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Designing an Effective Motivational Climate: Effects on Students' Effort and Achievement

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Abstract

We present a case study that demonstrates how instructors can intentionally design a positive motivational climate in online and hybrid courses. We also examine the extent to which students' perceptions of the motivational climate predict their effort and achievement across three different modalities (face-to-face [FTF], online, and hybrid) of the same course. We surveyed students in an undergraduate computer science course once a semester for three consecutive years (FTF in Year 1, online in Year 2, and hybrid in Year 3). Measures included motivation-related scales and final course grades. Our findings, based on survey responses from 981 students, demonstrate that it is possible to create a motivational climate in online and hybrid courses that is as good or better than the motivational climates in a FTF course. Across the FTF, online, and hybrid courses, students' perceptions of the motivational climate predicted their effort and achievement in similar ways, with perceptions of usefulness, interest, and success serving as the strongest predictors.

Keywords

Student Motivation, Effort, MUSIC Model of Motivation, Online Learning, Hybrid Learning, Student Engagement

Designing an Effective Motivational Climate: Effects on Students' Effort and Achievement

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We present a case study that demonstrates how instructors can intentionally design a positive motivational climate in online and hybrid courses. We also examine the extent to which students' perceptions of the motivational climate predict their effort and achievement across three different modalities (face-to-face [FTF], online, and hybrid) of the same course. We surveyed students in an undergraduate computer science course once a semester for three consecutive years (FTF in Year 1, online in Year 2, and hybrid in Year 3). Measures included motivation-related scales and final course grades. Our findings, based on survey responses from 981 students, demonstrate that it is possible to create a motivational climate in online and hybrid courses that is as good or better than the motivational climates in a FTF course. Across the FTF, online, and hybrid courses, students' perceptions of the motivational climate predicted their effort and achievement in similar ways, with perceptions of usefulness, interest, and success serving as the strongest predictors.

INTRODUCTION

In the spring of 2020, the COVID-19 pandemic forced many university faculty to reconsider how they taught their courses and to transition their courses from face-to-face (FTF) to fully online (Siegel et al., 2021). Even after the pandemic, some faculty have retained some of the teaching approaches that were found to be successful during the emergency remote teaching, sometimes by incorporating a hybrid modality that builds on the strengths of both FTF and online teaching (Brown 2022; Yuan 2022). In fact, online and blended learning approaches have been shown to work well, especially when used in combination with synchronous online activities and/or opportunities for face-to-face instruction (Zheng, 2023).

At the same time, there has been an increased interest in understanding the factors that can affect students' motivation and engagement within courses (e.g., Clarke et al., 2022; Jones, 2020). For example, Lishinski and Yadav (2019) noted the importance of considering students' motivation, attitudes, and dispositions, and that "the motivational and emotional parts of [students] are not complications to be abstracted away, but are endemic to the task of education" (p. 819). Unfortunately, COVID-19 not only affected students' mental health and well-being in the short-term (Son et al., 2020), it appears that some of these effects may have longer-lasting implications and could impact students' motivation and engagement in courses (McGill et al., 2023; Mooney & Becker, 2021).

The confluence of these three factors—an increase in online courses, an increase in the desire to understand students' motivation in courses, and the potentially negative effects of COVID-19 on students' well-being and engagement in courses—provided the impetus for the present study. We examined students' perceptions of the motivational climate across three years in a course that was delivered in three different modalities before COVID-19 (FTF) and during the COVID-19 pandemic (online and hybrid). This study serves two purposes. First, it provides a case study of how instructors can intentionally design courses to improve the motivational climate in courses and assess the climate using a validated measure of motivational climate. We describe how the changes in course instruction may have affected students' perceptions of the motivational climate within this context. This study can help educators and researchers to think about how an ambiguous concept such as "motivation" can be conceptualized and assessed in courses in ways that are consistent with current motivation theory to provide useful information to instructors. The second purpose of the study was to determine whether students' perceptions of the motivational climate predicted their effort and achievement in similar ways across the three course modalities. Understanding these relationships could help instructors to intentionally use motivational theory to better design motivationally appropriate instruction for each of these modalities.

LITERATURE REVIEW

Effects of Online Teaching and COVID-19

Some researchers have reported positive outcomes of the effects of online teaching in courses. For example, Allen and Vahid (2020; Vahid & Allen, 2020) investigated an online introductory computer science (CS) course over a seven-year improvement process and found that when designed properly, students' achievement can improve substantially in an online CS course (Vahid & Allen, 2020). They identified a few key components to the success of the online course, including synchronous meetings, strong learning content outside of class, simple class structure with many small tasks, and strong teachers who connect with students (Allen & Vahid, 2020). They also suggested that universities should offer the option of online courses because these courses offer scheduling flexibility, time savings, and speed for students, while improving the way that departments utilize classroom and teaching resources. Similarly, across three semesters, Nalbone et al. (2023) found that students in online courses obtained higher final course averages than the students in FTF courses. Lewis et al. (2021) found that most aspects of students' course experiences were either unchanged or improved (e.g., similar or lower stress levels, similar or less challenging course difficulty) during emergency remote teaching compared to pre-COVID, in-person teaching.

Other researchers have documented some of the negative outcomes of online teaching, such as increased dropout rates, increased student attrition, and higher drop/fail rates (Carr, 2000; Jamison & Bolliger, 2020; Lewis et al, 2021; Shaikh & Asif, 2022). Toti

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and Alipour (2021) found that the transition to remote teaching during the COVID-19 pandemic was challenging for students who reported that certain tasks (e.g., asking questions during video lectures and interacting with instructors) were particularly difficult. However, some of these negative perceptions may be related to poor online course design and inadequate pedagogy adopted by the faculty rather than to the course modality per se (Rovai & Jordan, 2004). Providing proper pedagogical guidance to students in an online course can be an especially challenging task for CS and engineering faculty because the students in these programs need to engage in hands-on programming activities (Basu, et. al., 2021; Krishnakumar, et. al., 2022). Therefore, well-designed online and hybrid courses may be crucial to fostering the engagement and the success of students.

It is unclear as to exactly how the emergency remote teaching that occurred during the COVID-19 pandemic has affected students' motivation in online courses. Kosycheva and Tikhonova (2021) surveyed students and determined that there were no significant differences in students' self-efficacy before and during the emergency remote learning. These students reported that the two main motives for continuing to attend online classes were their interest in the subject and desire to solve challenging problems. In contrast, Aguilera-Hermida (2020) reported that the self-efficacy and motivation of undergraduate and graduate students decreased during emergency remote teaching. It is likely impossible to generalize conclusions about the effects of emergency remote teaching due to the variation that may have occurred over different course designs and contexts. Therefore, in the present study, we provide specifics about the course and modalities so that readers can understand the context in which the findings were obtained.

Motivation in Computer Science Education

Although researchers have investigated the motivation of students in higher education courses, they have typically focused on one or a few motivation constructs in any one particular study. For example, in their review of student motivation in computing education, Lishinski and Yadav (2019) reviewed studies that included constructs such as self-efficacy, mastery and performance goal orientations, interest, and engagement. Other examples include a longitudinal study of an introductory CS course in which researchers considered the effects of improving course management on motivation constructs such as student interest and perceptions of usefulness (Nikula et al., 2011). Other researchers have investigated students' intrinsic motivation, extrinsic motivation, flow, expectancies, and values (McDermott et al., 2016; Säde et al., 2019; Sharmin et al., 2020). For instance, Säde et al. (2019) found that intrinsic value and usefulness were the most important factors influencing students' choice to start studying CS.

These types of studies are useful and can meet the intended purposes of the particular study. However, instructors should not be limited to considering only a few motivational constructs in their course; instead, researchers have found that it can be useful to consider a range of psychological constructs that affect student motivation because they likely have students in their courses that are motivated by a range of factors (Jones, Fenerci-Soysal, et al., 2022; Reschly & Christenson, 2022). Therefore, in the present study, we focused on five aspects of the motivational climate that have been shown to be associated with strategies that instructors can use to improve students' motivation and engagement (Jones, 2018), as discussed in the next section.

Motivational Climate in Courses

Student motivation has been defined as "the extent to which one intends to engage in an activity" (Jones, 2018, p. 5). When students are motivated for an activity, they are more likely to engage in an activity by thinking about the activity (cognitive engagement) or participating in it (behavioral engagement). Engagement is important because it tends to lead to improved learning and performance (Jones et al., 2023; Reschly & Christenson, 2022). Figure 1 shows the relationships between these variables for students within a course. The figure also shows that students' motivation is affected by the motivational climate in the course, which is affected by external (e.g., teaching strategies, ease of course, family, peers) and internal variables (cognition, affect, abilities). Students also make cost/benefit decisions to decide whether to engage in the course or in other activities (as noted by the "cost/benefit decisions" rectangle in Figure 1). Thus, student motivation is part of a cycle of factors that affect whether students choose to engage in course activities.

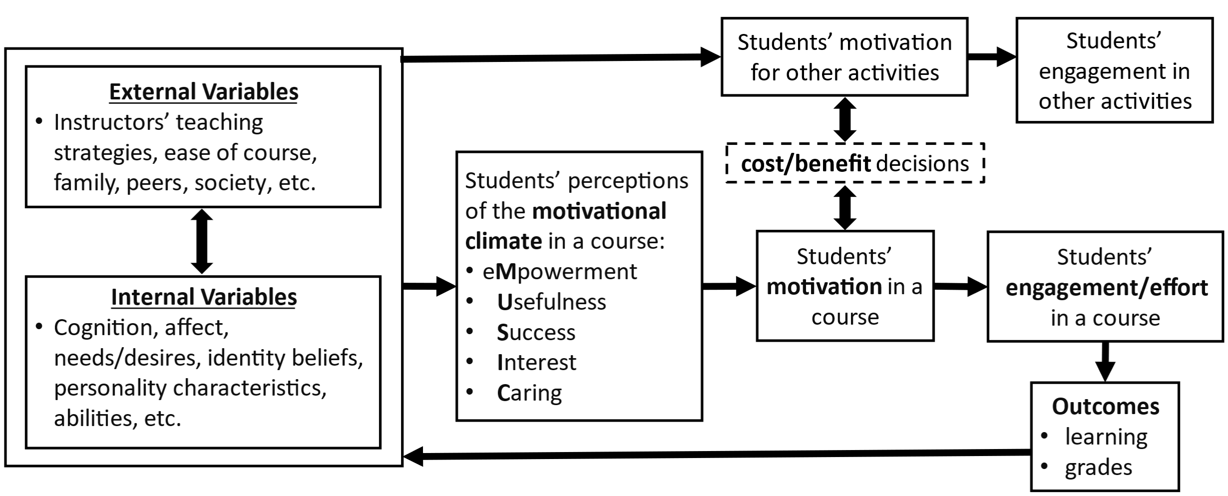

Figure 1. A Simplified Representation of the MUSIC Model of Motivation
Adapted from "Motivating Students by Design: Practical Strategies for Professors" by B. D. Jones, 2018, p. 13. Copyright 2018 by Brett D. Jones. Used with permission.

This approach to studying student motivation is part of the MUSIC Model of Motivation, (Jones, 2009, 2018, 2020) which focuses on five motivation variables that have been shown to influence students' motivation: eMpowerment, Usefulness, Success, Interest, and Caring (MUSIC is an acronym, www.theMUSICmodel.com). These five variables have been used as indicators of the motivational climate of a course, which is defined as "the aspects of the psychological environment that affect students' motivation and engagement within a course" (Jones, Miyazaki, et al., 2022, p. 1). These five variables have been studied by motivation researchers for a few decades (Reschly & Christenson, 2022; Wentzel & Miele, 2016) and have been shown to explain almost all (about 90%) of the variance in students' ratings of the instructor and course (Jones, Miyazaki, et al., 2022). We chose to focus on the five components of the MUSIC model in the present study because it provides a multidimensional approach to studying student motivation and the five components can be linked to strategies that instructors can use to improve student motivation.

In the MUSIC model, *empowerment* refers to students' perceptions of control and autonomy within the learning environment (Jones, 2009, 2018). Students are more motivated when they have some autonomy, such as by being able to make choices (Deci & Ryan, 2000). *Usefulness* refers to students' perceptions that what they are doing in a course is useful for their current or future goals. Students are more engaged in classes when they have higher perceptions of usefulness (e.g., Jones & Carter, 2019). *Success* includes students' perceptions that they can be successful in a course if they put forth effort. High perceptions of success have been linked to many different positive outcomes, such as increased effort and persistence (Bandura, 1986). *Interest* includes students' short-term situational interest, and their longer-term individual interest. Students who are interested in the course topics and find the course enjoyable tend to be more engaged in the course (Renninger & Hidi, 2015). Finally, the *caring* component refers to students' perceptions of the quality of relationships between themselves, the teacher, and other students in the course. The importance of care in higher education classes has been noted by several scholars (e.g., Parsons & MacCartney, 2023; Strachan, 2020). When students believe that others in the learning environment care about their learning and well-being, they are more likely to be motivated and engaged (Wentzel, 2022).

Students' MUSIC perceptions are correlated with their effort in FTF and online courses (Jones, 2010; 2019). However, when all five MUSIC perceptions are included in a statistical model at the same time to predict student engagement, some of the associations between the MUSIC variables and engagement are more significant than others depending on the course. As examples, in a large online undergraduate geography course, students' interest and perceptions of caring were found to be the strongest predictors of their effort in the course (Jones, Krost, et al., 2021). In contrast, in a large FTF undergraduate psychology course, empowerment and usefulness were identified as the best predictors of students' engagement in the course (Jones & Carter, 2019). As a third example, for undergraduate students in FTF English courses in China, the success and interest variables were the best predictors of students' effort in the course (Li et al., 2022).

THE PRESENT STUDY

One purpose of the present investigation was to present a case study of how an instructor can intentionally design a CS course to affect students' perceptions of the motivational climate, and then assess the impacts of the design on students' perceptions. Another purpose was to test whether the relationships hypothesized in the MUSIC model between motivational climate, engagement (i.e., effort), and grades could be confirmed across the three different course designs. In other words, do students' perceptions of the motivational climate predict their effort and achievement similarly in FTF, online, and hybrid courses? We chose to study an introductory CS course because it was a required course for many students, and the enrollment in the course was very high, with about 500 students enrolled each semester. Although the Year 1 course occurred before COVID-19 and the Year 2 and 3 courses occurred after the emergence of COVID-19, the present study was not designed as an experiment to compare variables pre- and post-COVID-19 because too many factors varied over the years. Instead, we view this investigation as a case study, and we will discuss the results within the context of COVID-19. Our specific research questions were the following:

> RQ1: To what extent do students' achievement and perceptions of the motivational climate, cost, ease, and effort vary across three different course modalities (i.e., FTF, online, and hybrid modalities)?
>
> RQ2: To what extent do the relationships between students' achievement and their perceptions of motivational climate, cost, and effort vary by course modalities (i.e., FTF, online, and hybrid modalities)?

For the first research question, we predicted that the following would occur across course modalities.

- *Empowerment* would be higher in the online (Year 2) and hybrid (Year 3) courses as compared to the FTF course (Year 1) because students had more autonomy given that (a) they had more control over when to study the "lecture" material in online and hybrid courses and (b) the labs in the online (Year 2) and hybrid (Year 3) courses were not timed. Researchers have found that online courses require students to be more self-disciplined and self-regulated to succeed than traditional FTF learning environments (Allen & Seaman, 2005). Because students' access to their instructors, peers, and campus resources are more limited in online courses, they need to maintain more active control over their learning process to succeed (Yen & Liu, 2009), which may lead to higher perceptions of empowerment.
- *Usefulness, interest, effort,* and *final grade* would be the same across all three course modalities because all modalities included similar topics and assignments.
- *Success* expectancies and the *ease of course* would be higher (and the *cost* of putting forth effort would be lower) in the hybrid (Year 3) course because the most difficult assignment was updated to streamline the program design and instructions. The assignment was also made more manageable by providing students with the code for the user interface, so they could focus on other parts of the assignment (e.g., back-end development).
- *Caring* perceptions would be lower in the online course (Year 2) than in the FTF (Year 1) or hybrid (Year 3) courses because students did not meet the instructors in person. As Tichavsky et al. (2015) noted, "Online

> courses present additional challenges for instructors in conveying a social presence in which students perceive them as 'real' people, beyond the facilitation of the course" (p. 7). Researchers have documented that decreased interactions between instructors and students, and a lack of sense of community in online courses can impact students' perceptions of caring negatively and hinder their ability to form relationships with their peers (Hehir et al., 2021; Jamison & Bolliger, 2020; Krishnakumar et al., 2022).

With respect to the second research question, we anticipated that cost and students' perceptions of the motivational climate—as measured by empowerment, usefulness, success, interest, and caring—would predict their effort, and that effort would predict their grade in the course. This model is consistent with the MUSIC model shown in Figure 1 and is based on the results of prior studies, which have shown relationships between these variables (e.g., Jones, 2010, 2019; Jones et al., 2023; Jones, Krost et al., 2021). We anticipated that success would predict not only effort, but also grade because students with high success expectancies may not need to put forth much effort to receive a high grade if they already have the abilities needed to earn a high grade.

METHODS

Participants

Participants were students enrolled in an introductory CS course in one of three semesters. The course was offered at a large public university in the southeastern US. The number of students who participated each year was 229 for Year 1 (FTF), 395 for Year 2 (online), and 357 for Year 3 (hybrid). Overall, 981 of the 1,439 students in the course (68.2%) consented to participate and were included in the study. The Year 1 (FTF) course took place prior to the COVID-19 pandemic in the Fall of 2019. The Year 2 (online, Fall 2020) and Year 3 (hybrid, Spring 2021) courses took place during the COVID-19 pandemic. The teaching approaches used in these courses were not emergency remote teaching; instead, they were designed intentionally prior to the beginning of the semester to be online (Year 2) and hybrid (Year 3).

Most of the students self-reported their sex as male (n = 750, 76.5%), while about a quarter reported it as female (n = 225, 22.9%) or other (n = 6, 0.6%). Almost half of the students self-reported their race/ethnicity as White or Caucasian (not Hispanic; n = 454, 46.3%) and about 40% reported it as Asian or Pacific Islander (n = 393, 40.1%). Other races/ethnicities reported were Black or African American (n = 40, 4.1%), Hispanic (n = 39, 4.0%), Native American (n = 1, 0.1%), more than one of the options provided (n = 45, 4.6%), or another race/ethnicity not provided as an option (n = 9, 0.9%). Most of the students were undergraduates, with 249 (25.4%) first year students, 506 (51.6%) sophomores, 193 (19.7%) juniors, 26 (2.7%) seniors, six master's students (0.6%), and one doctoral student (0.1%). Most of the students self-reported as a CS major or someone who intended to be a CS major (n = 599, 61.1%), and others reported being a CS minor (n = 163, 16.6%), a computational modeling and data analytics (CMDA) major (n = 158, 16.1%), a mathematics major (n = 13, 1.3%), or another major (n = 48, 4.9%).

Procedure

Students completed an online survey near the end of the course that included previously validated measures of the motivational climate (i.e., perceptions of empowerment, usefulness, success, interest, and caring), as well as measures of cost, ease, and effort in the course. Students received course credit for completing the survey. The survey included a consent form and only students who consented were included in the study. The study was approved by the Institutional Review Board at the university (IRB #17-057).

Description of Course

The course was an intensive computer programming course offered through a CS department that was part of a College of Engineering. The main topics for this introductory, 2000-level course were data structures and software design, and included: inheritance, polymorphism, class hierarchies; unit testing; array and linked implementation of data structures; introduction to algorithmic complexity; recursion and iteration; bags, sets, stacks, queues, lists, and trees; and introduction to searching and sorting. This 3-credit course also included a lab that allowed students to work on the programming assignments and receive assistance from a teaching assistant. The course was a requirement for all CS majors, all CS minors, all computational modeling and data analytics (CMDA) majors, and some math and neuroscience majors. The CS majors who were enrolled in the course were obtaining degrees within the CS department, while many of the CS minors were majoring in one of the other engineering departments at the university.

The same two instructors taught all three years of the course in which the students were surveyed. The categories of the assignments and their percentage of the final course grade were similar across all three course modalities. However, some minor updates were made to the course across the three years. Some lab assignments were removed and more short-form coding exercises were added: in Year 1, there were 14 lab assignments; in Year 2, there were 13 lab assignments; and in Year 3, there were 10 lab assignments. Over time, the course policies became more flexible and some of the projects were streamlined and simplified. A summary of the differences between course modalities by year is provided in Table 1 and more specific details are provided in the sections that follow.

Year 1, FTF

In Year 1, the in-person lecture was interspersed with clicker questions, and corresponding reading assignments and quizzes were assigned before the lecture. The basic structure of the course included reading and clicker quizzes, short-form coding practice, ethics reflections, design assignments, weekly lab programming assignments, and five larger programming projects. Students had pre-lab activities to help them prepare for the lab programming assignments; for example, writing unit tests or creating a design diagram. Lab programming assignments were to be completed during the 2.5-hour lab session and then students had an additional brief post-lab assignment due at the end of the week. The in-person lab sections were approximately 35 students who programmed in a classroom with the assistance of an undergraduate and graduate teaching assistant (TA). The lab and project programming assignments were typically to be completed individually, but the final programming project was designed and completed by students who worked together in teams. The course integrated some traditional textbook and eTextbook material, online programming practice, and automated grading (as described in Ellis et al., 2019).

Table 1. Differences in Teaching Approaches Between Course Modalities			
Approaches	**Year 1, face-to-face**	**Year 2, online**	**Year 3, hybrid**
Lecture	Reading quizzes In-person lecture Clicker questions	Lecture videos Checkpoints (success) Section quizzes (success)	Online material Attend in-person or online (empowerment) In-person coaching Short prog. practice in class (success)
Lab	Pre-lab In-person 2-hour lab Post-lab GTA and UTA 35 students 14 labs, drop 1, deduction up to 1 hour late	Pre-lab merged into lab Labs released 1 week in advance (empowerment) Online lab merged with online office hours 13 labs, drop 2, deduction up to 24 hours late	Online material Optional in-person labs (empowerment) 10 labs, drop 2, deduction up to 24 hours late, added many additional short prog practice exercises (success)
Policy updates	Late projects up to 3 days, 10 pts off per day In-person timed tests	Hardest project increased to up to 7 days 5 pts off per day (success) Online timed tests, test banks, no revisiting	Kept late policies Optional in-person or online test-taking (empowerment)

Student feedback on a survey at the end of the course in Year 1 was reviewed by the course instructors. In general, students responded positively to the course and took responsibility for their own learning success in the course. Some students provided comments that the TA grading was not always consistent and that they had difficulty scheduling a time to meet with the TAs. Most of the complaints were about the limited time for the labs and their struggles in completing the lab programming assignments under these constraints.

The survey comments led instructors to consider several course updates such as dropping two of the 14 lab scores from their final grades (previously only one of the lab scores was dropped), not having make-ups for excused absences, and reducing the amount of work necessary to complete the final two projects. In addition, the COVID-19 pandemic required the course to be fully online and there was an intensive effort over the next year to adapt course delivery to an online format. There was a simultaneous need to prepare students across the state for a new Master of Engineering in CS degree. Therefore, university stakeholders were eager to have a fully online offering and the university Technology-Enhanced Learning and Online Strategies (TLOS) center provided additional support to manage videos and set up material in the course learning management system, Canvas (as explained in Williams et al, 2022).

Year 2, Online

In Year 2, the fully online course differed from the FTF course in that the students watched videos asynchronously instead of attending class. The lecture content was divided into topics suitable for videos that were typically 3 to 15 minutes in length and interspersed with optional checkpoint quizzes and graded section quizzes, both of which contained additional and updated questions. Based on social cognitive theory (Bandura, 1986), which states that individuals' perceptions of success (i.e., self-efficacy) are influenced by their firsthand mastery experiences, the instructors anticipated that increasing the amount and frequency of feedback to students could lead to their increased perceptions of success as they practice their skills more often. The online lab programming assignments differed in that they were released a week in advance of the due date, which could contribute to students' increased perceptions of empowerment due to having more flexibility in when to complete the assignments. In addition, unlike the FTF course, students could complete the lab programming assignments on their own time and without a time limit. Face-to-face lab sessions were still provided in the online version of the course, but they were in conjunction with course office hours, and they were optional.

In Year 2, some course policies changed to address absences and increase flexibility, as was expected during the COVID-19 pandemic. The lowest two scores of both the homework and the lab assignments were dropped, as were the four lowest scores of the 38 possible quiz scores. The late policy for the most extensive individual project was extended and students were provided with the front-end code to lighten their load. A new team project was developed to make it easier for students to complete. Students were required to attend a virtual synchronous lab session for the design phase of the team project which assisted with online group dynamics and replaced one of the more challenging lab assignments (to increase students' perceptions of success).

Year 3, Hybrid

During Year 3, a hybrid course that used the online materials from Year 2 was developed, but students had the option of attending lecture and lab either in-person or online (which could lead to increased perceptions of empowerment). For both the in-person and online lecture, the instructors gave some announcements and a few tips, but then focused on answering questions while students worked on short-form coding exercises. In all offerings, students were supported with an active online discussion forum (i.e., Piazza) and extensive office hours by over 15 instructors and many graduate and undergraduate TAs.

By Year 3, improvements based on the Year 1 (FTF) student survey were implemented. The design, specifications, and testing feedback for the most challenging individual project were overhauled and streamlined to increase students' success. Additionally, the layout of the lab assignments was consolidated and no longer had both pre-lab and lab instructions because students were not required to complete the labs during the lab period. Also, two lab assignments were merged and two were removed, so the total number of lab assignments was only 10. Six of the labs still had post-lab assignments. Meanwhile, the number of short-form coding exercises was increased significantly to over 90 (which could help students obtain feedback more often and contribute to their success over time). In Year 3, there was also a slight adjustment made to the auto-grading tool that provided students additional feedback to identify bugs in their programming assignment (as explained in Senger et al., 2022).

MEASURES

The items in the measures presented in this section (except for grades) were rated on a 6-point Likert-format scale with descriptors at each point (1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Somewhat disagree*, 4 = *Somewhat agree*, 5 = *Agree*, 6 = *Strongly agree*). Students completed these measures as part of the online survey and the items were presented randomly to each student in a different order to avoid any potential bias due to item order.

Motivational Climate

The motivational climate was assessed using the 26-item MUSIC Model of Academic Motivation Inventory (College Student version; Jones, 2012/2022) that includes five scales: Empowerment (5 items), Usefulness, (5 items), Success (4 items), Interest (6 items), and Caring (6 items). Each scale assesses students' perceptions of the corresponding MUSIC model component. An example item from each scale follows: "I have the freedom to complete the coursework my own way" (Empowerment scale), "In general, the coursework is useful to me" (Usefulness scale), "I am confident that I can succeed in the coursework" (Success scale), "The coursework is interesting to me" (Interest scale), and "The instructor cares about how well I do in this course" (Caring scale). The complete MUSIC Inventory is provided in the *User Guide* (Jones, 2012/2022) along with instructions and validity information. The internal consistency reliability of the scale scores has been shown to be very good in other studies of undergraduate students (α = .82 to .87 in Chittum et al., 2019; α = .91 to .96 in Jones and Skaggs, 2016; α = .84 to .94 in Jones and Wilkins).

Time Cost

The extent to which students did not have the time to put into the course was measured using a three-item Time Cost scale. This scale was used in Jones, Krost, et al. (2021, α = .86) and was originally based on a scale developed by Kosovich et al. (2015). The scale items include (1) "This course requires too much time," (2) "Because of other things that I do, I don't have time to put into this course," and (3) "I'm unable to put in the time needed to do well in this course."

Ease

The extent to which students perceived the course to be easy was measured using the three-item Ease of Course scale (Jones, Krost, et al., 2021). The items in the scale include: (1) "This course is very easy for me," (2) "I don't need to work my hardest to get a high grade in this course," and (3) "In this course, I can get the grade I want with very little effort." This internal consistency reliability has been shown to be acceptable in other studies of undergraduate students (α = .73, Jones, Krost, et al., 2021; α = .82, Jones, Miyazaki, et al., 2022).

Effort in the Course

The amount of effort that students believe that they put forth in the course was measured using the 4-item Course Effort scale (Jones, 2019). An example item is, "In this course, I put forth my maximum effort", and the complete scale is available at Jones (2012/2022). The internal consistency reliability for the scores was good in other undergraduate courses (α = 0.93, 0.87, 0.94, 0.83, and 0.79 in Jones, 2019; α = 0.87 in Jones, Krost, et al., 2021).

Achievement in the Course

Achievement in the course was assessed using students' final end-of-course grade as a percentage that ranged from 0% to 100%. The instructors had calculated students' grades similarly in all three modalities with about one-third of the grade based on exams, one-third based on projects, and one-third based on labs, homework, and participation.

ANALYSIS

We computed the descriptive statistics, correlations, and Cronbach's alpha values for all of the study variables using SPSS version 27. For all of the other statistical analyses (i.e., MANOVAs, path analyses), we used SAS (Version 9.4). We set the alpha value at .01 to minimize the risk of a Type I error because we conducted multiple statistical tests.

To determine whether students' achievement and perceptions of the motivational climate, cost, effort, and ease varied across course modalities (RQ1), we conducted a one-way MANOVA to compare the means between courses. We identified the source of differences by conducting a one-way ANOVA for each dependent variable and used the Tukey-Kramer test to examine the multiple comparisons (Kramer, 1956; Tukey, 1953).

To determine whether the relationships between students' achievement and perceptions of motivational climate perceptions, effort, and cost varied by course modalities (RQ2), we conducted multi-group path analyses. Specifically, we first fit an unrestricted model (see Figure 2) to all three groups (i.e., the FTF group, the online group, and the hybrid group), followed by a restricted model in which we equated the following eight path parameters across the three groups: the five motivational climate (MUSIC) variables to effort, cost to effort, success to grade, and effort to grade. The invariance test of the eight path parameters, based on the comparison of model fit between the unrestricted and restricted models, can reveal if the relationships of interest vary by course modalities. We used the MLSB/MLM estimation method (i.e., maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic) because it can accommodate data from nonnormal distributions and generate scaled fit indices (Satorra & Benler, 1994). We only included the students who did not believe that the course was easy. When students believe that the course is easy, they do not need to put forth effort (Jones, Krost, et al., 2021). Because effort was central to the model tested, the model was only applicable to students who disagreed that the course was easy. Consequently, we only included students who rated the course ease as less than 4.0 (n = 801, 82% of students).

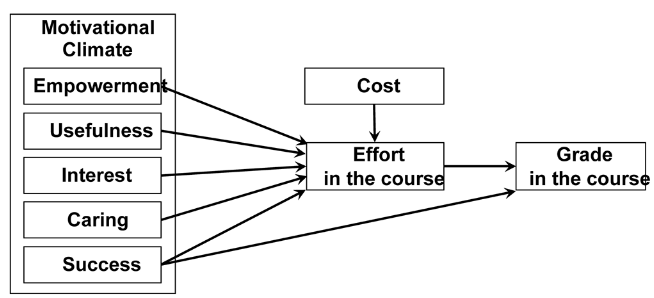

Figure 2. The Part of the MUSIC Model of Motivation Tested in This Study

RESULTS

Descriptive Statistics, Correlations, and Reliabilities

The variable means and distributions for all students in the study is provided in Table 2. Students' perceptions of the MUSIC compo-

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Table 2. Correlations, Cronbach's Alpha Values, Means, and Measures of Distribution for the Variables

Variable	M	U	S	I	C	Cost	Ease	Effort	Grade
Empowerment (M)	1								
Usefulness (U)	.45	1							
Success (S)	.49	.49	1						
Interest (I)	.67	.62	.51	1					
Caring (C)	.54	.46	.45	.58	1				
Cost	-.33	-.28	-.50	-.33	-.22	1			
Ease	.26	.06a	.47	.16	.11	-.29	1		
Effort	.22	.33	.17	.36	.25	-.12	-.24	1	
Grade	.16	.16	.42	.21	.17	-.30	.25	.22	1
α	.88	.90	.85	.88	.89	.75	.84	.88	n/a
M	4.3	5.2	4.8	4.4	4.8	3.4	2.8	4.8	87.9
SD	1.0	0.7	0.8	0.9	0.8	1.1	1.2	0.9	6.8
Skewness	-0.69	-1.29	-0.73	-0.71	-1.06	0.17	0.46	-0.97	-0.97
Kurtosis	0.48	3.02	0.76	0.78	2.23	-0.34	-0.27	1.36	1.44

Note. N = 981. $p < .001$ for all of the correlations unless noted otherwise.
[a] $p = .09$.

nents ranged from 4.3 (4 = *Somewhat agree*) to 5.2 (5 = *Agree*). The mean for time cost was 3.4 (3 = *Somewhat disagree* and 4 = *Somewhat agree*), the mean for course ease was 2.8 (3 = *Somewhat disagree*), and the mean for Course Effort was 4.8 (5 = *Agree*). The grades ranged from 54.4% to 99.3% with a mean of 87.9%. The skewness and kurtosis values were acceptable for all of the variables (|< 2|) except for usefulness and caring, which had slightly higher kurtosis values of 3.02 and 2.23, respectively, because some students rated both of these constructs a 6, which was the highest scale value. The Cronbach's alpha (*α*) values were good to excellent for all of the scales (George & Mallery, 2019) and ranged from .85 to .90 for the MUSIC Inventory scales. Similar to other studies of undergraduate students (e.g., Jones & Skaggs, 2016; Jones, Krost, et al., 2021), the MUSIC variables were moderately correlated (r ranged from .45 to .67).

Results for Research Question 1

The MANOVA analysis was statistically significant (Wilk's Λ = .881, $p < .001$); therefore, we conducted one-way ANOVAs. Statistically significant differences were identified between semesters for all of the variables except usefulness and interest (see Table 3). The Year 3 (hybrid) students reported higher values than the Year 1 (FTF) students for empowerment, success, effort, and grade, and a lower value than Year 1 students for cost. The Year 2 (online) students generally reported values similar to the Year 1 and Year 3 students; however, compared to the Year 1 students, they reported lower caring and cost, and higher effort and earned higher grades. A summary of how these results compare to our predictions is provided in Table 4.

Results for Research Question 2

To answer RQ2 and compare the results across course modality (i.e., FTF, online, and hybrid), we conducted a multi-group analysis and fit both unrestricted and restricted models to all three group. The fit indices shown in Table 5 for the unrestricted model were acceptable: SRMR (Standardized Root Mean Residual) < .08, RMSEA (Root Mean Square Error of Approximation) < .08, CFI (Comparative Fit Index) ≥ .95, NNFI/TLI (Non-Normed Fit Index/Tucker-Lewis Index) ≥ .95 (Hu & Bentler, 1999; Kline, 2013). The scaled chi-square difference tests (Satorra & Benler, 2010) indicated no significant difference between the unrestricted and restricted models, which indicated that the model does not vary by course modality.

Table 3. Means, Standard Deviations, and One-Way Analyses of Variance for the Study Variables by Course Modality

Variable	Year 1, face-to-face		Year 2, online		Year 3, hybrid		One-way ANOVA	
	M	*SD*	*M*	*SD*	*M*	*SD*	*F*(2, 978)	η^2
Empowerment	4.1[a]	0.9	4.3[a,b]	1.0	4.4[b]	0.9	8.13***	.016
Usefulness	5.2	0.7	5.2	0.7	5.2	0.7	0.05	< .001
Success	4.7[a]	0.8	4.8[a,b]	0.8	4.9[b]	0.8	7.18 ***	.014
Interest	4.4	0.8	4.4	1.0	4.5	0.9	1.36	.003
Caring	4.9[a]	0.8	4.7[b]	0.9	4.8[a,b]	0.8	6.51**	.013
Cost	3.7	1.1	3.4[a]	1.1	3.3[a]	1.0	9.90***	.020
Ease	2.7[a,b]	1.1	2.7[a]	1.1	2.9[b]	1.2	4.78**	.010
Effort	4.5	1.0	4.9[a]	0.8	4.8[a]	0.8	10.20***	.020
Grade	86.2	6.8	88.1[a]	6.5	88.7[a]	6.9	9.62***	.019

Note. n = 229 in Year 1 (FTF), n = 395 in Year 2 (online), n = 357 in Year 3 (hybrid). ANOVA = analysis of variance.
[a,b]Values in the same row with the same superscript are not statistically significantly different.
$^{**}p < .01$. $^{***}p < .001$.

Table 4. *Differences Between FTF and the Other Two Modalities*

	Year 1, face-to-face	Year 2, online		Year 3, hybrid	
	Baseline	Prediction	Result	Prediction	Results
Empowerment	—	Higher	— a	Higher	Higher
Usefulness	—	—	—	—	—
Success	—	—	— a	Higher	Higher
Interest	—	—	—	—	—
Caring	—	Lower	Lower	—	—a
Cost	—	—	Lower	Lower	Lower
Ease	—	—	—	Higher	—b
Effort	—	—	Higher	—	Higher
Grade	—	—	Higher	—	Higher

Note. A dash (—) represents the baseline (FTF) or no difference from FTF.
[a] The value was the same as the values for the other two modalities.
[b] The hybrid value was higher than the online value, but the same as the FTF value.

Table 5. *Chi-squared Values and Fit Indices for the Path Analyses*

	Unrestricted	Restricted
No. of parameters	93	77
χ^2	26.47	46.01
df for χ^2	15	31
p for χ^2	0.033	0.040
SB-scaled model χ^2	26.88	40.00
p for SB-scaled model χ^2	0.030	0.129
SRMR	0.022	0.042
RMSEA	0.055	0.033
RMSEA, Lower 90% CI	0.017	< 0.001
RMSEA, Upper 90% CI	0.087	0.060
CFI	0.992	0.994
NNFI/TLI	0.957	0.984
Scaled χ^2 difference	14.97 (p = .527)	

Note. The format analysis compared Year 1 FTF (n = 192), Year 2 online (n = 334), and Year 3 hybrid (n = 275). SRMR = Standardized Root Mean Residual; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; NNFI/TLI = Non-Normed Fit Index/Tucker-Lewis Index.

Table 6 provides the unstandardized and standardized estimates for the paths in the model shown in Figure 3 for the restricted model. Usefulness and interest were the only two MUSIC variables that were significantly, positively related to effort, while empowerment was significantly, negatively related to effort. Success and effort were significantly related to the grade in the course.

DISCUSSION

Variations in Motivation and Achievement Variables

Our first research question asked about the extent to which students' average achievement and perceptions of the motivational climate, cost, ease, and effort varied across three different course modalities (i.e., FTF, online, and hybrid). We identified several differences across modalities which are summarized in Tables 3 and 4. Overall, the hybrid course led to the most positive outcomes, followed by the online course. The FTF course was generally the least desirable in that students rated aspects of the motivational climate lower, put forth less effort, and achieved lower grades. These findings lead us to conclude that hybrid and online introductory CS courses are not only an acceptable alternative to FTF courses, but that they can be an improvement over FTF courses. We believe that this finding is due to the fact that the instructors took time to obtain feedback from students and intentionally designed the online and hybrid modalities in an attempt to adhere to effective teaching practices and the MUSIC model design principles (Jones, 2018). It is possible that some of the positive outcomes of the online and hybrid modalities would also have been documented if the instructors had made similar changes to the FTF course; unfortunately, we are not able to test this prediction in the present study due to the study design. Nonetheless, the findings do highlight the point that online and hybrid courses can be designed as an improvement to FTF courses with respect to the motivational climate and student effort and achievement. These results are consistent with other studies documenting that students achieve the same or higher grades (McFarlin, 2008; Muller

Table 6. *Unstandardized and Standardized Estimates for the Paths Between the Variables in the Restricted Model*

Path		B	SE	T	p	β
M	Effort	-0.110**	0.041	-2.71	.007	-0.110
U	Effort	0.223***	0.055	4.06	<.001	0.152
S	Effort	-0.004	0.065	-0.06	.952	-0.003
I	Effort	0.252***	0.056	4.51	<.001	0.214
C	Effort	0.092	0.048	1.93	.053	0.076
Cost	Effort	-0.022	0.036	-0.61	.542	-0.025
Effort	Grade	1.442***	0.304	4.75	<.001	0.193
S	Grade	2.881***	0.317	9.08	<.001	0.334

Note. n = 192 for Year 1 FTF, n = 334 for Year 2 online, and n = 275 for Year 3 hybrid.
**p < .01. ***p < .001.

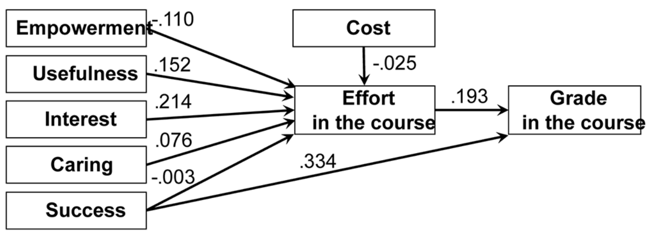

Figure 3. Standardized Path Estimates Between the Study Variables

& Mildenberger, 2021) and are more motivated (Ward, 2004) in hybrid courses compared to traditional lecture courses.

It is especially noteworthy that students' motivational climate perceptions, effort, and grades in the online section (Fall 2020) and hybrid section (Spring 2021) during the COVID pandemic were the same as or higher than in the FTF section (Fall 2019) prior to the pandemic (except for caring in the online section). These findings demonstrate that regardless of how the pandemic affected students' experiences at the university and in CS courses, it is possible to design instruction within those contexts that have positive effects on the motivational climate, effort, and grades within a CS course. Further research is needed to understand (a) how the COVID pandemic affected students' motivation-related beliefs, (b) whether any changes in motivation-related beliefs are temporary or more long-lasting, and (c) how these effects may vary by gender, race/ethnicity, and other individual characteristics (for example, students' sense of belongingness in CS has been shown to vary by gender and race/ethnicity in Mooney and Becker, 2021). In the following sections, we examine the results related to each study variable in more detail.

Motivational Climate

Students rated empowerment significantly higher in the hybrid course than in the FTF course; the online course was not rated significantly different from the hybrid or FTF course for empowerment. Students' increased empowerment (autonomy) perceptions in the hybrid course could be due to the fact that the instructors intentionally designed the course to include some more empowering elements. For example, students had more freedom as to when and how they completed course assignments, which is an aspect of courses that students have reported to give them control in online courses (Jones et al., 2012). Each week's work was released ahead of time, so students had up to 10 days to complete the work. Also, with the videos in the hybrid course, students were not required to listen to lectures at a specific time, they had the freedom to skip content or listen to it at a faster rate, and they had over one week to complete the lab programming assignments instead of being confined to their lab time.

The online course was also designed with some empowerment features, but students did not rate their empowerment higher in the online course than in the FTF course. It may have been that the option of whether or not to attend the in-person lectures and labs in hybrid courses (Year 3) was more empowering than in Year 2 when there was no synchronous lecture, and online labs were merged with office hours. Perhaps having no lab assignments for some weeks felt more empowering in the hybrid version even though they had an increase in short-form programming exercises. The increased number of assignment grades that they were allowed to omit (drop) from their final grade likely increased the students' empowerment to choose to miss an assignment.

As predicted, students rated success higher in the hybrid course than in the FTF course, likely due to the intentional changes in design implemented by the instructors. In the hybrid course, the larger projects were designed to be less overwhelming, students did not need to complete the labs under time constraints, and a significant amount of smaller practice assignments were added. The short-form coding questions that were added in the hybrid course likely increased students' perceptions of effort because the questions added to the workload. However, such practice can also contribute positively to their perceptions of success (self-efficacy). Therefore, these perceptions of success may be unrelated to whether the course is online or FTF; and instead, related to the changes in the assignments that could be implemented in any course modality. In the future, these types of changes to could also be made to assignments in the online course in an attempt to increase students' success perceptions.

Students rated caring lower in the online course than in the FTF course, while they rated the hybrid course similar to the FTF and online courses. Compared to the FTF course, the online course may have slightly lowered students' perceptions of caring because there were fewer opportunities for direct interactions between the students and the instructors and TAs. For example, students had opportunities to engage with the instructors and TAs before and after FTF class, and during in-person labs and office hours, which possibly humanized instructors in ways that made it more apparent that they cared about students' success. There were also more opportunities for friendly small talk and positive non-verbal communication (e.g., smiling) during FTF classes. Giray (2021) noted that students in their study preferred a FTF environment because of perceived instructor support and opportunities to collaborate and interact with other students. To create a more caring climate in the online course, it may be necessary for the instructor to communicate more through announcements and/or emails. Researchers have documented that students in online courses perceive instructors to be caring when they communicate frequently via email to the class (e.g., reminders, notifications), respond promptly to email inquiries, and communicate in a friendly or encouraging tone (Jones, Watson, et al., 2012).

As predicted, students across all three modalities reported almost identical values for usefulness and interest. This finding may be due to the fact that the content and activities were similar across the modalities. Although some researchers note that students are less interested in online courses because they may not enjoy using computers or they may prefer traditional classes due to time cost and effort required to learn necessary computer skills (Milligan & Buckenmeyer, 2008), that was likely not true in the present study because these students were familiar and comfortable to working and interacting online as CS majors or majors closely related to CS.

Cost, Ease, and Effort

Students reported putting forth more effort in the online and hybrid courses than in the FTF course. They also reported that the time cost of participating in the course was lower than in the FTF course. Although we did not anticipate these findings, they are a positive outcome because they suggest that students in the online and hybrid courses did not mind putting forth more effort because they believed that it was worth their time to do so. They also found the hybrid course slightly easier than the online course, whereas the FTF course was not perceived to be any easier or harder than the hybrid or online courses. We had predicted that the hybrid course would be easier than the FTF course due to the changes made to the individual programming assignment.

Students in the online and hybrid courses may have put forth more effort than students in the FTF course because they had all week to spend more time on their lab programming assignments (e.g., deliberating over small coding bugs) to earn a very high score. Also, the time students spent either watching the videos or hunting for materials to correspond with assignments, may have exceeded the amount of time they would have spent in an in-person lecture and reading the textbook. Because the videos included more demonstrations, they consumed more total time than live lectures in FTF courses. In the online and hybrid modalities, students also needed to take more ownership for keeping up with the material than simply showing up to an in-person class with fixed content.

Achievement

Students earned higher grades in the online and hybrid courses than they did in the FTF course. The lower grades in FTF course are not surprising because in the online and hybrid courses project specifications were refined, and students were provided with more information that was needed to complete the individual project (i.e., they were given the programming code for the front-end development). These changes likely led to assignments that were more manageable and increased grades on this particular assignment. And although others have found that FTF courses can work well (Allen & Vahid, 2020; Vahid & Allen, 2020), our study provides support that these topics can also be taught effectively in an online or hybrid environment. More research is needed to examine which elements of instruction help to foster a positive motivational environment and achievement in an online learning setting.

Relationships Between Motivation and Achievement Variables

Our second research question examined the extent to which the relationships between students' achievement and their perceptions of motivational climate, cost, and effort varied by course modality. We found that the relationships between these variables (as shown in Figure 3) were consistent across the FTF, online, and hybrid modalities. In other words, the importance of the relationships between variables was the same regardless of the modality of the course. These findings provide evidence that the MUSIC model can be used across different types of courses in a similar manner. Although prior studies had documented these relationships between these variables in online (Jones et al., 2021) and FTF (Jones & Carter, 2019) courses, this is the first study to compare these relationships within the same course across different modalities.

Usefulness and interest were the two most significant positive predictors of effort, while empowerment was a negative predictor of effort. Given that caring was a marginally significant predictor of effort (p = .053), and success was a predictor of grades, all of the MUSIC variables were relevant to the model in some manner. The fact that empowerment is negatively related to effort is inconsistent with the MUSIC model theory and prior research demonstrating relationships between choices and effort (Patall et al., 2008). Although the correlation between empowerment and effort is positive (which is consistent with MUSIC model theory), when the other motivational climate variables are added to the model, and the students who rated the course as easy were removed, empowerment became a negative predictor of effort. This finding may indicate that when students are struggling, they put forth less effort when they have too much empowerment. Based on flow theory (Csikszentmihalyi, 1990), it is likely that students will put forth the most effort when the challenge is at an appropriate level (i.e., the course activities are neither too hard nor too easy). It is also possible that empowerment is a negative predictor of effort when we remove those who think the course is easy because the remaining students who appreciate the flexibility of the course are the ones who indicate empowerment as high and do not want to attend class or lab. It may be reasonable for the students who think the course is easy to not want to attend, but students who do not think it is easy likely need the support and instruction provided in class and lab. Future research could examine whether this relationship is similar in other courses or if this was an anomaly.

The fact that time cost did not predict effort may be because the time involved was reasonable and was not perceived as being too much time to spend on this course. The mean value for cost was 3.4, which is almost exactly in the middle of the scale (3.5 is exactly in the middle). Finally, effort and success were positively related to grades as predicted. These findings are consistent with the MUSIC model and indicate that students' perceived effort predicts their grades.

Overall, the relationships between the variables in this study are similar to the relationships documented in other studies and provide support for the general structure of the MUSIC model. However, the magnitude of the relationships between the variables are somewhat different for the CS course in the present study when compared to these same relationships in other studies that conducted similar regression or path analyses. For example, in a FTF undergraduate engineering course in the US, only empowerment (by peers), usefulness, and interest were significant predictors of their effort (Jones et al., 2014). As another example, in an online geography course in the US, interest and caring were the only two significant positive predictors of effort (Jones et al., 2021). In a different study conducted in a China with undergraduate students in a FTF English course, success and interest were the only MUSIC variables that significantly predicted effort (Li et al., 2022). These findings indicate that it is important to measure all five MUSIC components of the motivational climate because the magnitude of their relationships with effort can vary by course. What is interesting about the present study is that the magnitude of these relationships between MUSIC and effort did not vary by modality. This finding indicates that the course topic (e.g., CS, English)— and perhaps the role of the course within students' degree studies—may influence the magnitude of these relationships more than the modality of the course.

IMPLICATIONS AND CONCLUSIONS

Overall, this case study demonstrates how an instructor can intentionally design a course to affect students' motivation, and then assess the impacts of the course design on students' perceptions of the motivational climate. Measuring all five aspects of the motivational climate provided a more comprehensive view of students' perceptions than if we had only investigated one or a few of these perceptions (e.g., self-efficacy, interest). Therefore, we have documented how a short survey administered to students can provide instructors with feedback that can be used to improve instruction.

One implication of this study for instructors, administrators, and the scholarship of teaching and learning literature more generally, is that it is possible to transition FTF courses to online and hybrid courses and maintain a similar or possibly "improved" motivational climate and learning experience. Through careful planning and implementation, the instructors were able to transition the FTF course to online and hybrid modalities without decreasing students' MUSIC perceptions, effort, or grades. In fact, students reported higher levels of empowerment, success, and effort in the hybrid course than they did in the FTF course. Students also earned higher grades in the hybrid and online courses than in the FTF course. These findings provide strong evidence that it is possible for online and hybrid courses to have benefits beyond those found in FTF courses. The non-experimental design used in this study does not allow us conclude that online and hybrid courses are more effective than FTF course in general, it simply informs us that it is *possible* for online and hybrid courses to have benefits over FTF courses.

Another implication is that the MUSIC Model of Motivation and the associated MUSIC Inventory can be used to provide instructors with feedback about how to improve courses. The inventory results were used in the present study to make improvements in the FTF course, which most likely led to students' higher perceptions of the motivational climate, effort, and achievement documented in the online and hybrid courses. Future studies could experimentally manipulate variables more systematically and provide a control group that would allow for causal inferences. However, even without conducting an experimental study, we were able to document significant changes in students' perceptions of the motivational climate and achievement.

Finally, we have provided evidence that students' perceptions of the motivational climate matter in CS courses because they are related to their effort and achievement in a course, regardless of course modality. Although prior studies have linked students' MUSIC perceptions to their effort/engagement and achievement in higher education courses (e.g., Jones et al., 2021; Jones et al., 2021; Jones & Carter, 2019), the present study demonstrated that these relationships also existed in CS courses; and therefore, the MUSIC model can be used to help CS instructors consider how students' motivational climate perceptions are related to their effort and achievement. Future studies can build on this foundation, such as by investigating how specific instructional strategies affect students' MUSIC perceptions, effort, and achievement using the MUSIC model.

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