



Disrupted Lessons in Engineering Robotics: Pivoting Knowledge Transfer From Physical to Virtual Learning Environments

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Abstract

This study examined the effects of an Arduino microrobot activity on college students' interest in robotics through three specific objectives: (1) determining how students' conceptual understanding regarding the basics of microcomputing and computer programming changes after engaging in an engineering robotics learning module, (2) assessing the impact of these changes on students' sense of competence in engineering robotics, and (3) explaining the role of students' perceived knowledge transferability in the relationship between their sense of competence and changes in their interest for pursuing engineering robotics. Participants ($n=58$) were recruited from two Engineering Physics courses and surveyed before (Time 1) and after (Time 2) an Arduino microcomputing learning activity. First, significant increases were reported post-activity for interest in robotics, as well as conceptual understanding of microelectronics and computer programming. Second, changes in the understanding of computer programming significantly predicted students' sense of competence at Time 2. Finally, high and low levels of competence and perceived knowledge transferability were related to changes in students' interest in robotics. Moreover, high levels of perceived knowledge transferability alone played an important role in students' interest in robotics. Transferring complex engineering ideas to novel situations was beneficial regarding students' learning gains associated with computer programming and with the Arduino microcontroller platform. An overview of the virtual lab architecture used is provided with suggested novel directions for teaching college-level courses about engineering robotics.

Keywords Robotics · Programming · Competence · Students · Interest · STEM · Knowledge transfer

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In the last decade, a growing number of studies have applied robotics to existing curricula to motivate students in their persistence toward STEM-related programs (Caron, 2010; Ivey & Quam, 2009; Yuen et al., 2014), while also increasing students' comfort level with practical applications of STEM (Grubbs, 2013). The latter is well-aligned with a critical goal in higher education and an important indicator

of educational success: The capacity to transfer or apply knowledge and skills that have been learned in a specific context into a novel context (Wang et al., 2020). Given how employers expect students to apply what they learned in schools immediately after graduation upon entry to the workforce, identifying factors that contribute to students' capacity building for knowledge transfer would be a valuable asset for curriculum development that also strives to meet this goal.

Recent digital technologies have shown great potential in making it possible to offer students authentic STEM learning experiences through gamification, visualization, and simulation (Ibáñez & Delgado-Kloos, 2018). Better performance outcomes have also been observed when digital applications are used to enhance student interaction, as well as develop STEM awareness and interest (Dalgarno & Lee, 2010; Rawat et al., 2018). Similarly, using open-source microcontroller technologies such as Arduinos during experimentations has also led to increases in students' problem-solving skills and self-confidence (Wahyuni & Analita, 2017) which in

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turn have resulted in significant learning gains in disciplinary knowledge (Papadimitropoulos et al., 2021). Moreover, technological advances have supported young students' understanding of science concepts, specifically procedural knowledge. For example, simulation environments provide worthwhile opportunities for students to exercise higher-order capabilities such as reflective thinking processes and abstraction, skills that are often measured as outcomes but in much older students (Falloon, 2019). Additionally, the effects of having participated in microcontroller and coding activities positively impact students' motivation toward STEM majors and careers (Bicer et al., 2018; Nite et al., 2020).

To date, most studies regarding knowledge transfer have focused on prior knowledge, cognitive load, and task difficulty (Billing, 2007; Day & Goldstone, 2012), without paying much attention to motivational factors that account for much of people's attitudes and behaviors (Belenky & Nokes-Malach, 2012; Burke & Hutchins, 2007; Perkins & Salomon, 2012). As such, this study uses the self-determination theory (SDT; Deci & Ryan, 1985a; Ryan & Deci, 2017) as a framework for understanding how certain motivational constructs influence students' perceived knowledge transferability (Bereby-Meyer & Kaplan, 2005) and their accrued interest in pursuing STEM disciplines (Wang & Degol, 2013). SDT-related variables applied in educational contexts have so far been recognized as reliable predictors of college students' motivation, learning behaviors, and overall academic performance (Hsu et al., 2019; Levesque-Bristol et al., 2020; Wang et al., 2020). For educational researchers and practitioners to design learning modules across the curriculum that have the characteristics to influence students' academic motivation and interest, understanding the quality of the associations between perceived knowledge transferability and SDT or other closely related variables (e.g., autonomy support, learning climate) would be imperative.

Theoretical Framework

Self-Determination Theory

This study is based on the self-determination theory (SDT), suggesting that individuals thrive in environments that satisfy the three basic psychological needs: autonomy, competence, and relatedness, which, in turn, foster learning, performance, and well-being (Deci & Ryan, 2015). In educational settings, autonomy refers to the freedom of choice provided by the instructor within a classroom structure. Competence is the ability to effectively accomplish tasks or master certain skills. This need is satisfied when instructors help students see the progress they are making in developing a skill through informational feedback. Relatedness denotes

feelings of connection and a sense of belonging through some form of interaction with peers, teachers, or learning artifacts. Empirical evidence has demonstrated that the satisfaction of these three needs is conducive to positive outcomes, which in turn enhances students' goal achievements (Jang et al., 2012).

Past research has shown how autonomy-supportive learning environments satisfy the three basic psychological needs, which then lead to more positive learning outcomes, including a greater sense of perceived knowledge transferability. While numerous studies have provided evidence of predictive paths leading to improved learning outcomes (Levesque-Bristol et al., 2010), empirical evidence on SDT and knowledge transferability is still scarce, especially in the field of education. So far, most studies have focused on demonstrating the positive relationship between self-determined motivation and college students' perceived knowledge transferability (Hsu et al., 2019; Levesque-Bristol et al., 2020; Wang et al., 2020); however, there seems to be a need to examine the unique effects of not only motivation but also other sources of variance influencing college students' perceived knowledge transferability.

Perceived Knowledge Transferability

Perceived knowledge transferability is the belief that what has been learned is important and can transfer beyond the immediate learning environment and into a new situation (Belenky & Nokes-Malach, 2012). The information presented is viewed as relevant to the learner, and therefore important to know, which enhances the likelihood of learning (Martin & Dowson, 2009). Evidence suggests that knowledge transfer is more likely when individuals feel competent in the subject matter because they are better able to cope with constraints in the new environment where they are trying to apply previously learned skills (Billing, 2007; Wang & Haggerty, 2009). As such, competence has been identified as a key variable in the learning process and a major antecedent of knowledge transfer and future performance (Hsu et al., 2019; Wang et al., 2020). Previous research suggests that college students who have had substantial learning experiences can provide accurate and appropriate data regarding their perceptions and ability to transfer knowledge to a novel setting or problem (Fedesco et al., 2019; McKay et al., 2015; Zilvinskis et al., 2017). It is, therefore, important to conduct longitudinal studies that would allow the evaluation of long-lasting effects of a learning experience and also provide feedback on what specific components of a learning activity influence students' competence, knowledge transfer, and interest in the field.

In the current study, perceived knowledge transferability refers to the extent to which students perceive the

connections between their initial learning in a given context and a new situation in which they can confidently apply the newly acquired knowledge. Although the connection between competence and knowledge transferability makes intuitive sense, this link has not been well explored. In addition, the focus of previous studies (Hsu et al., 2019; Levesque-Bristol et al., 2020; Wang et al., 2020) was not to examine the relationships between SDT-related variables and college students' perceived knowledge transferability, but rather on the differential role of various types of self-determined motivation or the extent to which some basic psychological needs were more salient in certain situations. In the present research, we use SDT as a framework for understanding how college students' perceived knowledge transferability may be influenced by competence and how this relationship impacts their interests in engineering robotics.

The Present Research

In line with previous research (Hsu et al., 2019; Levesque-Bristol et al., 2020; Wang et al., 2020), the current study used SDT as a framework to explore how competence in computer programming influences college students' perceived knowledge transferability and, ultimately, their interests in robotics. Students were recruited from two engineering physics courses that implemented a four-lab sequence on robotics based on the Arduino microcontroller platform (an open-source hardware and software prototyping platform) as an enrichment to the existing curriculum. The following research questions guided this study:

1. How do students' conceptual understanding of the basics of microelectronics and computer programming change after engaging in an engineering robotics learning module?
2. What is the impact of the changes in students' understanding of the Arduino platform and computer programming on their sense of competence in engineering robotics?
3. What is the role of students' perceived knowledge transferability in the relationship between their sense of competence and changes in students' interest in engineering robotics?

Based on prior research demonstrating learning gains after having interacted with digital applications (Dalgarno & Lee, 2010) and simulation environments (Martin & Bollinger, 2018), we expected students who participated in the four-lab sequence of Arduino microrobot learning activity to develop a more refined conceptual understanding of the basic concepts of microelectronics and computer

programming over time (H1). Second, unlike changes in students' understanding of the Arduino platform, it was expected that changes in students' understanding of basic concepts in programming would be more significantly associated with their sense of competence (Tsai et al., 2019) (H2). Feeling competent plays a significant role in the learning of programming concepts and this was especially important given the pivot to online learning in mid-semester due to the pandemic because these labs were never intended to be delivered virtually or through simulations. The plan had always been for in-person robotic learning activities.

To adapt quickly and preserve the lab goals, the last two labs which were originally designed to be completed through experimental and hands-on activities were redesigned with the assistance of two teachers with programming backgrounds. When the pandemic lockdown started, a search began to look at virtual options and continue the labs without sacrificing the learning objectives. The existing virtual environments such as Tinkercad had limitations when it came to the design of an algorithmic strategy that used the sensors and motors of the robot to solve a problem. For example, although a motor could be controlled by the simulated Arduino in Tinkercad and rotate properly, it could not affect any physical simulation (i.e., movement in the virtual simulation). Consequently, we gravitated toward a new open-source library that was released in early development AVR8js (<https://github.com/wokwi/avr8js>). This library is a JavaScript simulation of the microcontroller chip that powers the Arduino Uno board, which means it can easily run in a browser. We developed a virtual environment by building the robot simulation as a 2D web game that is controlled with an Arduino simulation based on AVR8js. Additionally, to meet the specifications of the real hardware and provide a faithful representation of what labs 3 and 4 would have been in a physical environment, we also developed an electronic simulation to simulate servo motors and the ultrasonic sensor.

This pivot (i.e., from a physical to a virtual learning environment) was expected to facilitate student learning, allow for the applications of concepts acquired in the classroom to realistic scenarios in a virtual setting, and, ultimately, foster a sense of accomplishment. Finally, given that the Arduino microrobot labs were originally designed as a classroom activity and later pivoted to an online environment, we expected students' perceived knowledge transferability to future learning experiences to moderate the relationship between their sense of competence and changes in their interest in robotics (Martin et al., 2013) (H3). This is in line with past research showing how teaching students complex systems can lead to deeper understanding more easily and more quickly than traditional science instruction (Wilensky & Reisman, 2006) and help students transfer knowledge in different disciplines (Goldstone & Wilensky, 2008).

The conceptual model of the study is displayed in Fig. 1.

Methods

Context and Sample

The participants were students ranging from 18–19 years old from an urban, public college in Eastern Canada that offered 19 pre-university and 22 technical programs to more than 10 000 postsecondary students and was well-known for its competitive programs in STEM fields. Participants ($n = 58$; 17F, 40 M, 1 missing) were recruited from two Engineering Physics courses that had been part of a campus-wide initiative for piloting Artificial Intelligence competencies. The engineering physics course was offered over five hours weekly (two days of 90 min of lecture and another day for a two-hour lab) during an entire semester and included topics related to computer programming and microelectronics using Arduino. Engineering Physics is an optional course offered to all students in their final semester of the Science program for which the requirements were Calculus and Mechanics. Most participants ($n = 46$) had already applied and been admitted to an Engineering program at university for the next term, while others were admitted in Architecture ($n = 3$) or fundamental sciences ($n = 5$) (4 did not answer).

Designing the Virtual Lab Pivot

A four-lab sequence was designed to introduce students to robotics using mobile robots.

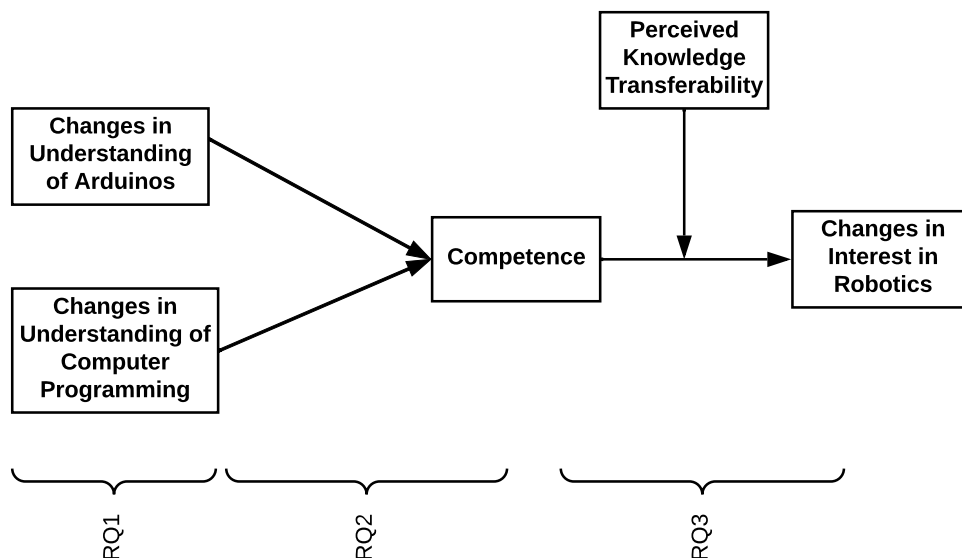
The basic components of any mobile robot are a controller, actuators, sensors, and a power system. Typical

programmable controllers that could be used for this activity include the Arduino Uno microcontroller board or the Raspberry PI single-board computer. With the addition of actuators like servos or DC motors for motion and sensors to collect feedback data about the environment, mobile robots can be programmed to perform navigation tasks. For example, an ultrasonic sensor can detect and measure the distance to obstacles. The sensor data can then be processed with the controller where the motors respond accordingly.

While there are many options for constructing basic mobile robots, they vary widely in price and complexity of use. As an open-source electronics prototyping platform with extensive documentation and an active online community sharing resources, tutorials, and example projects, Arduino was chosen for its accessibility and adaptability in the design of this robotics activity. The software to program the Arduino board is free and straightforward to install on most operating systems or ready to be used directly from a web browser. Also, given that the hardware is inexpensive, Arduino provides a cost-effective option for designing customizable educational robotics activities. This activity used simple two-wheel mobile robots with an Arduino Uno compatible board as the controller, two continuous rotation servo motors, one ultrasonic sensor, and a rechargeable 5 V power bank. These components were selected carefully to accommodate the requirements of the lab which included the cost of the robotics kit, the learning curve required to program the robots, the maintainability of the hardware used, and the relevance to the engineering physics curriculum.

Of the four-lab sequence, the first two took place in classrooms. The objective of lab one was to provide an overview of engineering robotics with microcontrollers, introduce the Arduino platform, assemble the robots, and then perform a simple control task using boilerplate code

Fig. 1 Conceptual model of study



(i.e., a standardized code that can be reused in new contexts or applications without requiring significant changes). Students, in groups of three or four, were presented with a demonstration and given instructions on how to assemble the robot and connect the servo motors to an Arduino Uno microcontroller. They were then introduced to the Arduino software and asked to upload a simple program to make the robots move. Finally, they were tasked with modifying one variable in the code to have the robots move in a straight line. In theory, there is an expected answer, but what the students were made to observe is that getting these robots to move in straight lines is a nontrivial problem that requires more than applying correct logic. A discussion about robot design, the uses of sensor feedback for control, and assigned readings exploring the programming basics needed for the project prepared students for the next lab. In lab two, students were introduced to the ultrasonic sensor and connected it to their robots. After exploring relevant C++ programming concepts for Arduino, students were then asked to plan a strategy for a wall-following task leading to straight-line motion. The problem given was to get the robots to move along a 4.00 m long narrow tape line at a distance of 50 cm from a straight wall (see Fig. 2). Groups were asked to submit their plans in plain language to be used as *pseudocode* logic for writing an Arduino program. The overall objective was to begin applying algorithmic thinking strategies needed for the navigation challenge in lab four.

When teaching moved to an online mode, due to COVID-19 restrictions, the last two labs which were originally designed to be completed through experimental and hands-on activities were redesigned with the assistance of two teachers with programming backgrounds. Hardware and robot simulations were created along with a virtual environment for carrying out an analogous navigation task to the original class challenge (lab 4). To prepare for lab three, students were asked to do some background research on the ultrasonic sensor. The goal was to understand more precisely how the sensor works and the programming basics needed to provide a solution to the more complex navigation challenge that builds on the “Follow the wall” problem. During lab three, presented in a Zoom meeting, students were directed to the created online resources to understand how to control the simulated hardware. To show that the simulator captured expected results from the actual hardware in the

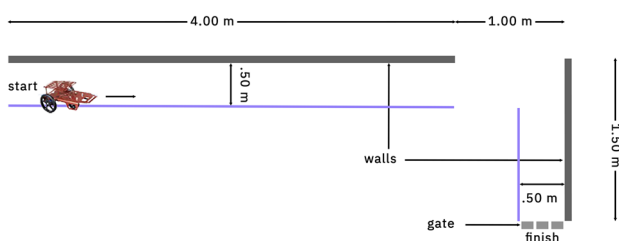


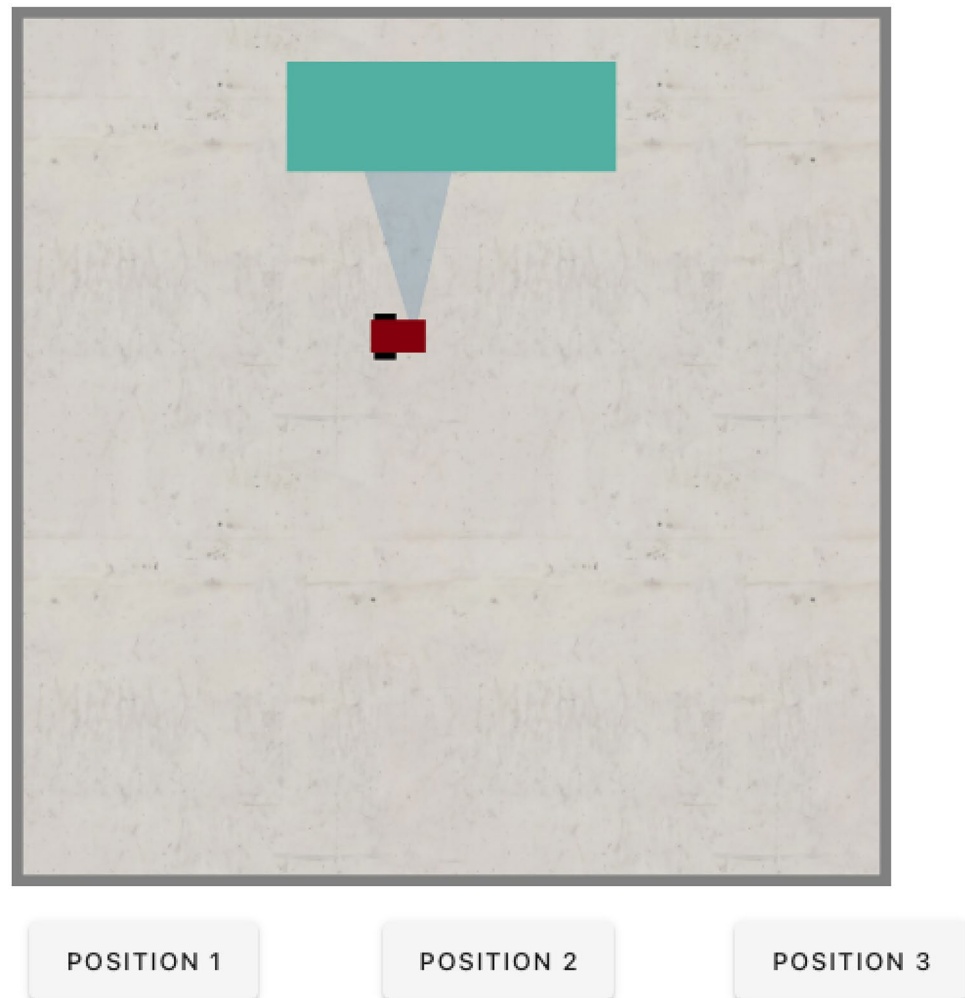
Fig. 2 Follow the Wall Problem (Lab 2)

lab, students were asked to apply programming logic from the boilerplate code of the ultrasonic sensor homework to a simple object detection task. The task was to convert timing signals, related to the interval between an emitted sonic pulse and a received pulse upon reflection from an object, into distances using prior knowledge about sound waves (see Fig. 3). Students were able to confirm the object distances set in the virtual environment and the teaching assistants reinforced the concept by demonstrating on screen how the real ultrasonic sensor worked with the same boilerplate code by moving their hands closer and away from the sensor and observing the time the sonic signal took. Students were then introduced to a follow the wall virtual problem analogous to the lab two in-class activity and asked to work on a group solution that applied their revised pseudocode strategies in breakout rooms. Finally, students were presented with the virtual navigation challenge and asked to begin programming their solutions in groups. Two weeks were given to collaborate on solutions to the challenge and then submitted just before lab four. Lab four was the challenge demo day. The final autonomous navigation challenge was: Using sensor feedback, program a robot to navigate along a complex path in the shortest possible time. During a zoom class, each group of students presented their solutions and explained the logic behind their program to solve the challenge. Then the teacher ran each solution submitted by the students on the simulation while sharing the screen and recorded the time it took for the robot to navigate through the virtual challenge. The assessment was given based on the degree of completeness of the task (i.e., based on the number of coins collected within a thirty-second time limit). All student groups were able to complete the challenge and were ranked according to the total time required to complete the challenge.

Reports were submitted describing their group strategies and an analysis of their performance along with speculations of how they could improve their solutions. Notably, the virtual navigation challenge was a faithful representation of the in-class challenge. While the students did not have the opportunity to test their solutions on real hardware, the virtual environments with the simulated hardware allowed the originally planned sequence of labs to be completed analogously.

Virtual Lab Design Considerations Although the virtual environment faithfully reproduced the design of what was intended in the “hands-on” part of working with the Arduino, the students were not able to use real hardware because the college was closed and all the robots remained at the college. They did, however, continue group work in Zoom breakout rooms where students collaborated on devising navigation strategies and writing programs to control the virtual robot. The missing criterion in the simulation over the real hardware was the actual connection of wires and

Fig. 3 Detection Task Using Ultrasonic Sensors (Lab 3)



electronics on a board because, in the simulation, the robot was already connected. However, in terms of programming the Arduino robot and writing a program in C++ to control the robot, the simulation was very close to the real robot. The students would have been able to take the same code that was used in the simulation and upload it to the real robot and expect a similar behavior to that of the simulation.

One criterion that we considered when deciding on the design of the virtual environment was student engagement with the inclusion of gamification elements. Given that the navigation challenge (lab 4) was a collaborative activity with a set of rules to follow and an end goal, we added game-playing elements such as points and timers. The addition of the gamification elements allowed us to design the virtual challenge by adding a set of coins lined up parallel to each wall at different unknown distances (see Fig. 4) and that needed to be collected by the robot within a set period. Additionally, we also debated the most appropriate online environment for students to be introduced to electronics needed for robotics in an engaging

way that included these gamification elements. We considered the Tinkercad environment as our first choice to help students understand how each electronic part worked separately through Arduino board simulation, but it was limited in its interactive elements. There was a simulation for the electronics, but none for the needed physics aspects of the electronics. For example, the ultrasonic sensor was not able to detect anything in the simulated environment except for a small ball that the user moved with their mouse pointer. This was a restriction with the Tinkercad environment as we could not construct a lab exercise that fully met the learning goals we had for these learning activities. As such, the Arduino platform was deemed appropriate in both the physical and virtual learning environment because it could integrate virtual objects with activities that incorporated physical counterparts using Arduino sensors.

For the virtual labs, students continued to work in teams of three or four using breakout rooms in Zoom and were provided with online tutorials (link to be provided for publication after peer review) to learn how to design algorithms that would help them complete the virtual navigation challenge.

```

Simulation Time
00:00.781

1 #include <Servo.h>
2
3 Servo leftservo;
4 Servo rightservo;
5 const int pingPin = 5; // Trigger Pin of Ultrasonic Sensor
6 const int echoPin = 6; // Echo Pin of Ultrasonic Sensor
7
8 void setup() {
9   leftservo.attach(9);
10  rightservo.attach(10);
11
12  //set up the Serial
13  Serial.begin(9600);
14  //setup the pin modes
15  pinMode(pingPin, OUTPUT);
16  pinMode(echoPin, INPUT);
17
18  leftservo.write(90);
19  rightservo.write(90);
20
21 }
22
23 void loop() {
24
25   long duration;
26   //clear the ping pin
27   digitalWrite(pingPin, LOW);
28   delayMicroseconds(2);

```

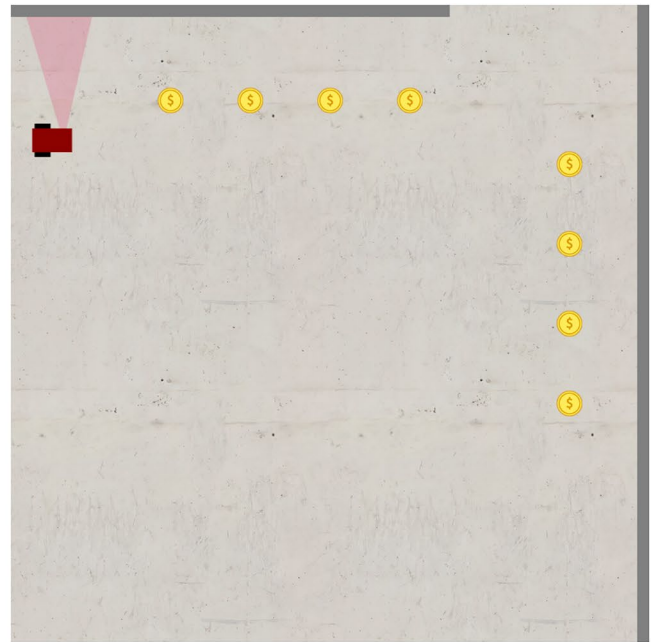


Fig. 4 Navigation Challenge Ported to a Virtual Lab Environment Instructions: The coins are approximately 110 cm away from the top wall and approximately 70 cm from the right wall. Use the data from the ultrasonic sensor to navigate the robot to collect all coins

The virtual environment allowed students to run their programs and observe the robot in the simulated environment as many times as they wanted in and out of class. Students were observed spending more time working on the labs outside the classroom which was not possible to do previously given that they were restricted to running their experiments in the college labs. Before COVID-19, students had to wait about two weeks between every lab session to get access to their robots and proceed with testing and debugging. The convenience of a flexible learning schedule, as opposed to a fixed schedule, was beneficial for students to control their own learning time and, consequently, engage in a more meaningful way in the online exercises. Additionally, the virtual lab was a web page that could be accessed from anywhere and the simulation ran in a browser.

The gamification was strictly related to the addition of the coins. It clarified the goal for each learning activity by facilitating students' visualization of the robot's performance (collecting several virtual coins). At the end of the four labs, students had acquired substantial learning experiences to know how to connect motors and sensors to a microcontroller and write simple programs in the C++ programming language to control the connected hardware.

Data Sources

A survey was administered by a research assistant during class time at the beginning (Time 1) and online at the end (after four weeks) of the robotics learning activity (Time 2). All 58 students participated at both times. In Time 1, a questionnaire was administered asking students about their interests in robotics, as well as their basic understanding of microcontrollers (1 locally developed item: I understand the basics of micro-computing platforms like Arduino) and programming (1 locally developed item: I understand the basics of computer programming). In Time 2, in addition to the questionnaire from Time 1, two more scales were used to assess college students' sense of competence and perceived knowledge transferability regarding the material covered in the Arduino microrobot activity. All scales ranged from 1 (strongly disagree) to 7 (strongly agree).

Perceived Knowledge Transferability Scale (PKT) PKT (Cronbach's $\alpha=0.90$) was measured using four items from Levesque-Bristol et al. (2010). The items were adapted to assess one's confidence in applying the course material in other classes and also in assessing its relevance to future

career options (e.g., “I feel as if the material covered in this activity is relevant to my future career.”).

Competence (CP) This six-item scale (Cronbach’s $\alpha=0.89$) was derived from the Modified Basic Psychological Needs Scale (BPNS) (Levesque- Bristol et al., 2010) and assessed the extent to which students perceived their need for competence was met. The scale was adapted and modified for the learning activity in this study (e.g., “Most days I feel a sense of accomplishment from this activity.”).

Interest in Robotics (ItRb) This three-item scale (Cronbach’s $\alpha=0.81$ at Time 1 and 0.88 at Time 2) was derived from the Academic Interest scale (Corbière et al., 2006) and assessed the extent to which students were interested in the Robotics learning module. The scale was adapted and modified for the learning activity in this study (e.g., “I like the field of robotics”, “I enjoy learning about robotics”, “Robotics is an important field of study for me.”).

Post-activity student reflections were also collected regarding the challenges and benefits of transferring the lab out of the classroom and into an online environment. Teams were evaluated based on their robot’s navigation of the final challenge and the time required for the completion. All students successfully completed the modules for the lab ($M=95.6$, $SD=9.8$, mark includes bonus points), the assigned homework in relation to the labs ($M=82.7$, $SD=20.8$), class tests ($M=79.0$, $SD=11.9$), and passed the course at the end of the semester ($M=83.6$, $SD=10.3$).

This study was conducted as per the ethical standards of the granting institution and the national funding organization. Informed consent was obtained from all participants included in the study.

Results

Data were checked for outliers and assumptions of regression were checked before analyses. Five multivariate and one univariate case with outliers were removed ($N=52$ final sample). Data were analyzed using PROCESS in SPSS. Correlations, as well as means and standard deviations at Times 1 and 2 of the study variables, are presented in Table 1.

RQ1: How do students’ conceptual understanding of the basics of microelectronics and computer programming change after engaging in an engineering robotics learning module?

We measured changes in students’ conceptual understanding regarding the basics of microelectronics and computer programming from Time 1 (prior to beginning the learning module) to Time 2 (after completing the learning activity) by using paired-sample t-tests. In Time 1,

students had displayed a basic understanding of computer programming ($M=4.53$, $SD=1.70$) and a limited understanding regarding microcontroller platforms like Arduinos ($M=2.75$, $SD=1.75$). At Time 2, significant increases were reported for computer programming ($M=5.69$, $SD=1.36$), $t(51)=5.60$, $p<0.001$ and understanding of the Arduino platform ($M=5.37$, $SD=1.28$), $t(51)=10.51$, $p<0.001$.

RQ2: What is the impact of the changes in students’ understanding of the Arduino platform and computer programming on their sense of competence in engineering robotics?

A backward stepwise regression analysis was conducted to develop a model predicting students’ sense of competence in the learning activity from the changes in their increased understanding of microcontrollers (i.e., Arduinos) and computer programming. Backward elimination was selected to consider the effects of the two variables simultaneously in the case of collinearity (the two predictors correlated at 0.60 at Time 1). To create a variable representing a change, the manifest residuals from the regression analyses (from Time 1 to Time 2) were used (Gunnell et al., 2017). The residual for a variable was obtained by conducting a regression analysis with the Time 2 measurement entered as the outcome and the Time 1 measurement entered as the predictor. The residual values from this analysis represented changes in the variable that were not predicted from the initial value.

The assumptions of independence, normality, linearity, and homoscedasticity were assessed and found to be met. A significant regression equation was found for Model 1 which included both predictors ($F(2, 49)=6.311$, $p<0.004$, with an R^2 of 0.205). In Model 2, changes in the understanding of the Arduino platform were removed using the backward criterion resulting in an $R^2=0.166$ which was not a significant decrease of R^2 from Model 1, $p=0.128$. The linear regression in Model 2 revealed that changes in computer programming alone significantly predicted students’ sense of competence, $F(1,50)=6.792$, $p=0.003$ (See Fig. 5).

RQ3: What is the role of students’ perceived knowledge transferability in the relationship between their sense of competence and interest in engineering robotics?

First, we measured changes in students’ interest in robotics by using paired-sample t- tests. At Time 1, students had displayed an above average interest in robotics ($M=4.15$, $SD=0.99$). At Time 2, significant increases were reported for students’ interest in robotics ($M=4.73$, $SD=1.25$), $t(51)=4.08$, $p<0.001$. A moderation analysis using the PROCESS plug-in from SPSS (Hayes, 2012) was used to assess perceived knowledge transferability (PKT) as

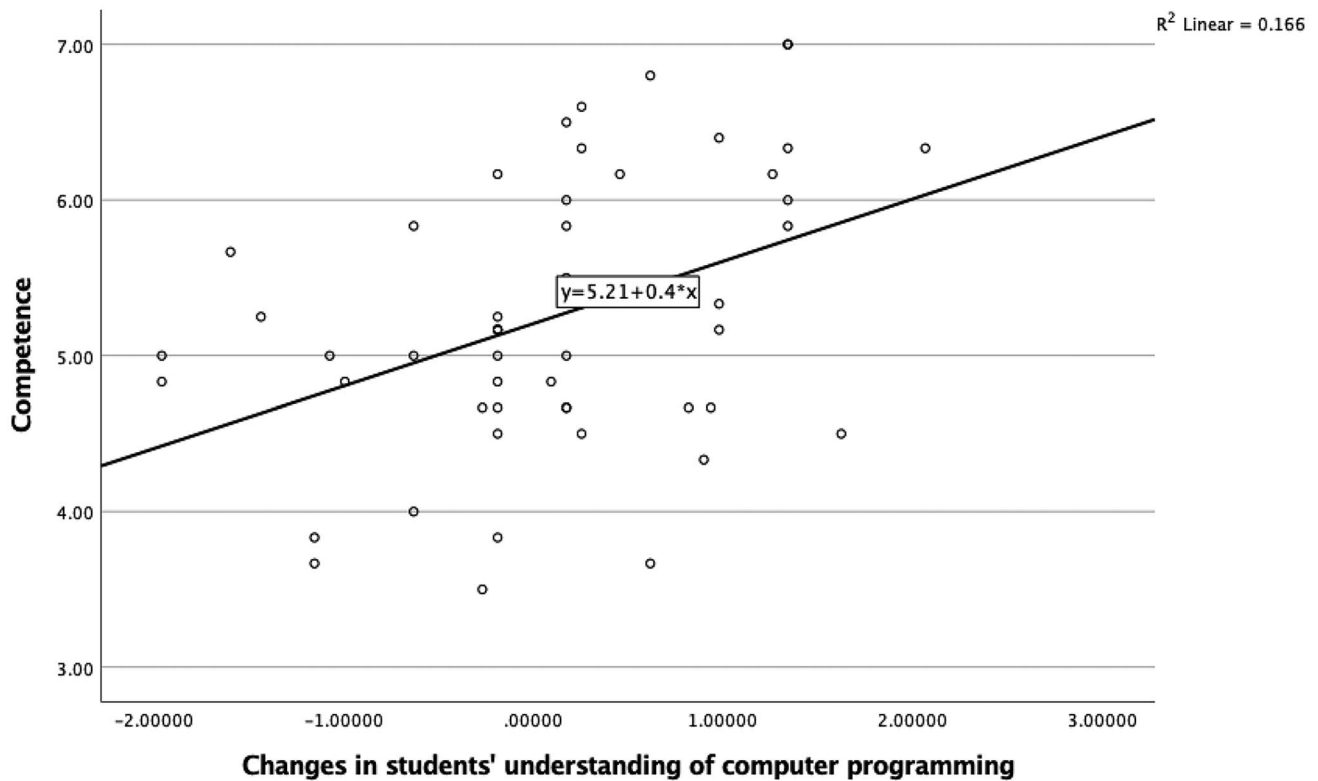


Fig. 5 Model Predicting Students’ Sense of Competence as a Function of Changes in their Understanding of Computer Programming

a moderator in the relationship between students’ sense of competence (CP) and changes in their interests in engineering robotics from Time 1 to Time 2 (from the beginning to the end of the learning module). The overall model was significant $F(3,48) = 6.60, p < 0.001, R^2 = 0.292$. Although students’ interest in robotics increased as CP and PKT increased, CP was not a significant predictor, $b = 0.10, t(48) = 0.61, p = 0.546$, whereas PKT was,

$b = 0.43, t(48) = 3.13, p = 0.003$. The interaction effect between CP and PKT was also non-significant, $b = 0.06, t(48) = 0.54, p = 0.595$.

Because of a non-significant interaction effect, we calculated only simple slopes.

Predicted values of mean changes in students’ interest in robotics from Time 1 to Time 2 were calculated across low (-1SD) and high (+1SD) values of CP and PKT

Fig. 6 Changes in Students’ Interest in Robotics as a Function of Sense of Competence and Perceived Knowledge Transferability

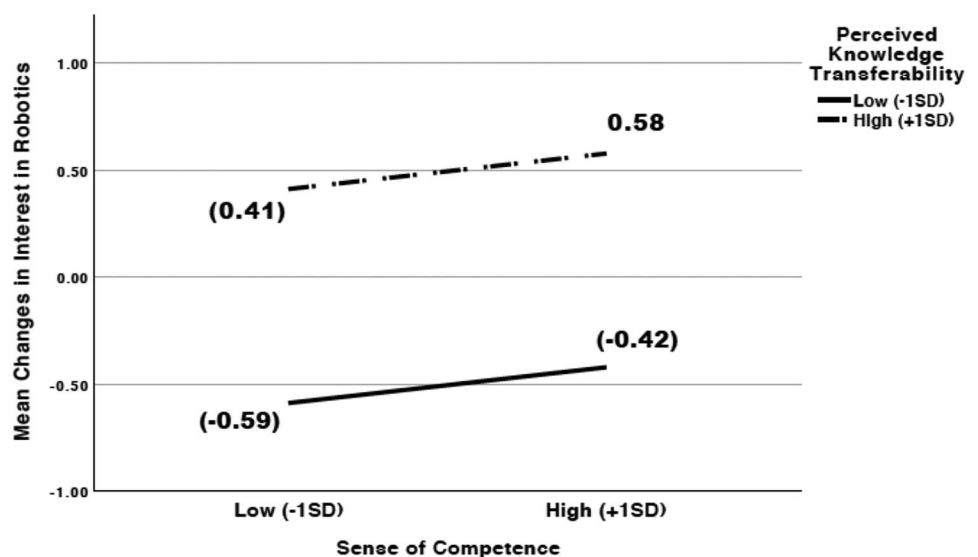


Table 1 Correlations, Means, and Standard Deviations at Times 1 and 2

	CP_T2	PKT_T2	Ard_T1	Ard_T2	Prg_T1	Prg_T2	ItRb_T1	ItRb_T2
CP_T2	5.25(0.90)							
PKT_T2	0.58***	5.40(1.13)						
Ard_T1	0.21	0.02	2.75(1.75)					
Ard_T2	0.45**	0.34*	0.33*	5.37(1.28)				
Prg_T1	0.06	0.02	0.60***	0.20	4.56(1.70)			
Prg_T2	0.40**	0.23	0.35*	0.59***	0.56***	5.69(1.36)		
ItRb_T1	0.20	0.26	0.55***	0.22	0.37**	0.23	4.15(0.99)	
ItRb_T2	0.42**	0.58***	0.32*	0.42**	0.18	0.35*	0.61***	4.73(1.25)

CP_T2: Sense of Competence at Time 2

PKT_T2: Perceived Knowledge Transferability at Time 2

Ard_T1: Understanding of Arduino at Time 1 + Ard_T2: Understanding of Arduino at Time 2

Prg_T1: Understanding of Computer Programming at Time 1 Prg_T2: Understanding of Computer Programming at Time 2

ItRb_T1: Interest in Robotics at Time 1 ItRb_T2: Interest in Robotics at Time 2

* $p < .05$; ** $p < .01$; *** $p < .001$

(see Fig. 6). The following linear regression equations as suggested for a 2×2 model (Gaudreau, 2012) were used to calculate the predicted changes in students’ interest in engineering robotics:

1. Y of Low CP-PKT = Intercept + (B CP. Low CP) + (B PKT. Low PKT).
2. Y of High PKT = Intercept + (B CP. Low CP) + (B PKT. High PKT).
3. Y of High CP = Intercept + (B CP.High CP) + (B PKT. Low PKT).
4. Y of High CP-PKT = Intercept + (B CP.High CP) + (B PKT. High PKT).

Based on the 2×2 model (Gaudreau & Thompson, 2010), we assumed that both CP and PKT would be present to varying degrees within each individual rather than differences that lie within the dimensions themselves. By focusing on the within-person combinations of low and high levels of CP and PKT, a more meaningful level of analysis could take place to differentiate the relationship between the two predictors. As such, changes in students’ interest in engineering

robotics could be examined based on the quantitative scores of CP and PKT at four distinct levels, while also delineating ways to examine hypotheses in the absence of a significant interaction.

Results indicated that high levels of both CP and PKT, compared to all other.

possibilities were related to the highest increases in interest in robotics ($M = 0.58$). Second, it seems that only a high level of PKT played an important role in students’ increased interest in robotics ($M = 0.41$) compared to only high levels of CP ($M = -0.42$). Finally, low levels of both CP and PKT were related to the most decrease in interest in robotics ($M = -0.59$). There were significant differences between all predicted values for changes in students’ interests in robotics as demonstrated by Cohen’s d (see Table 2).

At the end of the semester, all teams were able to successfully solve the culminating class challenge, addressing the primary goal of the pivot to a virtual lab setting from in-person learning.

Discussion

The purpose of the present research was to determine: (1) the impact of a microrobot learning activity on college students’ conceptual understanding of microelectronics and computer programming, (2) the relationship between students’ understanding of programming and their sense of competence within the activity, and (3) the role of perceived knowledge transferability and sense of competence in students’ interest in engineering robotics. The results generally supported our hypotheses. After having completed four labs designed around the Arduino microrobot activity, students’ understanding of microcontrollers (i.e.,

Table 2 Planned Comparisons of High and Low Levels of Competence and Perceived Knowledge Transferability

Planned contrasts	Cohen’s d
Low CP_Low PKT vs High CP_High PKT	1.18
Low CP_Low PKT vs Low CP_High PKT	1.01
Low CP_Low PKT vs High CP_Low PKT	0.17
Low CP_High PKT vs High CP_High PKT	0.17
Low CP_High PKT vs High CP_Low PKT	0.84
High CP_Low PKT vs High CP_High PKT	1.01

Arduinos) and computer programming showed significant increases, thus confirming H1. The results also suggested an intercorrelation pattern between students' understanding of programming and their sense of competence. Compared to an understanding of Arduino, the regression model identified the understanding of computer programming as a more important factor in influencing students' sense of competence which confirmed H2. Unexpectedly, perceived knowledge transferability, as opposed to competence, was a better predictor of students' increased interest in robotics which partially supported what we had hypothesized in H3. The present findings led to several implications for STEM-related pedagogical activities that strive to foster knowledge transfer.

Enabling students to grasp engineering concepts during later high school or in early undergraduate years often proves to be challenging. The introduction of an Arduino microcontroller into a learning activity designed for senior college students in an engineering physics course proved to be beneficial in the development of a key attribute for engineering: designing and developing solutions for real-life situations (Ziaeefard et al., 2017). This study replicated outcomes from past research associated with Arduino experiments in virtual and physical learning environments (Papadimitropoulos et al., 2021) by demonstrating significant increases in students' understanding of Arduino and computer programming. While initial knowledge about Arduino as a microcomputing platform was minimal as indicated by their mean scores at Time 1 (2.75 / 7), students' mean scores increased significantly at Time 2, after the four-lab sequence (5.37 / 7). Similar significant increases were observed in students' understanding of computer programming although their base knowledge was higher at Time 1 (4.56 / 7) compared to that of Arduino. Based on past studies (e.g., Hong et al., 2018), these significant learning gains were expected given that the pivot from a physical to a virtual learning environment went beyond the simple accompaniment of static visualizations. It promoted the activation of cognitive skills such as understanding and memorizing content while also fostering the application of procedural knowledge (Kump et al., 2015). The latter has implications on students' ability to organize complex knowledge in a meaningful way (Ambrose et al., 2010).

For example, this organizational structure facilitates the potential for knowledge transfer to new situations, a useful and effective skill for bridging concepts from high school to the first year of an engineering undergraduate program.

The present findings also align with past research that advocates the positive effects on students' interest in engineering education (Brophy et al., 2008) following the use of microcomputing platforms during hands-on learning (Ziaeefard et al., 2017). Furthermore, given that students interacted with both physical and virtual learning

environments in this study, they were provided with opportunities to remain engaged in a learning activity when physical laboratories were no longer accessible (Davenport et al., 2018). Therefore, students' interest in robotics still occupied an important place even though physical engagement had disappeared. The latter was demonstrated by their sustained interest after having completed four Arduino-based modules through blended representations due to the shift to online learning brought on by COVID-19. It seems that Arduino-based experiments can be designed to bridge the gap between virtual and physical learning environments, hence, creating opportunities that are conducive to the development of skills required for knowledge transferability. This suggests that both physical and virtual learning environments may be the ideal contexts for sustaining college students' motivation during laboratory experiments. The simulated environment, in particular, was advantageous given that students were observed spending more time working on the lab experiments outside the classroom, which is not always a possibility when in person given the scheduling conflicts with other courses taking place in those lab spaces. It seems that a blended combination of virtual and physical learning environments is more conducive to the development of competence for laboratory experimentation (Olympiou & Zacharia, 2012).

Another motivational factor for the ongoing development of students' interest in robotics was their sense of competence. Research has consistently shown that the satisfaction of basic psychological needs for autonomy, competence, and relatedness is associated with positive outcomes in education (Ryan & Deci, 2017). Our findings extend the SDT literature and highlight the role of competence in light of students' perceived knowledge transferability (PKT) in the context of postsecondary education. Specifically, learning gains in students' understanding of computer programming were strongly associated with their sense of competence, however, PKT was more predictive of increases in students' interest in robotics. This implies that interest in STEM develops when students are provided with opportunities to bridge theory and practice in novel learning environments (e.g., through lecture notes as well as physical and virtual labs), and not simply by drawing links between conceptualizations or static visualizations and highly controlled learning environments.

Designing and implementing a robotics learning activity in the curriculum of an engineering physics course provided opportunities for students to learn, apply, and experiment with competencies that often overlap between college and undergraduate levels. It seems that a blended combination of virtual and physical learning environments is more conducive to the development of competence for laboratory experimentation. Furthermore, the COVID-19 pandemic challenged the existing infrastructure of lab experiments by encouraging the emergence of blended environments, thus forcing a redefinition of authentic learning experiences.

For example, the Arduino-based virtual labs described in this study, inspired by the immediate need to pivot online, formed a fertile ground for a potential knowledge transfer and, ultimately, an increased interest in pursuing studies in STEM-related fields.

In sum, it seems competence and knowledge transfer pinpointed a differential influence on students' interest in robotics. Specifically, students who experienced high levels of perceived knowledge transferability and low levels of competence displayed a higher increase in interest in robotics than students who experienced high levels of competence but low levels of perceived knowledge transferability. This implies that students who feel a high sense of competence may have greater content mastery (Chi & VanLehn, 2012); however, this may be limited to in situ contexts and may not necessarily lead to knowledge transfer (Bonem et al., 2020).

Theoretical Contributions

Using self-determination theory (SDT), proposed by Deci and Ryan (1985b), as the motivational framework on which to base this study has led to a couple of theoretical implications. First, given that competence is one of the psychological needs as defined by SDT, individuals experienced greater perceived knowledge transferability through the satisfaction of their sense of competence. This has implications when considering how pedagogical design in engineering education can adequately address heightened feelings of competence, which in turn, leads to students actively engaging in learning tasks (Hsu et al., 2019; Reeve, 2013).

Second, this study investigated the relationships between competence and perceived knowledge transferability in an online learning context through the lens of SDT during the pandemic (Chiu, 2021). Although SDT has been widely applied to optimize student learning in face-to-face teaching and learning contexts (Ryan & Deci, 2017), it has been largely overlooked in online learning settings (Chen & Jang, 2010; Hsu et al., 2019). Moreover, in the majority of SDT-related studies, the core focus has been on how teachers should be acting while teaching, and not on technological design. The technological environment in this study provided preliminary evidence of how SDT could be applied (Ryan & Deci, 2020) in classroom-based research and how technologies in e-learning and remote classrooms can enhance students' interests. It contributed to SDT by demonstrating how instructors can use technological design to target the satisfaction of college students' competence by suggesting diverse strategies for online learning and, ultimately, increasing students' interest.

Finally, the findings of this study highlight how instruction and technology have the potential to differentially influence student learning and the extent to which they engage

with the content. Compared to the effects of technologically driven environments, instruction in face-to-face contexts have been researched much more thoroughly (e.g., Lietaert et al., 2015; Vollet et al., 2017). The potential of individualized impact from physical (classrooms) and virtual (digital support) learning environments is indicative that they should be designed separately and independently to contribute to student learning because although they are interrelated, they are operationalized and conceptualized as distinct.

Conclusion, Limitations, and Future Directions

The pivot to a virtual lab setting from in-person learning allowed for all students to complete the robotics activities. Transferring complex engineering ideas to novel situations, even with the challenges of the COVID-19 lockdown, proved to be beneficial for students' learning gains associated with computer programming and the Arduino platform. While acquiring knowledge might be the main purpose in education, knowledge usability in different contexts deserves equal attention as it plays an important role in preparing students to transition to the workforce, graduate school, and real life.

This study was conducted under some limitations which should be considered when interpreting the current findings. First, measures were mostly based on self-report scales, however, we did use a methodological process that was replicated by other authors who used more objective measures rendering similar outcomes when using a 2×2 model to interpret their findings (e.g., Gaudreau & Thompson, 2010; Gaudreau & Verner-Filion, 2012; Gaudreau et al., 2018; Schellenberg et al., 2019). Consequently, future research is needed to replicate the present findings either with more objective assessments regarding autonomy support or by triangulating findings with qualitative data such as individual interviews or videos of task analysis. Second, the participants in this study were from the same age group (18–19 years old) and the same program (sciences). It would thus appear important to replicate the present findings with other student populations from other disciplines (outside of science). Third, given that affordable and free learning kits such as Arduino kits employed for robotics education among pre-college students lack curricula for STEM educators, it is suggested (as indicated in the student reflections) that future iterations incorporate more instruction or tutorials regarding programming basics to improve learning outcomes. Finally, the female sample size was not sufficient to conduct any separate analyses and draw more specific conclusions. Given what is known about the impact of self-efficacy on females in computer science (Tsai et al., 2019), future research should consider investigating such factors in female-dominant areas of study (e.g., psychology, liberal arts).

The present research demonstrated the importance of looking at variables more dynamically (e.g., low and high levels) to ascertain conclusions. Future research in which the 2 X 2 model is used to examine such constructs in different disciplines and populations is encouraged to extend and replicate these findings. Future investigation also calls for more studies to examine promoting college students' perceived knowledge transferability by considering the meaningful contributions from constructs aligned with the self-determination theory in the context of higher education. Furthermore, these findings have practical implications for educators as they show the vital function that learning environments play in fostering students' interest and, ultimately, passion for a field of study (Bonneville-Roussy et al., 2011). Therefore, this study underscores another avenue for future research wherein training teachers to integrate pedagogical activities in the curriculum that offer the potential for students to transfer knowledge between physical and virtual learning environments.

Declarations

Ethical Statement Our research was conducted in accordance with the APA 7 ethical code of conduct and has received the approval of the first author's institutional review board.

Consent Statement Informed consent was obtained from all participants included in the study.

Disclosure of Potential Conflicts of Interest I declare that there is no conflict of interest among the authors on this manuscript.

References

- Ambrose, S. A., Bridges, M. W., DiPietro, M., Lovett, M. C., & Norman, M. K. (2010). *How learning works: Seven research-based principles for smart teaching*. John Wiley & Sons.
- Belenky, D. M., & Nokes-Malach, T. J. (2012). Motivation and transfer: The role of mastery- approach goals in preparation for future learning. *Journal of the Learning Sciences, 21*(3), 399–432. <https://doi.org/10.1080/10508406.2011.651232>
- Bereby-Meyer, Y., & Kaplan, A. (2005). Motivational influences on transfer of problem-solving strategies. *Contemporary Educational Psychology, 30*(1), 1–22. <https://doi.org/10.1016/j.cedpsych.2004.06.003>
- Bicer, A., Lee, Y., Capraro, R. M., Capraro, M. M., Barroso, L. R., Bevan, D., & Vela, K. (2018). Cracking the code: The effects of using microcontrollers to code on students' Interest in computer and electrical engineering. *IEEE Frontiers in Education Conference (FIE)*, 1–7. <https://doi.org/10.1109/FIE.2018.8658617>
- Billing, D. (2007). Teaching for transfer of core/key skills in higher education: Cognitive skills. *Higher Education, 53*(4), 483–516. <https://doi.org/10.1007/s10734-005-5628-5>
- Bonem, E. M., Fedesco, H. N., & Zissimopoulos, A. N. (2020). What you do is less important than how you do it: The effects of learning environment on student outcomes. *Learning Environments Research, 23*(1), 27–44. <https://doi.org/10.1007/s10984-019-09289-8>
- Bonneville-Roussy, A., Lavigne, G. L., & Vallerand, R. J. (2011). When passion leads to excellence: The case of musicians. *Psychology of Music, 39*, 123–138. <https://doi.org/10.1177/0305735609352441>
- Brophy, S., Klein, S., Portsmore, M., & Rogers, C. (2008). Advancing engineering education in P- 12 classrooms. *Journal of Engineering Education, 97*(3), 369–387. <https://doi.org/10.1002/j.2168-9830.2008.tb00985.x>
- Burke, L. A., & Hutchins, H. M. (2007). Training transfer: An integrative literature review. *Human Resource Development Review, 6*(3), 263–296. <https://doi.org/10.1177/1534484307303035>
- Caron, D. (2010). Competitive robotics brings out the best in students. *Tech Directions, 69*(6), 21–23.
- Chen, K. -C., & Jang, S. -J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior, 26*(4), 741–752. <https://doi.org/10.1016/j.chb.2010.01.011>
- Chi, M. T., & VanLehn, K. A. (2012). Seeing deep structure from the interactions of surface features. *Educational Psychologist, 47*(3), 177–188. <https://doi.org/10.1080/00461520.2012.695709>
- Chiu, T. K. F. (2022). Applying the self-determination theory (SDT) to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education, 54*(sup1), S14–S30. <https://doi.org/10.1080/15391523.2021.1891998>
- Corbière, M., Fraccaroli, F., Mbekou, V., & Perron, J. (2006). Academic self-concept and academic interest measurement: A multi-sample European study. *European Journal of Psychology of Education, 21*(1), Article 3. <https://doi.org/10.1007/BF03173566>
- Dalgarno, B., & Lee, M. J. (2010). What are the learning affordances of 3- D virtual environments? *British Journal of Educational Technology, 41*(1), 10–32. <https://doi.org/10.1111/j.1467-8535.2009.01038.x>
- Davenport, J. L., Rafferty, A. N., & Yaron, D. J. (2018). Whether and how authentic contexts using a virtual chemistry lab support learning. *Journal of Chemical Education, 95*(8), 1250–1259. <https://doi.org/10.1021/acs.jchemed.8b00048>
- Day, S. B., & Goldstone, R. L. (2012). The import of knowledge export: Connecting findings and theories of transfer of learning. *Educational Psychologist, 47*(3), 153–176. <https://doi.org/10.1080/00461520.2012.696438>
- Deci, E. L., & Ryan, R. M. (1985a). The general causality orientations scale: Self-determination in personality. *Journal of Research in Personality, 19*(2), 109–134. [https://doi.org/10.1016/0092-6566\(85\)90023-6](https://doi.org/10.1016/0092-6566(85)90023-6)
- Deci, E. L., & Ryan, R. M. (1985b). *Intrinsic motivation and self-determination in human behavior*. Plenum Press.
- Deci, E. L., & Ryan, R. M. (2015). Self-Determination Theory. In J. D. Wright (Ed.), *International encyclopedia of the social & behavioral sciences* (2nd ed., pp. 486–491). Elsevier. <https://doi.org/10.1016/B978-0-08-097086-8.26036-4>
- Falloon, G. (2019). Using simulations to teach young students science concepts: An Experiential Learning theoretical analysis. *Computers & Education, 135*, 138–159.
- Fedesco, H. N., Bonem, E. M., Wang, C., & Henares, R. (2019). Connections in the classroom: Separating the effects of instructor and peer relatedness in the basic needs satisfaction scale. *Motivation and Emotion, 43*(5), 758–770. <https://doi.org/10.1007/s11031-019-09765-x>
- Gaudreau, P. (2012). A methodological note on the interactive and main effects of dualistic personality dimensions: An example using the 2x2 model of perfectionism. *Personality and Individual Differences, 52*(1), 26–31. <https://doi.org/10.1016/j.paid.2011.08.022>
- Gaudreau, P., Franche, V., & Kljajic, K. (2018). The 2 X 2 model of perfectionism: Assumptions, trends, and potential developments.

- In J. Stoeber (Ed.), *The psychology of perfectionism: Theory, research, applications* (pp. 44–67). Routledge.
- Gaudreau, P., & Thompson, A. (2010). Testing a quadripartite model of dispositional perfectionism. *Personality and Individual Differences*, 48, 532–537. <https://doi.org/10.1016/j.paid.2009.11.031>
- Gaudreau, P., & Verner-Filion, J. (2012). Dispositional perfectionism and well-being: A test of the 2 × 2 model of perfectionism in the sport domain. *Sport, Exercise, and Performance Psychology*, 1(1), 29–43. <https://doi.org/10.1037/a0025747>
- Goldstone, R. L., & Wilensky, U. (2008). Promoting transfer by grounding complex systems principles. *Journal of Learning Sciences*, 17(4), 465–516.
- Grubbs, M. (2013). Robotics intrigue middle school students and build STEM skills. *Technology and Engineering Teacher*, 72(6), 12–16.
- Gunnell, K. E., Mosewich, A. D., McEwen, C. E., Eklund, R. C., & Crocker, P. R. (2017). Don't be so hard on yourself! Changes in self-compassion during the first year of university are associated with changes in well-being. *Personality and Individual Differences*, 107, 43–48. <https://doi.org/10.1016/j.paid.2016.11.032>
- Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling [White paper]. <http://www.afhayes.com/public/process2012.pdf>
- Hong, Z. -W., Chen, Y. -M., Yang, H. -K., Su, S. -Y., Shann, T. -Y., Chang, Y. -H., Ho, B. H. -L., Tu, C. -C., Hsiao, T. -C., Hsiao, H. -W., Lai, S. -P., Chang, Y. -C., & Lee, C. -Y. (2018). Virtual-to-real: learning to control in visual semantic segmentation. *27th International Joint Conference on Artificial Intelligence, Sweden*, 4912–4920. <https://doi.org/10.24963/ijcai.2018/682>
- Hsu, H. C. K., Wang, C. V., & Levesque-Bristol, C. (2019). Reexamining the impact of self-determination theory on learning outcomes in the online learning environment. *Education and Information Technologies*, 24(3), 2159–2174. <https://doi.org/10.1007/s10639-019-09863-w>
- Hsu, H. P., Wenting, Z., & Hughes, J. E. (2019). Developing elementary students' digital literacy through augmented reality creation: Insights from a longitudinal analysis of questionnaires, interviews, and projects. *Journal of Educational Computing Research*, 57(6), 1400–1435. <https://doi.org/10.1177/0735633118794515>
- Ibáñez, M., & Delgado-Kloos, C. (2018). Augmented reality for STEM learning: A systematic review. *Computers & Education*, 123, 109–123. <https://doi.org/10.1016/j.compedu.2018.05.002>
- Ivey, D., & Quam, G. (2009). 4-H and tech ed partnership gets students geeked about STEM. *Tech Directions*, 69(3), 19–21.
- Jang, H., Kim, E. J., & Reeve, J. (2012). Longitudinal test of self-determination theory's motivation mediation model in a naturally occurring classroom context. *Journal of Educational Psychology*, 104(4), 1175–1188. <https://doi.org/10.1037/a0028089>
- Kump, B., Moskaliuk, J., Cress, U., & Kimmerle, J. (2015). Cognitive foundations of organizational learning: re-introducing the distinction between declarative and non-declarative knowledge. *Frontiers in Psychology*, 6, Article 1489. <https://doi.org/10.3389/fpsyg.2015.01489>
- Levesque-Bristol, C., Knapp, T. D., & Fisher, B. J. (2010). The effectiveness of service-learning: It's not always what you think. *Journal of Experiential Education*, 33(3), 208–224. <https://doi.org/10.5193/JEE33.3.208>
- Levesque-Bristol, C., Richards, K. A. R., Zissimopoulos, A., Wang, C., & Yu, S. (2020). An evaluation of the integrative model for learning and motivation in the college classroom. *Current Psychology*. <https://doi.org/10.1007/s12144-020-00671-x>
- Lietaert, S., Roorda, D., Laevers, F., Verschueren, K., & De Fraine, B. (2015). The gender gap in student engagement: The role of teachers' autonomy support, structure, and involvement. *British Journal of Educational Psychology*, 85(4), 498–518. <https://doi.org/10.1111/bjep.12095>
- Martin, T., Berland, M., Benton, T., & Smith, C. P. (2013). Learning programming with IPRO: The effects of a mobile, social programming environment. *Journal of Interactive Learning Research*, 24(3), 301–328.
- Martin, F. & Bolliger, D. U. (2018). Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning*, 22(1), 205–222. <https://doi.org/10.24059/olj.v22i1.1092>
- Martin, A. J., & Dowson, M. (2009). Interpersonal relationships, motivation, engagement, and achievement: Yields for theory, current issues, and educational practice. *Review of Educational Research*, 79(1), 327–365. <https://doi.org/10.3102/0034654308325583>
- McKay, D., Banner, R., Sherif, V., & Rhodes, A. (2015). *Learning, independence, and relationships: The impact of supported higher education on students with intellectual disabilities*. University of Kentucky.
- Nite, S. B., Bicer, A., Currens, K. C., & Tejani, R. (2020). Increasing STEM interest through coding with microcontrollers. *IEEE Frontiers in Education Conference (FIE)*, 1–7. <https://doi.org/10.1109/FIE44824.2020.9274273>
- Olympiou, G., & Zacharia, Z. C. (2012). Blending physical and virtual manipulatives: An effort to improve students' conceptual understanding through science laboratory experimentation. *Science Education*, 96(1), 21–47. <https://doi.org/10.1002/sce.20463>
- Papadimitropoulos, N., Dalacosta, K., & Pavlatou, E. A. (2021). Teaching Chemistry with Arduino Experiments in a Mixed Virtual-Physical Learning Environment. *Journal of Science Education and Technology*. <https://doi.org/10.1007/s10956-020-09899-5>
- Perkins, D. N., & Salomon, G. (2012). Knowledge to go: A motivational and dispositional view of transfer. *Educational Psychologist*, 47(3), 248–258. <https://doi.org/10.1080/00461520.2012.693354>
- Rawat, K. S., Lawrence, E. E., Mangham, R. R., & Gooden, O. D. (2018). K-12 Aerospace Academy: An Out-of-School Authentic and Experiential STEM Learning Experience for College and Career Pathways to Aerospace/Aviation. *2018 ASEE Annual Conference & Exposition, USA*, Article 22847. <https://doi.org/10.18260/1-2--30742>
- Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. *Journal of Educational Psychology*, 105(3), 579–595. <https://doi.org/10.1037/a0032690>
- Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Publications.
- Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective. Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, 61, 101860. <https://doi.org/10.1016/j.cedpsych.2020.101860>
- Schellenberg, B. J. I., Verner-Filion, J., Gaudreau, P., Bailis, D. S., Lafrenière MK, & Vallerand, R. J. (2019). Testing the dualistic model of passion using a novel quadripartite approach: a look at physical and psychological well-being. *Journal of Personality*, 87(2), 163–180. <https://doi.org/10.1111/jopy.12378>
- Tsai, M. J., Wang, C. Y., & Hsu, P. F. (2019). Developing the computer programming self-efficacy scale for computer literacy education. *Journal of Educational Computing Research*, 56(8), 1345–1360.
- Vollet, J. W., Kindermann, T. A., & Skinner, E. A. (2017). In peer matters, teachers matter: Peer group influences on students' engagement depend on teacher involvement. *Journal of Educational Psychology*, 109(5), 635–652. <https://doi.org/10.1037/edu0000172>
- Wahyuni, T. S., & Analita, R. N. (2017). Guided-inquiry laboratory experiments to improve students' analytical thinking skills. *AIP Conference Proceedings*, 1911. <https://doi.org/10.1063/1.5016010>
- Wang, M. T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy-value perspective to understand

- individual and gender differences in STEM fields. *Developmental Review*, 33(4), 304–340. <https://doi.org/10.1016/j.dr.2013.08.001>
- Wang, Y., & Haggerty, N. (2009). Knowledge transfer in virtual settings: The role of individual virtual competency. *Information Systems Journal*, 19(6), 571–593. <https://doi.org/10.1111/j.1365-2575.2008.00318.x>
- Wang, C., Zhang, Y., Moss, J. D., Bonem, E. M., & Levesque-Bristol, C. (2020). Multilevel factors affecting college students' perceived knowledge transferability: From the perspective of self-determination theory. *Research in Higher Education*, 61(8), 1002–1026. <https://doi.org/10.1007/s11162-020-09592-x>
- Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition & Instruction*, 24(2), 171–209.
- Yuen, T. T., Mason, L. L., & Gomez, A. (2014). Collaborative robotics projects for adolescents with autism spectrum disorders. *Journal of Special Education Technology*, 29(1), 51–62. <https://doi.org/10.1177/016264341402900104>
- Ziaefard, S., Miller, M., Rastgaar, M., & Mahmoudian, N. (2017). Co-robotics hands-on activities: A gateway to engineering design and STEM learning. *Robotics Autonomous Systems*, 97, 40–50.
- Zilvinskis, J., Masseria, A. A., & Pike, G. R. (2017). Student engagement and student learning: Examining the convergent and discriminant validity of the revised national survey of student engagement. *Research in Higher Education*, 58(8), 880–903. <https://doi.org/10.1007/s11162-017-9450-6>

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