A Personalized Learning Approach to Support Students with Diverse Academic Backgrounds

Bowen Hui
Computer Science
University of British Columbia
Kelowna, Canada
bowen.hui@ubc.ca

***Abstract*—Teaching design thinking and human-computer interaction (HCI) from technical disciplines are challenging due to the need for frequent content refreshes using up-to-date technology examples and students' negative preconceptions about the material. In particular, students typically find the course content too easy and the grading too subjective. Beyond these issues, the problems in our HCI course are exacerbated by the diversity of academic backgrounds in the student population. Over the years, we have struggled to deliver the course material at a pace that is appropriate for everyone and to develop assessments that can fairly evaluate the relevant design and technical skills involved. Here, we propose a personalized learning approach to tackle the problem of delivering content that suits students with diverse academic backgrounds. Specifically, we designed four features to personalize assessments in the HCI course: alternative pathways, flexible timing, multiple test attempts, and choice in programming options. Our study with 360 students showed a high uptake in all the personalization features and a positive impact on student performance and perception of the course. This case study describes how we implemented these personalized learning features successfully in a large university class to improve the student's learning experience. We discuss implementation tradeoffs and the generalizability of these features.**

***Index Terms*—Personalized learning, equitable participation, flexible timing, alternate pathways, student choice, computer science education, HCI education**

I. Introduction

Human-computer interaction (HCI) educators have reported many unique obstacles and negative student preconceptions that view the course content as being too easy, the grading too subjective, and the difficulty level not challenging enough (e.g., [1], [13], [28]). Beyond these challenges, the issues in our HCI course are exacerbated by the diversity of academic backgrounds in the student population. Historically, this course was created as an elective in the computer science (CS) degree. To attract interdisciplinary students, the content focused mostly on design topics. In later years, while recognizing the important role that HCI plays in computing careers, our department made the HCI course mandatory in the CS program. In a given year, about 80% of the students are CS majors while the rest come from other disciplines, such as mathematics, management, and psychology. The enrolment has also increased to nearly 200 students in recent years. Since this is the single HCI course offered by our department, it is also cross-listed as a graduate-level course (although graduate students are evaluated somewhat differently). Thus, balancing theoretical and practical content and teaching at a pace that is suitable for each student subgroup became very challenging.

What we need is a personalized approach tailored to the needs of each student subgroup. *Personalized learning* is a student-centered approach where the learning experience is customized for an individual student's needs, skill levels, and/or interests. This concept is not new; many empirical studies in personalized learning have shown benefits in student learning outcomes (see [3], [4], [27], [37] for example). However, much of this literature takes place in settings where class sizes are small and the teacher-to-student ratio is arguably more suitable for providing individualized learning. In the context of our HCI course, we would like to explore the feasibility of implementing personalized learning techniques in a large university course and the potential benefits this approach might offer for students. Furthermore, we are unaware of the use of personalized learning to improve HCI education.

Our primary objective is to improve the student learning experience in HCI while considering their diverse backgrounds and interests. Since some topics may be more familiar to students with certain backgrounds, we wish to design our course to enable more experienced students the flexibility to quickly advance material familiar to them. We also recognize students have external constraints and may take different lengths of time to master the same material. To make the circumstances more equitable, we wish to incorporate flexibility in the student assessments and provide opportunities for reassessment. Using these criteria, we experimented with four personalization features in our HCI course: alternative pathways, flexible timing for deadlines, multiple test attempts allowing self-paced mastery, and student choice in project options. These features are specifically designed to be content-independent so that they could be incorporated into other courses to promote further adoption of personalized learning. However, before we invest additional effort in personalizing more courses, we wish to investigate the effectiveness of these features. Our research questions are:

- RQ1: Do students take advantage of the personalization features provided in the course?
- RQ2: Does student performance improve with personalization?
- RQ3: What is the student perception of the personalized learning approach in the new course design?

To provide context for our approach, we present an overview of related work in Section II. We describe the course context and implementation details in Section III. Section IV presents the results of the research questions raised. Generally, we saw evidence of students using each of the personalization features and found a positive impact on both student performance and perceptions. Section V examines our results in the context of the existing literature, discusses the implications of implementing these features in other courses, and proposes an extension to a personalization framework. Ultimately, we are interested in gaining a better understanding of course design techniques that can be adapted to accommodate diverse student populations and generalized across different courses.

II. Related Work

Issues faced in teaching diverse student populations have been addressed by equitable grading and personalized learning techniques. We are unaware of HCI studies that use these approaches. As such, we review these fields independently.

A. Equitable Grading

In any given class, students often have different interests and background knowledge about the subject, or even pursue different majors of study if the class has general prerequisites. With a diverse student population, instructors must carefully deliver course content to maintain student interest and present information at a suitable pace for everyone. At times, students may face personal constraints and deadlines from other courses that prevent them from demonstrating their full potential. Thus, flexibility is crucial in helping students succeed.

Equitable grading practices seek to accommodate students who may be dealing with (potentially temporary) circumstances that interfere with their performance. Feldman explains the negative impact on student learning in traditional assessment methods, especially for students who are underserved or vulnerable [15]. In his book on equitable grading, Feldman provides specific implementation techniques to help teachers adopt fair assessment practices that have been shown to improve student learning outcomes. To reduce implicit bias in how teachers may interpret differences across gender, race, and culture, the author suggests grading should focus on assessing knowledge rather than aspects that can be influenced by environmental or behavioral factors (e.g., late submissions and varying levels of participation).

The controversy over using grades has sparked conversations about alternative grading approaches. For example, proponents of *mastery learning* recommend assessments that support individualized formative feedback, help students learn at their own pace, and allow multiple chances for success [6]. Another approach is *specifications grading* which assesses student competency against outcomes that are aligned with learning objectives and the evaluation is done based on whether the student has met (passed) or not met (failed) the expectations [25]. Finally, *ungrading* uses a continuum of learning and emphasizes the importance of formative feedback for the learner [7]. These approaches share common characteristics, such as using formative assessments, increasing flexibility (e.g., with submission deadlines), and providing second chances for tests. Thus, instructors may combine ideas from these approaches and implement them in a complementary way.

B. Personalized Learning

Educators have long argued for the need to personalize the student's learning experience based on their skills, preferences, personality, emotional state, demographic characteristics, and sociocultural context, among other variables [3], [4], [27], [37]. From a theoretical perspective, these studies examine the relationship between specific learner variables, the adaptations implemented, and the observed learning outcomes. A recent systematic review revealed that most studies in personalized learning lack theoretical alignment and tend to develop adaptive systems in an exploratory manner [4]. Thus, the field lacks explanatory theory to guide pedagogical choices.

Many empirical studies seek to investigate strategies that support a personalized learning experience. Among 376 empirical studies reviewed, one report found the most common learner characteristics to motivate the adaptation are students' prior knowledge and preparedness to learn (38%), followed by learner preference (27%) and student interest (18%) [4]. Most of the studies use some form of technology, either the LMS or specialized adaptive systems, to create a personalized learning experience. As such, technology has played a key role in enabling the adaptation of instruction (in terms of content, sequence, and choice), content delivery and pace, feedback, and assessment toward individual learners [4], [37]. Common measures that determine the success of personalized learning implementations include the use of academic performance, metacognition (such as self-regulation and self-efficacy), and attitude (including perception and engagement) [4], [37], [39].

To capture the variety of approaches taken in this field, an overarching taxonomy of adaptivity was proposed to illustrate the relationship between learner variables, adaptation, and learning outcomes [27]. One differentiating feature of this taxonomy is its classification of adaptations based on five general categories: the core learning activity, activities to prepare the learner beforehand, resources offered to the student during the activity, the type of assessments used, and progression to and from other courses. The taxonomy also lists specific elements in each category that may be adapted. For assessments, the system can adapt the testing frequency, the test item difficulty, the modes of responses presented, and how the test results are displayed to the learner. In contrast to these elements, our personalization features integrate aspects of equitable grading in adapting the assessments – which assessment to do (alternate pathway), the due date (flexible timing), the number of chances allowed (multiple attempts), and the options available (student choice).

C. HCI Education

Many efforts in HCI education have emphasized challenges unique to teaching HCI in contrast to traditional areas of CS. Specifically, activities surrounding design thinking are generally poorly received by HCI students housed in technical disciplines because they are used to the formal and technical content that can be assessed with a right answer. As such, many case studies have reported that students perceive HCI content to be "too easy", "too fuzzy", or that it is "all common sense" [1], [13]. Studies that attempt to overcome these issues used strategies such as involving real users or an external client [1], [17], [24], [26], changing the culture of individualized summative assessments common in technical disciplines [5], focusing more on the design process rather than design outcomes [13], [17], conducting design critiques [24], [33], [35], creating a platform to enable students to experience and explore a design space [26], allowing students to work on projects based on student interests [38], and proposing to rebrand the HCI discipline globally [23].

Another major challenge is the rapid changes in technology, which inevitably leads to increased growth in user populations and diversified user needs [11]. In their report, Churchill et al. surveyed HCI professionals from over 30 countries and found a lack of consensus on what and how to teach HCI globally [11]. Consequently, many scholars have identified what we need to teach in HCI as a moving target. Inspired by the ongoing changes in the field, the authors proposed that a group of *progressionals* (researchers, educators, and practitioners) be formed to maintain the core values, tenants, and perspectives unique to HCI. As such, new design methodologies to account for the changes in new technologies are needed but they are often not readily available for teaching purposes. As a result, researchers proposed to place the pedagogical focus on helping students develop skills and competencies rather than content knowledge in the field [13], [30], [36].

The constant changes in HCI education were later termed a *living HCI curriculum* [10]. The idea is for HCI educators to embrace change so that the curriculum would evolve alongside the changes observed in the field. The vision of this proposal would offer a flexible, global, and frequently refreshed curriculum. Major challenges in this initiative include defining the co-design process in developing such a curriculum and the ongoing maintenance of the material. Nonetheless, vibrant discussions began to pursue this goal, including efforts in understanding pedagogical trends in specific geographies [8], [12], [20], [21], [29], [34] and workshops on implementing the living curriculum internationally [19], [28], [31], [32].

III. Course Context and Redesign

Our HCI course is offered as a third-year undergraduate course by the CS department and it introduces a broad range of concepts. The student population is diverse; a typical class has some students with minimal or no programming training as they come from other disciplines (e.g., management, media studies, psychology, and mathematics), a large group of CS majors, and a few graduate students in the mix. We collected data in 2021 and 2022 with a total of 360 students. In 2021, there were 1 graduate CS student and 160 undergraduates (29 females; 131 males), 14% of which were non-majors. In 2022, there were 6 graduate CS students and 193 undergraduates (29 females; 170 males), with 17% non-majors.

The classes ran over a 13-week semester in a partially asynchronous format. Although we wished to maximize flexibility, giving students complete autonomy over their schedules can cause procrastination and anxiety. Thus, we offered synchronous classes each week to align student progress with our expectations based on a weekly class schedule. Class time is used to provide support for students who need help with their work. Our personalization features described below were offered as adaptable aspects of the assessments so that the students maintain agency and directed their own learning. These features give students more control over their pace of learning and choices that speak to their interests.

A. Module Structure with Alternate Pathway

To accommodate the diverse background and interests of the students, we modularized the content into 10 modules so that each module is aligned with a calendar week and can be completed separately. As illustrated in Figure 1, every module has a pre-test, reading material, an optional (individual) tutorial activity, a (group) main activity, and a post-test. Navigation within a module is designed so that students must complete the pre-test before accessing the rest of the content. Each module has 5 to 10 pages of readings and an interactive quiz at the end of each page. Students are required to view all the pages before completing the synchronous group activity and taking the post-test. Students who want extra practice may additionally complete a tutorial activity (a)synchronously before the group activity. This tutorial activity also serves as an alternative assessment for the module pre-test for students who do not like taking tests. The readings counted for 15% of the overall grade, the module pre-tests and post-tests each counted for 20%, and the group activities counted for 25%.

B. Flexible Timing

To accommodate for varying abilities to achieve mastery, we allowed a maximum of three attempts on tests over a 3-week window so that students who need more time or assistance may seek help during that period. Modules are placed in a sequence in the learning management system (LMS) so that students can access the module content as long as the pre-test and associated prerequisites (i.e., the previous module's post-test) have been completed. Students may choose to work

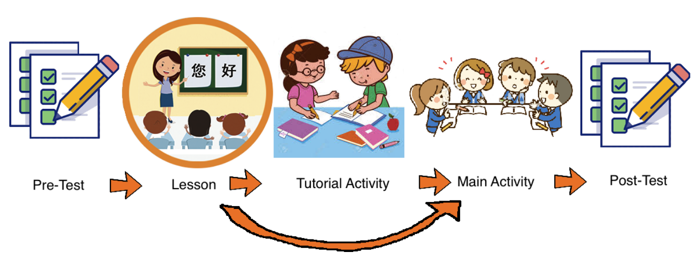

Fig. 1. An illustration of the navigation options for completing the core activities in each module.

on all the modules and individual assignments in a condensed timeframe if desired. This setup can help students plan their deadlines with other courses accordingly.

C. Mastery Learning and Deliberate Practice

Many studies have successfully implemented aspects of mastery learning in the curriculum [22]. Furthermore, studies in medical sciences highlight the additional use of *deliberate practice* so that learners have specific targets and areas of improvement when they are reassessed [14]. Online assessments with autograding capabilities can implement these ideas by allowing students to resubmit their work and get targeted feedback to improve their learning. However, when the number of resubmissions is unlimited, recent work found that students "over-submit" and engage in trial-and-error behavior that does not seem conducive to learning [2], [16]. To encourage more thoughtful attempts, these studies explored alternative submission policies, such as applying regression penalties to subsequent attempts that scored a lower mark. While the number of submissions lessened, these studies reported that the penalties negatively impacted students' exam anxiety.

To minimize exam anxiety and to allow students more practice opportunities, we allowed for a maximum number of three attempts per test and kept the best score so there is no risk in making subsequent attempts. Furthermore, the pre-tests are designed to help students do well in the post-tests because they follow the same format and topics assessed. For example, if a module pre-test has 7 questions, each question addressing a particular concept in the reading, then the module post-test would also have 7 questions addressing the same set of concepts. Thus, pre-tests operate as the modules' learning objectives, and students who do not score well on certain questions can hone in on the associated concept areas.

D. Student Choice in Assignment Options

The course has an additional programming project that is worth 20% of the grade and is broken up into six individual assignments. Inspired by our previous study that offered programming options for CS majors and non-programming options for non-CS majors [17], we incorporated a choice of techniques that students can select from. Specifically, three of these assignments ask students to program two interaction or gesture recognition techniques. In each case, students were given three options and must successfully implement two to obtain full marks.

IV. Results

A. RQ1: Uptake of Personalization Features

First, we review to what extent students made use of the four personalization features. To explore the use of alternate pathways, we analyze the number of students who completed tutorials to replace pre-test scores. Table I shows 19% of the students completed the tutorials at the beginning of the class and decreased to 1-2% by the end of the semester. We suspect the decline is due to the effort required by the tutorial activities in comparison to taking a subsequent pre-test attempt.

TABLE I
NUMBER OF STUDENTS WHO MADE TUTORIAL SUBMISSIONS BY MODULE AND YEAR ("M" REPRESENTS A MODULE, THE TOP ROW IS DATA FROM YEAR 2021, AND THE BOTTOM ROW IS FROM YEAR 2022)

M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
30	11	11	13	3	4	4	3	–	–
36	27	29	16	11	4	5	2	2	4

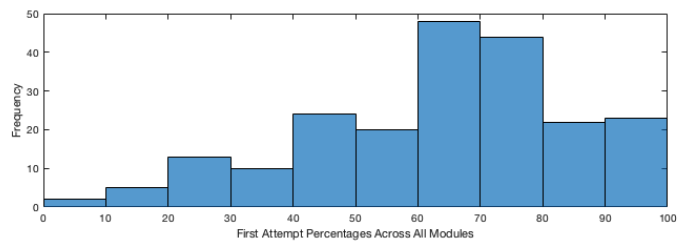

Fig. 2. Histogram of first attempt scores across the module pre-tests where a tutorial submission was made.

Among the tutorial submissions, the distribution of the first attempt pre-test scores shown in Figure 2 indicates that most students submit tutorials when they do not get a perfect score. Across both years, 101 students made 215 tutorial submissions Among these students, 87 of them also submitted a second or third attempt on the pre-test. Furthermore, the histogram shows there are 23 tutorial submissions with a pre-test score of 90% or above. These patterns lead us to believe that even when students score well on the tests, they are using tutorials to further explore the topic to gain a deeper level of mastery.

To assess the uptake of flexible timing, we investigated when students start working on a module. Since every module begins with a pre-test, we took the pre-test's first attempt submission time as an indication of the start of a module. Initially, we planned to have 10 modules in both years, but 2 of them were canceled in 2021 (due to COVID complications with many students). We show the data for all 18 modules as a histogram in Figure 3 where the x-axis indicates the

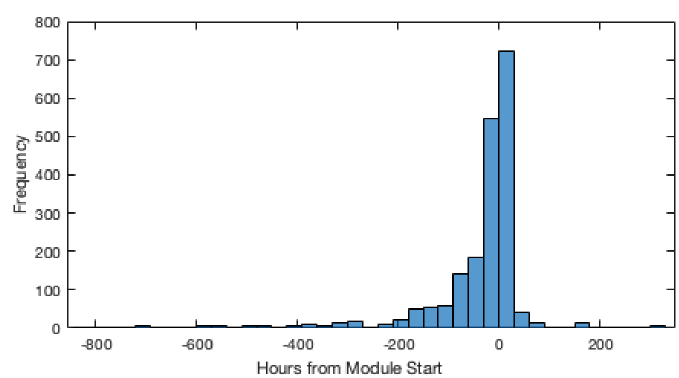

Fig. 3. Histogram of hours before the first attempt pre-test due date for all modules across both years. (A few data points beyond -800 hours are not shown.) Zero denotes the deadline, negative numbers denote early submissions, and positive numbers denote late submissions.

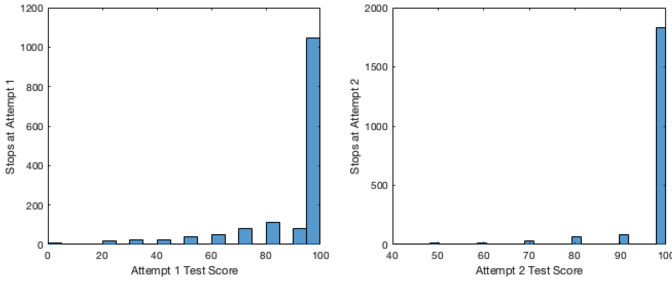

Fig. 4. Histograms of test scores of students who stop after only making one attempt (left) or two attempts (right). The total possible number of attempt sequences across both years is 6,480 (360 participants × 18 modules).

submission time in terms of the number of hours relative to the intended start of the module (labeled as "0"). On average, students started the modules 2 days before the intended start time (with a mean of -47.9 hours), with the majority of the submissions ranging from 8 days before the start time and 6 days after it (a standard deviation of 138 hours). At the extreme end, some students submitted their first pre-test attempt as early as 1,424 hours (8.5 weeks) before the start time and some students started as late as 323.6 hours (13.5 days) after the intended start time. This cutoff is bounded by the 3-week window when all the tests close for each module in the LMS.

Our next personalization feature is to allow multiple test attempts in the module pre-tests and post-tests. While we see that the decision to take multiple attempts is largely based on the test score, we found that a small portion of students did not make subsequent attempts even when their scores are not perfect. As shown in Figure 4, some students choose to not make use of the multiple attempts to improve their scores. Although we do not have follow-up data to explain this behavior, we suspect that students stopped early because they may not have enough time or they are simply satisfied with the grade for that test.

Conversely, we checked for the reverse pattern to verify if students are making additional attempts with the goal of improving their scores. Interestingly, we see a small percentage of students who got a perfect score on a previous attempt, yet they continue to make a subsequent attempt. In particular, Figure 5 shows that among those who stopped after attempt 2, 17 (out of 2057 cases) got 100% on the first attempt, with

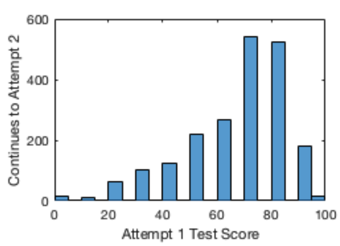

Fig. 5. Histogram of first-attempt test scores for individuals who only made two attempts.

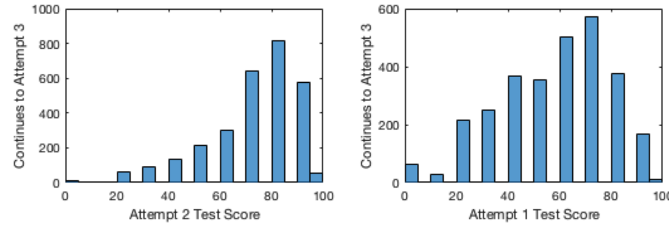

Fig. 6. Histogram of first- and second-attempt test scores for individuals who made all three attempts.

3 of those getting a lower mark the next time. Similarly, we see in Figure 6 that among those who did all 3 attempts, 56 (out of 2909 cases) got 100% on the second attempt, with 26 of those getting a lower mark the next time. Also from this group, 12 (out of 2909 cases) had 100% on the first attempt but continued to make two additional attempts, with 12 of those resulting in a lower mark in attempt 2 and 5 of those resulting in a lower mark in attempt 3. These patterns suggest that these students are exploring alternative responses, possibly as a way to understand whether the other answers would also be correct.

The fourth type of personalization feature we investigate is the choices made in the assignment options. Table II shows the percentage of student choices made when three available options were given for assignments A3, A4, and A5. Since students were asked to select two of these options to implement per assignment, these percentages do not add up to 100%. These percentages reflect the relative popularity of the available options. The top part of the table shows the student choices for the three assignments in the years 2021 and 2022. We also combined the data across both years to look at student choices according to the students who are undergraduate CS majors, undergraduate non-CS majors, and graduate students. In all cases, we see that all three options are chosen in every assignment and that the least popular option was chosen by 14-43% of a given group.

B. RQ2: Changes in Student Performance

Next, we compare changes in academic performance using the overall grade averages from 2015 to 2022. Our ANOVA results showed a statistically significant improvement in 2021, but the improvement in 2022 was only statistically significant when compared to 2016, 2017, and 2018. Note that the same instructor taught this course in 2016, 2018, 2021, and 2022.

TABLE II
PERCENTAGE OF STUDENT CHOICES IN 3 ASSIGNMENTS ("T" REPRESENTS INTERACTION TECHNIQUE AND "G" REPRESENTS GESTURE)

Group	A3			A4			A5		
	T1	**T2**	**T3**	**G1**	**G2**	**G3**	**T1**	**T2**	**T3**
Year 2021	93	74	19	79	91	18	86	70	17
Year 2022	75	53	21	80	82	39	84	66	34
CS Majors	84	64	20	79	88	29	86	68	27
Non-Majors	82	52	18	84	79	30	82	66	21
Graduates	86	86	14	71	100	43	86	100	29

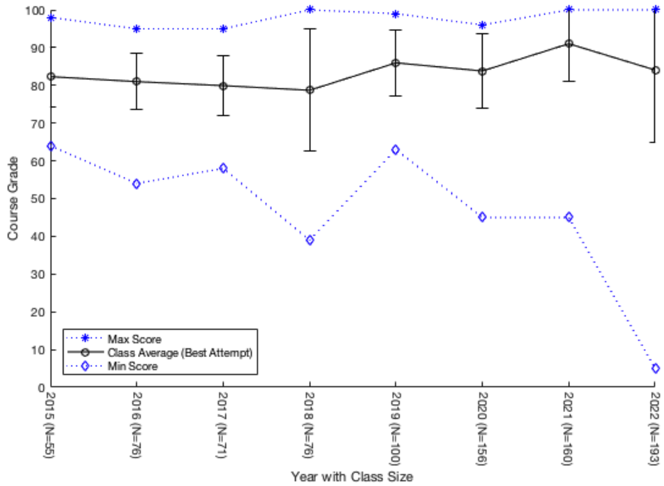

Fig. 7. Class averages with standard deviations (shown as error bars), maximum scores (denoted by *), and minimum scores (denoted by o).

We suspect the improvement observed in 2021 and 2022 is attributed to allowing students to take multiple attempts on the tests. However, in 2022, there was a group of students who failed the course because they failed the programming assignments and chose not to withdraw from the course, unlike the previous year. In particular, Figure 7 shows that the minimum score in 2022 is close to 0. This indicates some students did not engage in the course and did not drop out, hence, pulling down the class average.

Taking a closer look at the performance between majors, non-majors, and graduate students, we found their average performance as shown in Table III was not statistically significantly different via t-test analysis. To maintain the privacy of the small sample of students in that group, note that one of the averages is not presented in the table. Contrasting their failure rates, we found only 3 students failed in 2021 and no significant difference was found across the subgroups due to the small sample size. On the other hand, in 2022, 21 majors and 6 non-majors failed the course. The performance of these students is due to failing the programming project and a lack of engagement in the course.

C. RQ3: Student Perception from Teaching Evaluations

Lastly, we investigate student perceptions of the new course design in 2021 and 2022. Due to the small sample of graduate students, their evaluations were not released and therefore excluded from this analysis. Overall, the course evaluations reflecting student perceptions show that this course redesign was highly successful. In contrast to previous years that had the same instructor, we found that the student evaluations from the undergraduate population drastically improved. Quantitatively, we compare the average overall instructor rating on a 5-point scale, with 5 being the highest value. With the old course design, the average ratings were 3.4 (with a standard deviation of ± 1.43, a response rate of 45%, and 76 students enrolled in the course) and 3.5 (with a standard deviation of ± 1.18, a response rate of 78% response rate, and 76 students total) in 2016 and 2018 respectively. With the new course design, the average ratings increased to 4.94 (with a response rate of 56% from 160 students) and 4.60 (with a response rate of 55% from 193 students) in 2021 and 2022 respectively. Due to changes in the questionnaire at our university, we are unable to provide further statistical comparisons.

We also coded the open-ended responses in the student evaluations for these four years using thematic analysis [9]. Specifically, we reviewed the comments from each year for the questions[1] "What were the strengths of the course?" and "What were the weaknesses?" We segmented each student's comment into non-overlapping phrases and logged each phrase with an initial code. Thus, a verbose comment with multiple ideas was split into multiple phrases each with a separate code. Comments that do not address the question directly were not coded. For example, in answering the weakness question, if a comment included a statement about the strength or a new idea, then that phrase was not logged. Thereafter, we grouped similar phrases together and identified common themes. Due to privacy reasons, we only had one coder in this analysis.

We see from Table IV that the top four strengths mentioned in the new course implementation are organization (77), content/resources (66), professor (42), and the new test approach (27). Many students recognized the change in the course design and appreciated the consistency of the content delivery and test approach. Students also explained that they enjoyed the readings provided in the modules while getting interactive feedback and ensuring the materials were short, easy to understand, involved many examples, presented in different mediums, and had simple questions that test one's understanding. Although "professor" evolved as a theme, we suspect it is other aspects of the course that the students attributed to the professor. In addition, the new pre/post-test approach offers deliberate practice and affords students second chances (8) at test-taking, which in turn reduces students' stress levels (6). Although flexibility (14), synchronicity (12), and self-pace (15) were marked as different themes, these ideas were not mutually exclusive in how they were implemented in the new course design. Some students also mentioned that the synchronous classes helped them maintain progress in the course (6). As many comments revealed, many students appreciated how the whole course was put together as a whole (everything, 23). Although none of the students explicitly mentioned choice as a strength, a few students commented on the tutorial activities being helpful (3). The detailed counts

TABLE III
OVERALL COURSE AVERAGES FROM STUDENT SUBPOPULATIONS.

Year	CS Majors	Non-Majors	Graduate Students
2021	91.2	90.1	NA
2022	84.4	83.7	87.3

[1]In 2021, the questions were reformulated as: "Please identify what you consider to be the strengths of this course." and "Please provide suggestions on how this course might be improved."

TABLE IV
COUNTS AND EXAMPLES OF COMMENTS IN EACH THEME BEFORE (YEARS 2016 AND 2018) AND AFTER THE REDESIGN (YEARS 2021 AND 2022). THE BOTTOM 7 THEMES ARE UNIQUE TO THE NEW COURSE DESIGN.

Themes	Before	After	Examples
Professor	4	42	professor's knowledge and enthusiasm; professor was extremely accommodating; professor genuinely cared about the students
Support	2	8	many TA hours; [professor] and the TAs also made themselves available for help well outside of their own lab hours
Guest Speakers	5	2	guest speakers; insightful interviews; interviews with experts
Organization	1	79	very well organized; modular layout; well structured; it was engaging to have it split up the way it was
Clarity	2	13	expectations laid out bare from day one
Maintain Progress	0	6	made sure you were always on pace with the course; preventing [students] from falling behind
Fair Evaluation	5	14	marking rubrics are transparent; Realistic marking scheme; your grade directly reflects the effort you put in
Exams	5	7	No final; instead of midterms
Low Stress	0	6	reduced stress; It was not stressful; made testing less stressful
Project	8	16	project assignments were enjoyable; The final project is great to use in my portfolio; project assignments were fun and challenging
Design Activities	17	11	design challenges helped make the concepts more clear; the design challenges were fun and novel; Design challenges encourage critical thinking; lots of activities to improve teamwork skills
Content/Resources	31	66	Basic but full coverage of HCI;
Tool/Technique	6	0	prototyping; tracking design decisions
Relevance	23	7	important for the degree; practicality; relatable to my daily life; importance of HCI in the real world
Easy	2	1	This course was easy; it's pretty easy, which is a welcome break
Difficulty	1	8	assignments and tests are challenging but they also give a lot of information to benefit from; The tests were not only challenging they also really helped a lot in retaining the info
Apply Knowledge	5	10	apply what we have learnt from the modules; materials delivered are really hands-on; focus on hands-on collaborative learning; smaller emphasis on memorizing concepts than I expect[ed]
Nothing	3	1	None; Nothing; NA; –
Everything	3	23	I love this course; My favorite course; This course is interesting, fun, and motivational for my learning
Student Interest	3	7	getting students interested in the course material; This course definitely piqued my interest in the field; am more interested in it now than when the course began, which never happens
Student Feedback	6	2	really good [at] incorporating student feedback which I really appreciate; listening to student[s'] feedback
Participation	3	2	encouraged class participation; class time was for help; class time is activities
Teaching Style	2	19	taught in a very engaging and interesting way; A new way of teaching; approach to teaching; taught the content superbly; The style of how this course was taught was a huge strength
Online Format	1	15	perfectly adapted to fit an online environment; online format was very streamlined
Redesign Effort	0	5	You could tell [she] put A LOT of effort into building this course
New Test Approach	0	27	mini-tests; many small quizzes; focus on what we need to study; intent for the student to succeed
Second Chance	0	8	multiple attempts; focus on actually learning the content
Alternate Pathway	0	3	make up for lost marks with tutorials; The tutorials looked very interesting and helpful
Flexibility	0	14	work on material within a window; helpful when dealing with pressure from other courses
Asynchronicity	0	12	offline portion; asynchronous part gives a lot of flexibility
Self-Pace	0	15	study in their own time; learn at your own pace; Being able to go at your own pace
Total	**138**	**449**	

and examples of each theme under strengths are shown in Table IV. Overall, we believe the student feedback points to the pedagogical features of the new course design and reveals a drastic improvement in the course.

In total, we coded 587 strengths and 31 themes. Among these, 138 strengths belonged to the years 2016 and 2018 before the course redesign and 449 strengths belonged to the years the new course design in 2021 and 2022. Considering there were 94 respondents before the redesign and 197 respondents in the new design, the number of phrases coded indicates that the comments on strengths were nearly twice as verbose in the years with the new course design. Due to space limitations, we omit the discussion on weaknesses.

V. DISCUSSION

Our results revealed a positive impact of personalized learning for each of the research questions addressed in this paper. In this section, we discuss our work in the context of the related literature from Section II.

A. On Equitable Grading

Our course redesign adopted specific techniques that support equitable grading. Our analysis of academic performance also showed there was no significant difference across CS majors, non-majors, and graduate students. This result indicates that students from various backgrounds all have the same chance of success in this course. We also saw evidence that students made use of the flexible submission window and multiple test attempts which are strategies promoted by mastery learning and ungrading. However, there was a small percentage of students who scored low marks on the tests and did not pursue subsequent attempts. More work is needed to better understand the rationale behind these choices and how best to help students succeed. Although we did not explore equitable grading directly as one of our research questions, the design of our personalization features was motivated by an equitable lens to accommodate students with diverse academic backgrounds. Beyond the typical measure of using academic performance and student perceptions, alternative assessments of student learning outcomes need to be explored.

B. On Personalized Learning

Many students took advantage of the personalization features provided in this course. We observed students pursuing alternative learning activities, choosing different options in the project work, submitting their work over a long period of time, using varying numbers of test attempts, and expressing flexibility or having options as a strength in their evaluations. Although our initial goal was to accommodate diverse student skills and preferences, we also found evidence that suggested these features improved student learning where students' tutorial and test-taking patterns showed exploratory learning behavior that help them gain a deeper level of mastery. We also saw student feedback comments that pointed to the use of pre-test being a "brilliant idea" because it helped them focus on what to learn in the module. These are encouraging findings from our work and we believe personalization met its purpose.

From a practical perspective, instructors must evaluate the cost of developing a personalization feature and the benefit to the student's learning experience. Features such as alternate pathways using additional assessments, deliberate practice via pre-tests, and student choice in projects are typically quite demanding on the development overhead. On the other hand, flexible timing requires little to no added development work, but potentially more overhead in the administration and grading support needed. Allowing students multiple attempts on tests may at first appear to be low cost. Logistically, if the same question is used each time and the question has a small solution space (e.g., a multiple-choice question with 4 possible answers), students may resort to guessing rather than learning [18]. On the other hand, if the questions are open-ended and autograding is not possible, then additional grading support will be required for each attempt. Thus, course designers must decide carefully each type of personalization they wish to incorporate and consider the logistics involved.

Recall the personalization taxonomy from Section II that models adaptations centered around the core learning activity [27]. Our study demonstrated four ways to adapt assessments that are not included in the taxonomy. As a research contribution, we propose to extend the taxonomy by adding these four personalization features into their assessment component. Future adaptations to the taxonomy may also be needed due to changes in technology and pedagogy.

C. On HCI Perceptions

Overall, the students' perceptions of our new HCI course were very positive. This finding aligns with other studies that have also received positive feedback from students in courses that use personalized learning and mastery learning techniques. To decipher potential changes in student perceptions, we would ideally ask the students specific questions on what they think about the course and the topic. Unfortunately, we did not conduct a controlled study before and after the course redesign. As an alternative approach, we use the data from the coding analysis to approximate this issue. Considering the themes used in our coding analysis from Table IV, we believe that the strengths from the following categories are factors that influence student perceptions of HCI: "professor", "organization", "project", "design activities", "content/resources", "relevance", ' 'difficulty", "everything", "student interest", "teaching style", "new test approach", "second chance", and "alternate pathway". While some of these themes are arguably more related to course delivery, we believe they contribute to the student's ability to focus on learning the material. Taking the counts from these themes and normalizing them against the total counts reported in those years, we see that the old course design had 67.4% (93 out of 138) of the strengths in these themes while the new course design had 70.4% (316 out of 449). This comparison suggests we achieved an improvement in the student's perception of the HCI course.

Lastly, the increase in student perceptions may also be due to the increase in the instructor's teaching experience, since this study compares four years of course delivery from the same instructor.

VI. Conclusion

In our introductory HCI course, we sought to design personalized learning features to support the varying needs of the diverse student population in an equitable way. In particular, we redesigned the course by incorporating alternate pathways, flexible timing, multiple test attempts, and student choice in assignments as aspects of personalized assessments. Based on two years of data with 360 students, we found evidence of high uptake with all of these features. Specifically, we saw behavior that suggests the students tried different ways to master the content using tutorial submissions. A wide variability showing when students started the modules indicates that students learned at their own pace. Many students used multiple test attempts — some of whom took subsequent attempts despite already getting a perfect score. When several options were available, students chose different alternatives to work on. In comparison to previous offerings of the course taught by the same instructor, we saw a significant improvement in student performance and very positive feedback in the student evaluations both quantitatively and qualitatively.

Our findings suggest that personalized learning has a positive impact on the student's learning experience in HCI. In large university classes where student backgrounds and interests are diverse, personalized learning can be used to tailor the experience to accommodate the needs and preferences of each student. Our work serves as a case study to illustrate the successful implementation of several ways to personalize assessments that can be generalized to other courses. Much future work lies ahead for analyzing the impact of specific personalization features on student subgroups and investigating the potential benefits of other personalized learning designs. An interesting direction to pursue is to explore the relationship between a learner variable, their motivations and rationale for using or not using a personalization feature, and the impact on learning outcomes beyond academic performance.

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