Motivations for Using AI Tools in an Introductory Programming Class

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Abstract

A growing concern for the field of computer-human interaction is human interaction with artificial intelligence (AI). A concern about the use of AI tools is that automating tasks reduces the opportunity to learn how to do them. We explore antecedents to this outcome in the context of AI tools for programming in an introductory class. We hypothesize that if students are intrinsically motivated to learn to program, they may avoid using tools in order to engage with the material, while students with extrinsic motivations may use the tools to get work done. Counter to our expectations, analysis of a survey of learning motivations and log data of AI tool use suggests that students with higher extrinsic motivation actually use the AI tool less, while those with higher intrinsic motivation use it more, and that there is no correlation between the level of AI use and grades. These findings suggest that to understand the impact on skills, it is necessary to examine how AI is used in detail, not just the overall level of use.

CCS Concepts

• **Human-centered computing** → *Empirical studies in HCI*; • **Social and professional topics** → **Computing education**; • **Computing methodologies** → **Artificial intelligence**.

Keywords

Skill development, generative AI use for programming, motivation

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1 Introduction

A growing concern for the field of computer-human interaction is human interaction with artificial intelligence (AI). This poster reports on early pilot work for a study of the effects of generative AI tool use on skill development and retention [6], specifically on skills for programming [2, 3, 8]. General-purpose AI chatbots such as Claude or ChatGPT can effectively write software of low or moderate complexity [4]. More specialized tools such as Cursor can nearly automate code generation, with extensive caveats [15]. However, over-reliance on AI tools can harm learning by eliminating students' need to do the work themselves and thus the engagement needed to build skills [23].

In this poster, we explore reasons why students might expose themselves to such a possible loss of learning. We suggest that if students are not motivated to learn to program, they will not care if AI use deprives them of the opportunity to do so and so will be more likely to use the tools. We also examine the possibility that students who feel pressure to complete classwork will use AI as a short cut. We explore these hypotheses in a study in an undergraduate introductory programming course, combining survey data, log data from an AI chatbot and scores on an exam testing programming skills. Our results suggest that, counter to expectations, students with higher extrinsic motivation to learn to program actually used an AI tool less, and students with higher intrinsic motivation, more. Further, we do not find a direct relationship between AI use and learning outcomes. Our results suggest that focusing on AI use in the aggregate is too simplistic: different motivations may lead to different kinds of use, with different kinds of outcomes.

2 Theory

In this section, we develop three hypotheses to guide our study, while noting that the exploratory nature of our study means that these hypotheses are starting points for further hypothesizing rather than ones we can definitively test. First, skill acquisition theory suggests that skills typically develop by proceduralizing and automatizing knowledge through practice [10, 11]. Experimental studies demonstrate that while AI can save time and improve output quality, users often adopt AI-generated content with minimal editing [e.g., 17], requesting complete solutions rather than using AI to enhance understanding [21, 25]. Over-reliance on AI programming tools in particular may generate a sense of complacency and illusion of competence [20], with beginning programmers particularly prone to these effects. In other words, using AI often leads replacement of work, meaning less practice of the skills and so

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lower mastery. We therefore hypothesize: H1: Students who use an AI tool more will learn less than students who use it less.

Second, we note that students differ in their reasons for learning and those difference might explain difference in tool use. A number of studies have examined the impact of AI use on motivation [e.g., 7, 28]. Here we examine the opposite relation: differences in motivation leading to differences in use. Self-determination theory [9] suggests that intrinsically motivated learners seek mastery and understanding, while extrinsically motivated learners focus on external outcomes like grades or completion. Therefore, we expect that students who are learning to program for an extrinsic reason will be satisfied with a tool that gets the work done, even if it means that they learn less. In contrast, intrinsic motivation shapes the commitment of programmers to support skill development and retention [1, 11, 19]. We therefore expect intrinsically motivated students to avoid tools that might shortcut their learning process, preferring hands-on engagement with the material. Accordingly, we hypothesize: H2a: Students with extrinsic motivation to learn to program will be more likely to use AI to solve problems. H2b: Students with intrinsic motivation will be less likely to use AI to solve problems.

Finally, we consider that students might feel driven to use an AI tool by external pressures. Specifically, students who feel that they are under time or academic pressure to succeed might chose to use a tool to complete work more quickly [14] or with better quality than they feel they can achieve themselves [26]. Accordingly, we hypothesize: H3a: Students perceiving more time pressure will be more likely to use an AI tool to solve problems. H3b: Students perceiving more academic pressure will be more likely to use an AI tool to solve problems.

3 Methods

We collected data in three ways. Data about motivations to learn programming and perceived academic or time pressure were collected through an online survey. Data about actual AI use were collected from logs of interactions with a tool provided for the course. Data about programming skill development were collected from the midterm exam. We discuss each in turn.

3.1 Data elicitation techniques

An online (Qualtrics) survey instrument was created to collect data. The items to measure motivation came from the Academic Motivation Scale [22, 24], a validated scale that includes four items each for three types of intrinsic motivation (to know, toward accomplishment and to experience stimulation), three types of extrinsic motivation (external regulation, introjected and identified) and amotivation (i.e., lack of motivation). The original scale was developed in French for attending CEGEP (roughly, college), but we used an English-language translation, replacing references to being in school with learning to program. We added three items to measure if students were taking the course only because it was required. We administered two scales from the Inventory of College Students' Recent Life Experiences [18], specifically the time pressure and developmental challenge subscales, with items such as not having enough free time or sleep and not meeting one's own standards or lower grades than hoped for, respectively. We revised some items to be positively worded to vary the expected responses. The survey included three attention check questions. All items used seven-point Likert scales. We also asked demographic questions and about programming experience and AI tool use.

As a basis for analyzing use of AI, we analyzed a log of students' interactions with an AI chatbot provided for the class. To incentivize students to use this tool rather than the many available alternatives, it was provided with information about the course and the assignments, allowing it to reply more precisely to questions on these topics. The chatbot was built on the GPT-4o-mini LLM and configured with a system prompt to guide generations that were tailored to the course style. The tool could answer questions about specific assignments, explain course concepts, provide code examples, and work out solutions if prompted. Students could ask follow-up questions, making it potentially more useful than general-purpose chatbots for course-specific tasks. However, we did not require students to use our tool and some likely used other tools, which is a limitation of the study. From the logs, we can extract summary measures such as the number of prompts, number of sessions (a sequence of prompts in the same browser window, as recorded by the AI tool) and potentially more detailed measures such as prompt length, presence of source code, etc. We also included a question on the survey asking how often an AI tool was used for programming on a 4-point scale from never to extensively.

3.2 Subjects

Subjects in the study were undergraduate students in an introductory Python course at a private university in the United States. Students were recruited for the study as the start of the semester, giving their consent for the collection of their AI logs and grades. They were separately recruited for participation in the survey. It is relevant to note that students are not computer science majors, meaning that we do not expect them to necessarily be interested in programming. For most, the course is simply a degree requirement. The study was approved by our institution's IRB, subject to conditions to protect the students, e.g., the class instructor was not informed about students' decisions to opt into or out of the study.

The study was agreed to by 51 students (i.e., we have grades for 51 students). Of these, we have AI log data for 33. The survey received 38 responses. After removing students who failed multiple attention checks, we were left with 26 usable responses, equally split between males and females. We have midterm grades for 23 of the survey respondents and AI logs for 18. The limited sample sizes mean that the work presented here is the basis for developing research hypotheses and instruments for future work, rather than drawing firm conclusions.

3.3 Scale validation

For the survey data, we first verified the reliabilities of the scale items. The motivation scales performed well, with alpha scores all above 0.80 for all 8 subscales (3 each for intrinsic and extrinsic motivation, plus amotivation and required) and 0.94 for intrinsic motivation and 0.88 for extrinsic motivation (combining items for the three subscales respectively for each). Intrinsic and extrinsic motivation were somewhat correlated, but not significantly ($\rho = 0.33$, $p = 0.097$).

Unfortunately, the time pressure and developmental challenge scales exhibited low reliability, 0.72 and 0.54 respectively. An exploratory factor analysis revealed that the positively-worded time pressure items were loading separately from the negatively-worded items and that some items from the two subscales were loading together (e.g., not enough sleep from the time pressure scale with hard effort to get ahead from the developmental challenge scale). In other words, it seems to have been a mistake to change the wordings of the scales, a problem to avoid in follow on studies. To continue the data analysis, it was decided to form three subscales based on the factor analysis results: 1) fives items that assess workload demands (items 5, 27, 41, 15 from the time pressure scale and item 32 from the developmental challenges scale in [18]); 2) three positively-reworded time pressure items (items 13, 18 and 29); and 3) four developmental challenge items related to grades and meeting standards (items 11, 14, 25 and 30), interpreted as evaluative pressure. These scales had acceptable reliabilities of 0.78, 0.77 and 0.81 respectively. We accordingly expanded H3 to H3a, H3b and H3c, respectively, namely that workload, time and evaluative pressure will predict more AI use. Descriptive statistics for the key variables are shown in Table 1.

4 Findings

As mentioned above, we had both self-reported AI tool use and actual use from the logs. Interestingly, there was almost no correlation between these two (Spearman's $\rho = 0.086$; Spearman's ρ, as our data are skewed). Henceforth we examine actual tool use.

To identify factors predicting tool use, we ran a negative binomial regression, using the number of AI sessions as the dependent variable. Because of the small sample size, we reduced the number of predictors to overall intrinsic and extrinsic motivation and the three time and academic pressure variables. To account for the many students who had not used our tool, we used a zero-inflated model. A check of the model diagnostics did not reveal violations of model assumptions. The results are shown in Table 2. Interestingly, the results are counter to our expectations: extrinsic motivation was a predictor of less AI use and intrinsic motivation, of more (though marginally significant), that is, H2a and H2b are contradicted. Converted to regular odds, a 1-unit increase in the extrinsic motivation score predicts a 39% reduction in the number of sessions; a 1-unit increase in intrinsic motivation, a 25% increase. Perceived evaluative pressure was a marginally-significant positive predictor of use (a 25% increase), so the new H3c is somewhat supported, but not H3a or H3b for workload or time pressure. We ran the same analysis using total number of prompts as the dependent variable, and got similar results (not shown), though intrinsic motivation was not significant in this model. We also experimented with a hurdle model, which again gave nearly the same results.

Finally, as an assessment of AI usage intensity, we estimated a mixed-effects random intercept model to predict the number of interactions in a session, with user as a random effect (Table 3). We again found a negative impact of extrinsic motivation and a positive impact of evaluative concerns, meaning that extrinsically motivated students had shorter sessions with the AI.

We considered that there might be systematic differences in which students chose to use our tool vs. another tool or perhaps no tool. However, t-tests between the two groups did not reveal significant differences on any of the variables we had measured (admittedly with low power), nor did they predict zeros in the zero-inflated model. Accordingly, in the model reported in Table 2, the zero-inflation model is an intercept-only model to reduce the number of parameters to be estimated given the small sample size: it predicts a 31% chance of a structural zero, which matches the observed 8/26 students who had no recorded sessions.

We next examined the relationship between AI use and learning as reflected in the midterm grade, first restricting our analysis to the 33 students who had used the tool. We found that that the correlations between use and grades were near zero, Spearman's

Table 1: Descriptive Statistics of Key Variables

Statistic	N	Mean	St. Dev.
Intrinsic Motivation	26	3.65	1.36
Extrinsic Motivation	26	4.68	1.19
Amotivation	26	2.36	1.22
Required	26	3.06	1.90
Workload Pressure	26	4.94	1.10
Time Pressure	26	4.47	1.32
Evaluative Pressure	26	3.76	1.43
AI Tool Use (Self-Reported)	26	2.12	0.95
Midterm Grade	51	28.24	6.52
Number of AI Sessions per student	33	20.21	16.47
Total AI Prompts per student	33	141.48	168.70

Table 2: Zero-inflated Negative Binomial Regression Results for Number of AI Sessions

Constant	3.033 (1.900) **
Intrinsic Motivation	0.222 (0.120) $^{+}$
Extrinsic Motivation	-0.500 (0.131) **
Workload Pressure	0.201 (0.135)
Time Pressure	-0.026 (0.126)
Evaluative Pressure	0.224 (0.121) $^{+}$
Observations	26
Log Likelihood	-86.98
Note: (SE)	$^{+}$p<0.1; *p<0.05; **p<0.01

Table 3: Mixed Effects Random Intercept Negative Binomial Model Results for Session Length

Constant	2.555 (0.539) ***
Intrinsic Motivation	-0.004 (0.062)
Extrinsic Motivation	-0.237 (0.074) **
Workload Pressure	-0.062 (0.070)
Time Pressure	-0.033 (0.065)
Evaluative Concerns	0.155 (0.067) *
Observations	515
Log Likelihood	-1401
Note: (SE)	$^{+}$p<0.1; *p<0.05; **p<0.01; $^{***}p < .001$

Table 4: Regression Results Predicting Midterm Grades

Constant	38.83 (7.91) **
log(AI Sessions + 1)	−2.37 (1.78)
Intrinsic Motivation	0.86 (0.92)
Extrinsic Motivation	−3.39 (1.41) *
Workload Pressure	3.57 (0.94) **
Time Pressure	0.81 (0.76)
Evaluative Pressure	−1.97 (0.84) *
Observations	15
R^2	0.719
Adjusted R^2	0.507
Note: (SE)	+p<0.1; *p<0.05; **p<0.01

Table 5: Regression Results Predicting Midterm Grades with Interactions (variables interacted with log(AI Sessions + 1))

Constant	28.74 (1.13) **
Intrinsic Motivation x	−0.04 (0.68)
Extrinsic Motivation x	−0.19 (0.82)
Workload Pressure x	2.48 (0.98) *
Time Pressure x	0.73 (1.00)
Evaluative Pressure x	−1.63 (0.75) +
Observations	15
R^2	0.634
Adjusted R^2	0.430
Note: (SE)	+p<0.1; *p<0.05; **p<0.01

$\rho = 0.03$ for total number of prompts and Spearman's $\rho = 0.09$ for number of sessions, meaning that H1 is not supported. A regression predicting midterm grades just for those who used our tool showed no effect of AI use (see Table 4), though the small sample size means these results are suggestive rather than conclusive. We did not hypothesize the effect of the motivation or pressure factors on grades but found a marginally-significant negative effect of extrinsic motivation, a positive effect of workload pressure and a negative effect of evaluative pressure.

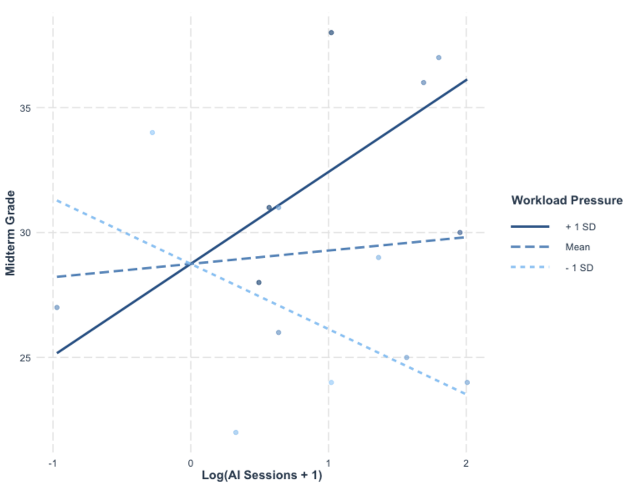

Figure 1: Interaction Plot Showing the Effects of Workload Pressure and AI Use on Midterm Grades

Finally, we were interested in whether AI use had a differential impact on students depending on their motivations or perceived pressures. A model testing an interaction between these variables and AI use (Table 5) revealed a significant positive interaction with workload pressure, meaning that those with higher reported workload pressure had higher midterm grades with more AI use. The relationship is shown graphically in Figure 1 (note that variables were centred for this regression). As well, there was a marginally-significant negative interaction between evaluative pressure and AI use, that is, for students reporting more evaluative pressure, increased use of AI was associated with a lower midterm grade, while the opposite was true for those reporting less pressure.

5 Discussion

Our data suggests several implications. First, an important methodological finding is that self-reported AI use seems unreliable, witness the low correlation between self-report and recorded AI use. Indeed, one respondent reported never using AI, despite logging multiple sessions.

Second, we were surprised to find that higher levels of extrinsic motivation were associated with less AI use and that AI use was not associated with lower exam scores. These results show that there is not a simple connection between AI use and skill development. We propose rather that the effect depends on how the AI is used: it can be used to self-automate, eliminating learning, or to act as a tutor, supporting learning. Indeed, we see examples of both behaviours in the detailed AI log data (see Figure 2), with some students asking for explanations of Python concepts (what [13] described as "instrumental help seeking") and others for complete solutions to problem set questions ("executive help seeking"). Many of the later prompts are just cut and paste of the problem set questions or of non-working code or error messages, even including reflection questions like "Were you prepared for this assignment?". It could be that those who are extrinsically motivated are getting solutions to their problems quickly while those who are intrinsically motivated are spending more time exploring concepts, nuances that are not captured by simple usage counts. Preliminary analysis of prompt and response characteristics supports this interpretation: intrinsically motivated students received significantly longer AI responses ($\beta = 16.18, p < 0.05$, compared to an overall average response of about 200 words).

These finding suggest that the assumption behind our original H2, that AI use necessarily shortcuts learning, is too simplistic. AI can short cut learning but it can also support it. A revised pair of hypotheses is that the extrinsically motivated students seek to use AI to solve problems while students with intrinsic motivations use it to support their learning [27]. Further, we can amend H1 to state that the first kind of AI use will reduce grades, while the second will improve them [12]. To explore these possibilities, we have started to code interactions for the nature of the request, dividing them into executive (about half the coded interactions) vs. instrumental help seeking (about 1/3 of the interactions, with miscellaneous codes

Example instrumental help seeking prompts	**Example executive help seeking prompts**
how can I skip a line in a file that I am printing if it has a str that I don't want to be printed	How exactly should I go about creating a story for this homework? *<Problem set text>*
i dont understand this type, int, str stuff... what does it mean?	can you give me the full code
I have a question about Fred's fence estimator... dont tell me the code but i want to know if for step 1 i am supposed to make a number up for the variable in the input for length and width or is that given to me?	give me steps for sentiment function and steps for main function

Figure 2: Example prompts

accounting for the rest). Our coding is still preliminary, but our initial results are that the fraction of a student's interactions that are executive help seeking is strongly and significantly negatively correlated with their midterm grade, while instrumental help seeking is strongly and significantly positively correlated, evidence for our revised H1. However, the correlations of these kinds of interaction with intrinsic and extrinsic motivation, while in the predicted direction, are not significant, perhaps due to the small sample sizes. Future analysis will examine the nature of the interactions in more detail [16].

The finding that perceived evaluative pressure is associated with lower exam scores makes sense, though it could be reverse causation: recall that one of the items relates to dissatisfaction with grades. The finding that workload pressure is associated with a higher grade could reflect that busy students are more prepared for the exam. Finally, the interaction effects are interesting, that those who are anxious about evaluative pressure seem to be harmed by AI use, while those who are stressed by the workload make positive use. However, the small sample size cautions against over-interpreting these results: rather they should be followed up in future work.

6 Conclusions

Our results suggest that simply examining the frequency of AI use is insufficient to understand its impact on learning. A major limitation of the current study is the small sample size, which means our results are suggestive of hypotheses to consider rather than conclusive. To increase the sample, we are continuing the study in the current semester, which has higher enrollment. A further complication is the high level of non-use of our tool. To encourage use, we are further emphasizing its utility for the class given its training on the course materials. We also are giving students more explicit training in how to make effective use of an AI tool and to encourage them to use it as a tutor. Specifically, we have modified the tool to give students an explicit choice between an AI chatbot trained to be pedagogic [5] vs. one that focuses on doing the work. We anticipate that examining the impact of these interventions will help clarify the impacts of AI use on skill development.

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