UK, figures demonstrate that women represent only 19.9% of students who study CS at university level [17]. In the US, just 21% of CS undergraduate degrees were awarded to women in 2019, with the same figure having remained at or below 19% between 2004 and 2018[10]. Previous work on why students drop CS has highlighted the multi-dimensional nature of this issue [20]. Kinnunen and Malmi, for example, found that students who dropped out of one CS1 course cited a lack of time and motivation as the primary reasons for doing so [21]. However, these reasons were underpinned by a range of other factors, including the perceived difficulty of the subject, challenges around time management, and a preference for another subject. A decade on from Kinnunen and Malmi's study, Petersen et al. found a similarly complex set of interrelated reasons for students dropping their CS1 course, including a lack of time, poor study skills, and prioritisation of other subjects [29].

Studies have also examined why women, in particular, leave the subject behind. Dee et al., for example, identify what they term the "macho geeks problem", referring to the geeky "know it all" male culture that dominates CS classrooms [8]. Meanwhile, Taylor-Smith et al. note that the exclusion of women from CS is a self-perpetuating problem, reinforced through gender stereotypes of computing, and women's experience of male-dominated work and study

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environments [34]. These cultural stereotypes are also said to produce a 'gate keeping' effect, with academics in fields such as CS "driving girls away from certain fields and constraining their learning opportunities and career aspirations" [6]. Meanwhile, DuBow et al. identified factors that help ensure that female students continue to study CS, including community support, exposure to computing, and encouragement from others[11]. By corollary, the absence of such support influences female students' decision not to persist with CS.

Motivation factors play a significant role in student retention in CS programs. One of the most well-known models developed to account for the role of motivation in different academic domains is the Eccles et al. model of expectancy and achievement [12]. The model suggests that the two most important predictors of students' academic choices are task-specific beliefs and the value they attach to the corresponding domain. Meanwhile, Marsh's internal/external frame of reference model posits that academic self-concept – a major predictor of academic choice – is influenced by students' comparisons of their achievement across different domains and with the perceived performance of their classmates [23]. To our knowledge, no prior research has investigated the reasons that students decide to drop CS courses by using the Eccles et al. model together with Marsh's internal/external frame of reference as a lens of interpretation. This study, then, uses these models to help address the following two research questions:

- What factors influence undergraduate students' academic choice in relation to CS?
- To what extent can Eccles et al.'s model of expectancy and achievement and Marsh's internal/external frame of reference be used to explain these factors?

To address the above questions, we surveyed 32 students from the University of Glasgow. Undergraduate students at the host institution typically take three subjects in their first and second years, before choosing the area in which they wish to specialise, and dropping their other subjects. For many of the students who drop CS, it is simply the case that they never intended to complete a degree in the subject. For students who plan to undertake a degree in maths or physics, for example, choosing CS as their second or third subject makes sense, given the complementary nature of the discipline. However, there are also those students who choose CS in their first year with the intention of completing a degree in the subject and subsequently drop it. Here, we examine these students' motivations for dropping CS. Given the ongoing issue of gender imbalance in CS and the problem of the so-called 'leaky pipeline' through which female students and professionals are lost[3, 8], we also examine how these motivations differ across genders.

2 THEORETICAL FRAMEWORK

Achievement motivation theorists have endeavoured to explain students' persistence, performance, and choice of task. Within these theories, a variety of constructs are employed to explain the relationships between motivation and academic choice and performance. In this study, we focus on two such theories: the expectancy-value model of achievement-related choices and the internal/external frame of reference model.

2.1 Expectancy value model of achievement-related choices

In 1983, Eccles et al.[12] suggested the expectancy-value model of achievement. The basic premise underlying this model is that an individual's choice, persistence and performance in a domain, and their motivation to perform a task, can be explained by two factors: a. their beliefs about succeeding in the activity, namely, expectancy for success, and b. the degree to which they value the activity, namely, the subjective value individuals attach to a task [38].

Expectancy for success refers to beliefs about how well one will perform on an upcoming task [37]. In comparison with ability beliefs, which focus on present ability (i.e., beliefs about current competence), expectancies focus on the

future. *Subjective task value* is the second major component in the Eccles et al. model. It refers to the qualities of a task that will appeal to an individual, and consists of four components:

- The utility value of the task, or the values related to one's immediate rewards or long-term goals. For instance, taking a course to fulfil a degree requirement.
- Intrinsic value, or the enjoyment of executing the task.
- Attainment value, or the importance of doing well on a task and the value a task has because participating in it is consistent with one's self-image, needs and personal values. For instance, if having an impact on society is of importance to someone's self-image, then she places a higher value on occupations that achieve this.
- The cost of engaging in the task, or the perceived cost of participating in an activity. This is influenced by factors such as anxiety and emotions, loss of time from other activities, and the effort to accomplish the task. Activities that cause an individual to dedicate time to another activity she values, increase the subjective cost of engagement [13].

The model predicts that students' choices regarding their occupation or course choices are influenced by the value they assign to the tasks available to them. In fact, the model assumes that task value is at least equally important to expectations for success. For example, task value is important to course choice, while efficacy beliefs are important to engagement and perseverance [16, 22, 27].

2.2 Generalized Internal/External Frame of Reference Model

Self-concept is described as a compound view of oneself [32] and in educational psychology is regarded as individual beliefs about one's strengths and weaknesses. Although self-concept can be seen as a multidimensional structure, in educational research attention has been given to academic self-concept; that is because academic self-concept is positively related to academic achievement and is a predictor of academic choices [35]. To develop domain-specific self-concepts of ability, students incorporate information regarding their achievements in various subjects. According to the Internal/External frame of reference model [23], self-concepts are shaped by both external and internal frames.

The *external frame* is the comparison students make between self-perceptions of their ability in one subject and their perceived ability of other students in the same frame. Students use these comparisons as references for their self-concept in a subject. This sometimes is also called 'social reference', basically highlighting the importance of social comparisons to students' self-concept. Students, for instance, who perceive that their maths achievement is higher than their classmates, will have a higher math self-concept. Thus, students use their perceived performance and that of their classmates to create frames of reference for self-evaluations [32]. Through the *internal frame*, students assess their self-perceived domain abilities against their self-perceived abilities in another domain and use these comparisons as a means to develop their domain self-concept. This is also called a dimensional frame of reference. Thus, a high achiever in one subject may develop an average self-concept in that discipline if her performance is worse than that in another subject [25]. A central assumption of the dimensional comparisons is that their effects are moderated by the perceived similarity of the compared subjects [24]. That means that for subjects that are not similar (far comparisons), like maths and English, comparisons result in contrast effects. Whereas, for subjects that are more closely related (near comparisons), like maths and physics, comparisons lead to smaller contrast effects or assimilation effects. Thus, the relations between achievement and self-concept of related domains are expected to be positive whereas far comparisons invoke negative correlations [1].

3 METHODS

For the purposes of this study, student data for currently enrolled third and fourth year undergraduate students were queried to identify those who studied CS in their first or second year, and were no longer enrolled in any CS courses[1]. These queries yielded 104 results. Given sensitivities around the use of student data, a legitimate interest assessment was undertaken to establish the grounds for additional processing of the students' records. The basis for using these data to identify students was clear, given that gender diversity is an ongoing issue within our CS cohorts, and that advocating for diversity and inclusion is written into the university's strategy. Furthermore, tackling gender imbalance on our courses is part of the School's Athena Swan Action Plan[2].

Current students who had dropped CS as a subject received an email invitation, asking them to complete a survey in return for a £10 Amazon voucher. The researchers were based within a subject area that participants had, by definition, left behind. Therefore, the researchers had no influence over the participants' subsequent academic attainment. Ethical approval for conducting the study was obtained from the College Ethics Committee. The survey received 33 responses (a 32% response rate). In line with best practice [33], participants were also given the option to self-describe or not disclose their gender, although none chose to do so here. Of the responses received, 11 (33%) identified as a woman, 21 identified as a man (64%), and one (3%) identified as non-binary. 23 respondents (70%) reported that they were aged between 16 and 18 when starting their degree, six (18%) were between 19 and 21, and four (12%) were aged 22 or more. In addition to these demographic questions, respondents were asked to explain why they didn't continue to study CS, and how their gender affected their experience of studying CS, if at all. Finally, respondents were asked explicitly if their gendered experience had influenced their decision to drop CS, and how.

The responses to each of these three open questions were analysed by both authors using a deductive thematic approach, with themes drawn from the Eccles et al. model (see above). A further round of open coding was carried out by the authors, noting codes that did not correspond to those identified *a priori*. Each author analysed the data independently, then met to discuss and agree upon the codes, and the overarching themes.

4 RESULTS

After the coding process, eight main themes emerged from the data. In the following sub-sections, we describe the themes – beginning with those derived from the Eccles et al. model – and highlight representative responses from the students' data.

4.1 Utility

The *Utility* theme refers to the degree of usefulness of computing science to students' future goals. In total, 42% the students talked about their decisions not to continue with computing as this did not align with their future academic goals. For instance the following was mentioned by a male student:

> *"I am doing a physics degree which requires physics and mathematics. I chose to do computer science in first year because I enjoyed it at school and thought it would be useful to do a little at university, but never intended to continue after that. I did really enjoy the computer science courses in first year but still wanted to continue with my physics degree."*

[1]The work described here was carried out in a Scottish university, where students typically choose three subjects in the first year, before deciding on their 'major' (to use the familiar US-centric term) at the end of the second year. While this arrangement is not typical of all higher education contexts, it does provide an opportunity to follow up with students who drop a particular subject.

[2]Athena Swan is a framework used in the UK and beyond to effect gender equality in higher education. See https://www.advance-he.ac.uk/equality-charters/athena-swan-charter.

Both female and male students ascribed similar importance to the utility value of computing for their future academic goals. In total, 36% of female and 43% of male students referred to factors falling under this theme. The following comes from a female student:

> *"It was not my main degree, I took it to use up credits in level 1. I would have loved to continue to Level 2 however the courses offered were too high in credits for the amount i had left over from my main subjects."*

4.2 Cost

The *Cost* theme reflects how the respondents' decision to continue with CS limited access to other activities or required a lot of time and emotional effort. In total, 28% of the students reported factors related to the cost of engaging with CS. Our analysis revealed two important sub-themes: a. time, referring to the time and effort of engaging with CS and b. affect, referring to the emotional impact of engaging with CS. Regarding the first sub-theme, *Time*, one of the male students reported:

> *"I really enjoyed computing science however it was very time consuming. I was doing joint honours (Business being my other subject) and I had to pick between economics and computing science as I couldn't do them both in combination with each other. Because comp sci took up a lot more time and I work whilst as university it lead to me selecting economics as I enjoyed them both equally, but just time wise economics worked better for me."*

Regarding the second sub-theme, *Affect*, the main emotions reported by students were stress, frustration, and feeling overwhelmed by the intensity of the course. For instance, a male student mentioned that *"It was my elective, and was quite intense. I felt I was stressing about it more than my main subjects, so chose to drop it"*, while a female student reported that *"The frustration I experienced wasn't worth it although I enjoyed the satisfaction of understanding and having the code run"*. When it comes to gender differences, female and male students placed similar importance on the cost of engaging with programming, with 27.7% of females and 28.5% of males referring to this theme.

4.3 Intrinsic value

The *intrinsic value* theme groups together factors referring to students' interests in studying CS for reasons intrinsic to computing. In total, 23% of students mention factors for not continuing to study CS that fall under this category. For example: *"...in the end my choice to switch course had more to do with not loving the subject itself"*. Another female participant stated:

> *"I realised that I didn't enjoy it and didn't actually want to continue doing computing science for the rest of my life. I especially didn't like all of the (what felt like) unnecessary maths."*

27% of female responses were categorised in this theme, while 19% of male respondents referred to intrinsic value as a factor in their decision to study CS further.

4.4 Expectancy of success

This theme refers to students' beliefs about how well they would perform in CS. 13% of students reported that one reason for not continuing with CS was their belief they would not perform well in the course. Overall, slightly more female students (18%) referred to expectancy of success than men (10%); for example, one female student stated:

> *"I was already struggling with computing science at level 1 so I didn't want to risk getting worse grades in level 2. I really enjoyed the subject at level 1 but it got too complicated at times for me."*

4.5 Attainment

This theme includes students referring to their self-image, personal values and beliefs – it relates to students' identity. In total, 13% of the students mentioned factors that align with this theme. For instance, one female student reported *"I didn't see myself doing programming as a future career"* and another, *"It also didn't come naturally to me, although it was fun at times."*. Most of the references to this theme were reported by female students (27%) and only 5% by male students.

4.6 Comparisons

The *Comparisons* theme – derived from Marsh's framework – refers to the students' decision not to continue with CS as a result of the comparisons made between CS and another subject. In total, 25% of the students compared CS with another subject in order to justify their academic choices. Two main sub-themes fall under this theme: a. the external frame, which refers to the comparisons students made regarding their perceived ability and their peers' ability, and b. the internal frame, which refers to the comparisons students made between CS and another subject. Regarding the *External frame*, a female student reported:

> *"I also was scared to ask questions sometimes as the people in my labs were very good at programming while I was more of a beginner" while another one said, "There wasn't many girls in my class and it felt too difficult to start speaking to group of guys who know a lot about coding. Did feel little out of place".*

In the framework described by Marsh, the *Internal frame* focuses on achievement comparisons between subjects [23]. However, our students included other comparison measures such as the time and effort required by two subjects. For example:

> *"I really enjoyed computing science however it was very time consuming. I was doing joint honours (Business being my other subject) and I had to pick between economics and computing science as I couldn't do them both in combination with each other. Because comp sci took up a lot more time and I work whilst as university it lead to me selecting economics as I enjoyed them both equally, but just time wise economics worked better for me."*

Regarding gender differences, slightly more female students (36%) made subject comparisons than male students (19%). Interestingly, the external frame, which refers to comparisons between a student's perceived ability and that of their peers, was only reported by female students; male students did not refer to comparisons with their peers' abilities as a factor in dropping CS.

4.7 Social

The emergent *social* theme refers to factors related to having a supportive environment and a social network that students can draw upon to ask for help or to make them feel that they belong to CS. In total, 23% of the students referred to the lack of this supportive environment as the main factor for dropping CS. For example: *"I was always one of only a few non boys in all of my classes so I didn't really feel like I belonged."*. The single response from a non-binary student also cited social factors, stating that *"I was fairly anxious due to my being trans so it kept me from connecting with other students"*. Another of our female students reported:

> *"I didn't feel too comfortable in group projects and struggled to get my ideas across. The lack of girls also made it more difficult to make friends which meant that there was no social aspect that would make me continue studying CS."*

In comparison with other themes, social factors are significantly more important for female respondents than male respondents. In total, 55% of female students reported social factors affecting their decision to drop CS in comparison to only 5% of male respondents.

4.8 Difficulty

The second emergent theme, *difficulty*, reflects the perceived difficulty of CS as a subject. This theme is distinct from *Expectancy of success* above, because the fact that the subject is perceived as difficult does not always mean that it will influence someone's expectation of success. Furthermore, expectation of success may be influenced by factors other than the difficulty of the subject. In total, 42% of the students referred to deciding not to continue with CS due to the challenges they faced during the course. For instance, a female student mentioned that *"The course is well designed, but there are some parts I find quite challenging and hard to keep up"*. Interestingly, the percentage of female students (63.6%) who reported that the course's difficulty was one of the main factors for not continuing with CS was more than double the percentage of males (28.5%).

5 DISCUSSION

The question of how educators can increase students' interest and motivation in CS endures; although substantial research has been conducted in this area and practices that can be applied to retain diversity in CS classes have been suggested, disparities in participation persist. In this study, we were mostly interested in investigating this issue by employing the expectancy-value model of achievement developed by Eccles et al. [12] and Marsh's model of internal/external frame of reference [23].

Our findings suggest that both models may explain students' decisions to drop CS and, in fact, they complement each other, as they both refer to factors that can extend both models. Eccles et al.'s model hypothesises that achievement-related choices (e.g., educational and occupational choices) are dependent on psychological factors which are influenced by one's experiences, cultural and social norms, and background: a. one's expectations of success b. and the subjective task value. Indeed, our findings do fit this model but, surprisingly, they further suggest that expectancy of success – which has often been studied in relation to CS (e.g., [9, 30, 36]) – may not be such a strong a predictor; only 13% of our participants cited this factor as the reason for not continuing in CS. In fact, for most participants, the substantive task value was the most important factor. Particularly, the *utility value* was the component of the model that was mentioned the most. This strongly suggests that highlighting the value of CS to students' future goals is critical for attainment. Research in CS education has highlighted the importance of linking computing to students' future goals and lives. For instance, educators are encouraged to make an interdisciplinary connection to CS by emphasising how it is used in other domains, and to incorporate students' own interests (e.g., [2, 31]).

We find that the two models are complementary. On the one hand, the Eccles et al. model does not explicitly consider Marsh's factors – these are comparisons with peers' performance within the same subject and comparisons of one's performance in different subjects. Meanwhile, Marsh's model includes only these two factors while students, in our data, compared also their state of affect (e.g., stress, anxiety) in different subjects, which is captured by the Eccles et al. model under the Cost theme.

An important finding of this research relates to the perceived cost of participating in CS (e.g.,[4, 14, 28]). As it was evident, the *cost value* was the second most frequently cited factor affecting students' academic decisions. The participants here mentioned mostly the time and effort that the course required as well as affective factors like feeling stressed or overwhelmed. Indeed, Flake et al. [15] argue for cost as the forgotten component of the expectancy-value model as it is usually ignored in empirical studies. Nonetheless, our study highlights cost as an important factor that calls for further investigation.

While utility value has been mostly linked with extrinsic motivation (e.g., [7]), activities that have intrinsic value are significantly more motivating. Although we expected intrinsic value to play a more important role in students' decisions to drop out, it is worth mentioning that some of the students did enjoy the course but other factors impacted their decision not to continue in CS e.g., the utility value. That explains why some researchers, e.g., [18], argue that initially, interest must be developed by external events and once students engage with a task, the intrinsic value of the activity needs to be realised [18].

It is evident that Marsh's internal/external frame of reference model complements the observations above, especially those related to cost. The model indicates that to develop domain-specific self-concepts of ability, students incorporate information regarding their achievements in various subjects, and those of their peers. Indeed, our findings corroborate this point but also extend it to include comparisons between subjects in relation to cost. The students in our sample referred to their perceived abilities and those of their peers (external frame) as well as comparisons with another subject (internal frame) which could be about their performance or the cost discussed above. It seems then that when it comes to students making decisions about future academic choices, the interplay between utility, cost, and the comparisons with other subjects all play a significant role that needs to be investigated further.

Finally, other factors like the course difficulty and social concerns were emphasised by our participants, and significantly more so by female students. Female respondents referred to feelings of not belonging and how difficult it was to relate to male students who seem more knowledgeable. Several studies have identified belonging as an important factor in CS participation, highlighting the need to create an inclusive community based on collaborative learning and other interactions between students (e.g., [5, 19]).

Thus, in answer to our research questions, we have identified eight factors that influence students' academic choice in relation to CS. Furthermore, we have demonstrated that Eccles et al.'s model of expectancy and achievement and Marsh's internal/external frame of reference may be used to explain many of these factors, except for the Social and Difficulty factors that were identified in our analysis. We also noted gender differences in relation to Marsh's internal/external frame, with female students, for example, making comparisons between their perceived ability and that of their peers, while male students did not.

6 CONCLUSION AND FURTHER WORK

The aim of this study was to investigate why students drop CS courses by applying motivation theories that explain students' academic choices. We found that two motivation theories, the expectancy-value model of achievement developed by Eccles et al. [12] and Marsh's internal/external frame model [23], explain students' decisions to drop CS and, in fact, complement each other. In terms of the Eccles et al. model, we note that subjective task value played a much more significant role than the expectancy of success. Of particular importance were the utility and cost, rather than attainment value. In relation to Marsh's model, students did make comparisons between themselves and their peers, and between CS and other subjects. These comparisons refer not only to their perceived achievement but also to other cost measures like stress and anxiety, as encapsulated in the Eccles et al. model. We also identified two distinct

factors that are not explained by the models: social concerns, and the difficulty of the subject. Our results call for further investigation of the interplay between all of these factors and CS students' motivation and academic choices. Our future research aims to delineate these relationships by examining them with respect to gender and different minority groups. Acknowledging the limitations of a survey-based approach, we propose that this future work make use of in-depth semi-structured interviews, designed with reference to the expectancy-value model and the preliminary findings presented here.

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