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Robots, Motivation, and Academic Success*

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Educational literature has long supported strong correlations between student motivation and academic success. STEM literature has more recently shown mechatronic experiences to have positive impacts on these constructs, albeit limited empirical grounding. Therefore, the purpose of this study was to conduct a pilot experiment to empirically quantify differences in undergraduate student motivation and academic success in a mechatronic vs. a non-mechatronic experience, as well as examine the correlation between student motivation and academic success in both groups. We used a quasi-experimental, non-equivalent control vs. treatment design to collect $n = 84$ responses from multiple sections of a single undergraduate course. The multivariate dependent variable of student motivation was measured using the *Motivated Strategies for Learning Questionnaire's* motivational orientation items. Our multivariate dependent variable of academic success was based on final course grades, final project scores, and quiz scores. Using ANCOVA and differences of proportions, we found no statistical difference in motivational orientation—specifically *value choices* and *expectancy beliefs*—in the mechatronic vs. non-mechatronic experience. In contrast, statistically significant differences in project scores and final course grades were observed in the mechatronic experience group. Additionally, we found no significant correlation between student motivation and academic success. These results indicated that students in the mechatronic experience, while earning significantly higher grades, did not exhibit different levels of motivation, leading to no association between student motivation and academic success. Even so, future research is needed to further understand the nuanced dynamics of motivational orientation within a mechatronic experience.

Keywords: mechatronics; robotics; motivation; engagement; academic success; student learning

1. Introduction

Student motivation is contextual and educators in all fields have the ability to structure ". . . the learning environment [to] increase the number of students who stay engaged and motivated . . ." [1, p. 7]. Furthermore, real-world projects in the classroom have the potential to motivate students to engage in learning [2]. In engineering and technology classrooms, mechatronic experiences have been found to enhance students' motivation and learning [3–7]. With the multi-disciplinary nature of robotics, it is not surprising this topic is being implemented in a growing number of science, technology, engineering, and mathematics (STEM) curricula. A systematic review by Haughery and Raman [8] examined the influences that mechatronic experiences have had on student engagement. Using data from more than two decades of engineering and technology education literature, Haughery and Raman found positive influences on student motivation and self-efficacy following mechatronic experiences. However, gaps in the literature were highlighted in this review. Specifically, limited usage of control vs. treatment designs or pre/post data collection, limited explanation of experimental methods, only basic descriptive analysis of quantitative results, no treatment effects of dependent variables (i.e., no effect sizes of academic success or student motivation), and only anecdotal examples of qualitative findings were found [8]. Therefore, more rigorous research is needed to validate whether mechatronic experiences improve student motivation and/or academic success.

1.1 Research purpose

Based on the limited empirical evidence supporting the impacts of mechatronic experiences on student motivation and academic success, we conducted a pilot experiment to determine the viability of further research into these effects. Specifically, our objective was to quantify differences in undergraduate student motivation and academic success in a mechatronic experience vs. a non-mechatronic experience, which was underpinned by the perspective that a symbiotic link exists between student motivation and academic success and that mechatronic experiences have the potential to positively impact this interplay. Three primary questions guided our study:

1. Do students in a mechatronic experience report different levels of student motivation and academic success vs. students in a non-mechatronic experience?
2. Do mechatronic experiences motivate a differ-

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ent proportion of students vs. non-mechatronic experiences?

3. What is the relationship between student motivation and academic success when considering mechatronic vs. non-mechatronic experiences?

1.2 Academic success

According to Meece, "The goal of any educational program must be to create a learning environment that supports or elicits students' intrinsic interest in learning" [1, p. 34]. While many would argue that achieving a certain level of learning equates to academic success, York, Gibson, and Rankin [9] found this term poorly and ambiguously defined in the literature. In an attempt to bring clarity, they used a grounded theory approach to synthesize a high-level, six-faceted framework of academic success that included academic achievement, satisfaction, attainment of learning outcomes, persistence, career success, acquisition of skills and competencies [9].

Light [10, 11] denoted student engagement (i.e., student involvement in learning) as a critical factor in educational development, while Kamphorst, Hofman, Jansen, and Terlouw [12] indicated it as pivotal to student persistence. Wilson et al. [13] postulated that student engagement is an intermediate outcome to academic success that is evident in students sooner than the six facets proposed [9]. Nelson et al. [14], suggested student engagement is directly proportional to academic achievement, while Pintrich, Smith, García, and McKeachie [15] suggest engagement to be a function of student motivation. They indicate that students' motivational beliefs affect cognitive engagement.

1.3 Student motivation

Meece defined motivation as the "desire to work and learn" [1, p. 5]; Clark, borrowing from the work of Bandura [16], defined motivation as ". . . the amount and quality of the 'mental effort' people invest in achieving goals" [17, p. 2]; Pintrich and Schunk defined motivation as ". . . the process whereby goal-directed activity is instigated and sustained" [18, p. 4]. In these complementary descriptions of motivation, one starts to see the multifaceted nature of motivation.

In Clark's *Choice and Necessary Effort* (CANE) model, he described how an individual's commitment to, or motivation towards, a goal is affected by *goal choice* and the *effort* needed to reach that goal. Clark [17] hypothesized that these two components are continually re-examined to regulate an individual's level of motivation towards a goal. The first component, *goal choice*, is strongly affected by the factor of *goal value*, which is comprised of *utility* (i.e., the usefulness of a task in light of future goals) [18], *interest* (i.e., the enjoyment or intrinsic inquisitiveness towards a task), and *importance* (i.e., the significance of succeeding in a were). The second part, *effort*, is strongly affected by *task assessment*. This factor is comprised of *self-efficacy* (i.e., Can I do it?), and *personal agency* (i.e., Will I control my destiny?). Finally, positive and negative mood characterizes *emotion*. Positive mood is directly proportional to goal commitment while negative mood is inversely proportional [17].

From an expectancy model perspective, Bandura [16] proposed that an individual's motivation is affected by one's beliefs of *self-efficacy* and *control of outcomes* (i.e., Do I have control of my success or failure?). In this expectancy model, the component of self-efficacy is dissected into two distinct elements: (1) outcome expectations (i.e., the belief that one's behaviors affect outcomes), and (2) efficacy expectations (i.e., the belief that ones' behaviors can be effectively performed) [19]. Wilson et al. [13] further aligned self-efficacy theory with student engagement. They state that the strength of engagement is directly proportional to the strength of the belief that students have in their ability to accomplish a task. Many more suggest that self-efficacy is a strong predictor of performance, persistence, and engagement [20–23]. Many classify student self-efficacy as a significant construct within the framework of student motivation [15–18, 24].

Extending this, Pintrich, Marx, and Boyle [2] combined *expectancy beliefs* with *value choices* and *meta-cognition* to form a *social cognitive* perspective of motivation. In their motivation-cognition model, value choices are comprised of *goal orientation*, *interest*, and *importance*; expectancy beliefs are comprised of *self-efficacy*, *attributions*, and *control beliefs*; and meta-cognition is comprised of *self-regulated learning*. This motivation-cognition model takes the perspective that meta-cognition and motivation form a symbiotic and dynamic relationship. A person continually evaluates intrinsic and extrinsic feedback to dynamically adjust their motivation towards learning [25]. When this happens, a student is said to be self-regulating their learning (termed *self-regulated learning*), with the cognitive "energy" expended being labeled as *motivation* [25, p. 306]. Self-regulated learning has been defined to include three primary phases: (1) *forethought* (including task analysis and self-motivated beliefs); (2) *performance* (including self-control and self-observed strategies); and (3) *self-reflection* (including self-judgment and self-reaction) [25, p. 375]. As a person works through these phases, motivation determines the degree to which each later phase is performed, and subsequently the level of achievement that is reached. Therefore,

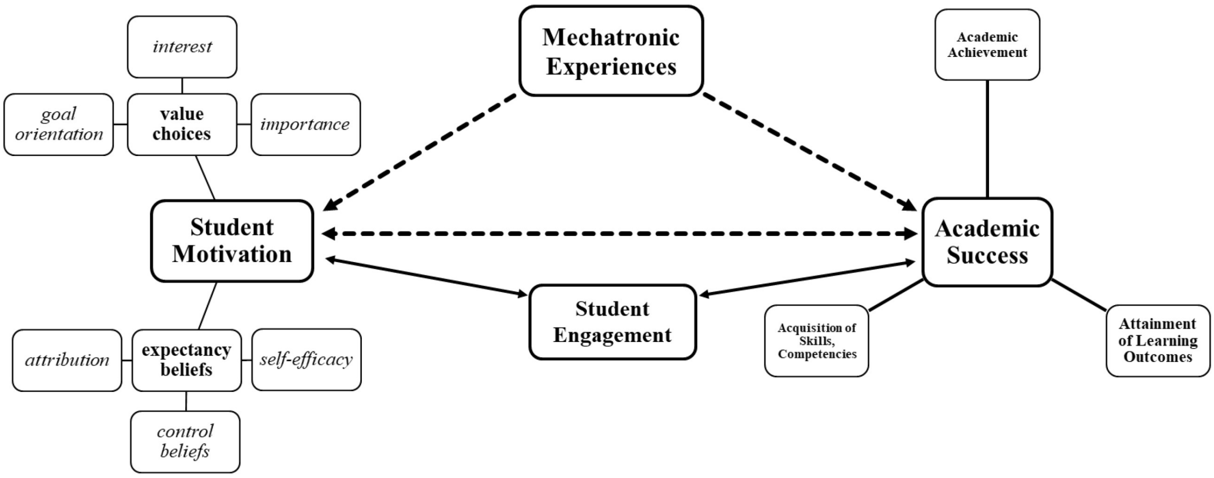

Fig. 1. Theoretical framework of the relationship between mechatronic experiences, student motivation, student engagement, and academic success. Dashed arrows indicate the relationships that this study analyzed.

student motivation and academic success form a symbiotic relationship within a student's mental cognition.

1.4 Framework of the research

The theoretical framework of this research is depicted in Fig. 1. It illustrates the connections between student motivation, student engagement, academic success, and mechatronic experiences. The level to which students succeed academically has been linked to their level of motivation [1]. This link is often mediated by students' level of engagement [10, 11], Moreover, mechatronic experiences have been illustrated as tangible experiences that impact undergraduate engineering and technology students' motivation and academic success [26]. Specifically, the scope of our pilot study was to quantify differences in student motivation and academic success in a mechatronic experience vs. a non-mechatronic experience.

2. Materials and methods

2.1 Quasi-experimental design

Our study used a quasi-experimental, non-equivalent control vs. treatment design [28]. The treatment group (n = 61) experience was administered during the spring semester of 2016, with the control group (n = 23) experience occurring the following fall semester. Our "quasi" designation stemmed from the non-random assignment of participants to the treatment and control groups (i.e., we could not dictate which students enrolled in which course sections). Using adaptive sample size calculations [29], we found that a control group sample size of $n \geq 22$ was required to statistically support an effect. This was based on the *pwr* package [30], initial treatment group sample of n = 61, power = 0.80, α = 0.05, and assumed "medium" effect sizes (e.g., Cohen's d = 0.70 and h = 0.70 for research questions one and two, respectively). Our assumption of medium effects was due to a lack of published effects for similar research. Therefore, we followed Cohen's suggestion that a medium effect is "likely to be visible to the naked eye of a careful observer" [31, p. 156], which appeared to be evident in the literature. Furthermore, our multi-semester, convenience sample design mirrored others [32] who have conducted similar research using the same instrument to measure motivation (i.e., Pintrich and colleague's [24] *Motivated Strategies for Learning Questionnaire* (MSLQ)).

2.1.1 Treatment group experience

An eight-week mechatronic experience (see Table 1 semester weeks 8–15) served as our experimental treatment (n = 61). The first four weeks of the experience (weeks 8–11) required students to individually complete five software (program code) and hardware (motor and sensor) activities. With this foundation, students were given the last four weeks (weeks 12–15) to develop, test, and implement solutions to the mechatronic project. This project required groups of three to four students to develop a software program that integrated the mechanical and electrical hardware systems of a mobile robot to autonomously navigate through one of three predefined mazes. Fig. 2 illustrates an example maze used in the mechatronic project, while Appendix A includes a detailed description of the mechatronic project requirements. The reader is further pointed to Haughery and Raman [33] for a detailed description of the capital and labor time and costs associated with developing this project. Finally, the project's administration was significantly informed

Table 1. Detailed semester schedule of treatment and control group experiences (differences in experiences highlighted in bold text)

	Weekly Topic		Project Requirements	
Week	**Control**	**Treatment**	**Control**	**Treatment**
8	Introduction, IDE, Structure Variables, Data Types	Introduction, IDE, Structure Variables, Data Types	Complete **five** Programming Activities	Complete **two** Programming & **three Mechatronic** Activities
9	Arithmetic, Constants Flow Control, Switch Case, Break	Arithmetic, Constants Flow Control, Switch Case, Break		
10	Digital & Analog I/O, Time	Digital & Analog I/O, Time		
11	Data Acquisition & Visualization **Serial Monitor Printing**	Data Acquisition & Visualization **Motor & Sensor Functions**		
12	Challenge Task Development	Challenge Task Development	Complete **three Data Analysis Project** tasks	Complete **one of the Mechatronic Project** task
13	Challenge Task Development & Testing	Challenge Task Development & Testing	**1. Counting Significant Figures**	1. Manufacturing Part Delivery Task
14	Challenge Task Testing	Challenge Task Testing	**2. Sorting Random Numbers**	2. Agricultural Harvesting Task
15	Challenge Task Completion/Presentation	Challenge Task Completion/Presentation	**3. User Interface: Multiple Equations**	3. Animal Science Health Monitoring Task
16	Finals Week	Finals Week		

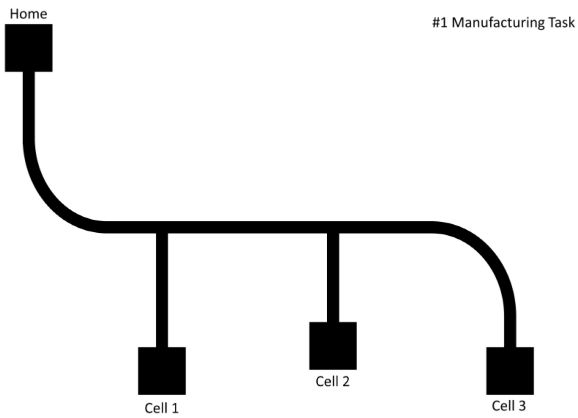

Fig. 2. Treatment (robot) group experience example maze. Students were tasked with programming the robot to autonomously navigate the maze starting at the "home" position, entering and exiting each "cell" in sequence, and returning to the "home" position. The robots could not leave the black line or enter cells 1–3 more than once.

by the methods and lessons learned from others [3–7, 34, 35].

2.1.2 *Control group experience*

Our control group experience ($n = 23$) mirrored that of the treatment group experience, until week 11 (Table 1 bold text). For the control group, instruction covered serial communication and character string parsing functionality. Additionally, during weeks 12–15, students were tasked with a data analysis project, as detailed in Appendix B. These tasks required students to solve three distinct data analysis problems within a computer software environment (i.e., not in a tangible, hands-on environment). The same grading rubric was used for both groups and is included in Appendix C. Therefore, the key difference in treatment vs. control groups was the mechatronic vs. non-mechatronic project. It is also important to note that the same instructor taught both the control and treatment group experiences. This was intended to remove variation due to the instructor. However, no mention of mechatronic content was discussed with the control group.

2.2 *Survey sample population*

The theoretical population for our study was undergraduate students enrolled in fundamental engineering, engineering technology, technology, or applied engineering courses. Within this population, we focused on a convenience sample of n = 84 undergraduate students enrolled in a technical problem-solving course, offered by the Department of Agricultural and Biosystems Engineering at Iowa State University, United States of America (USA). The term "fundamental course" was defined as a first-year class that occupied the core requirements of the department's Industrial Technology and Agricultural Systems Technology majors. Eighty-four percent were pursuing degrees within the department, while the remaining 16% were pursuing a range of degrees in agricultural business, agricultural exploration, agricultural studies, agronomy, and food or animal science. Male/female splits were 92% to 8% (compared to our department's typical 95% to 5% split), respectively, while the ethnicity split was of 91% non-underrepresented (i.e., White/Caucasian) students to 11% underrepresented students (compared to our department's typical 10%). Furthermore, students 18–19 years old made up 82%, students 20–23 years old made up 15%, and students over 23 years old made up the remaining 3%. Students taking part in this study had a wide level of previous mechanical, electrical, and computer systems experience. However, most did not consider programming skills as a primary goal in their education.

2.3 Measures

We measured student motivation using the motivational orientation items of Pintrich and colleague's [24] MSLQ. This instrument takes a meta-cognitive perspective of student motivation and learning and is predicated on the motivational constructs of *value choices*, *expectancy beliefs*, and *self-regulation*. Furthermore, it has been validated and generalized across gender, race, and educational levels [15] and has a substantial evidence base in the literature [32]. As endorsed by the MSLQ manual [24], we used all 14 questions of the *value* construct and 12 questions from the *expectancy* construct of motivational orientation as our multivariate measure of student motivation (Table 2). Likert Scale values for each item (e.g., CLB) were calculated as the average of the per question responses, ranging from 1 ("*not at all true of me*") to 7 ("*very true of me*"), for each of the questions (e.g., 2, 9, 18, 25). For more details regarding this instrument, including full questions, we point the reader to the MSLQ protocol [24].

Academic success was measured using final course grades, final project scores, and quiz scores. Values for these measures were normalized to a range of 0.00 to 1.00 by dividing the graded score by the total possible score or each assignment. The final course grades were assessed using a weighted combination of ten quizzes (10%), 15 in-class activities (15%), 12 essay questions (25%), one mid-term project (30%), and one final project (i.e., mechatronic project and data analysis project; 20%), all of which focused on applying a systematic, data-driven methodology for solving technical problems. Scores for the activities, essay questions, mid-term project, and the final project were evaluated by the course instructor and teaching assistants using the same rubrics for the control and treatment groups. All students were provided these rubrics before the completion of each assignment. Quiz scores were calculated as an average across five programming-centric quizzes. The grading of these quizzes was assessed using close-ended answer keys. This measure was used to answer our first and third research questions. Additionally, the academic preparedness of our experimental groups were not significantly different, based on a two-sample t-test of composite ACT scores (USA standardized placement test) for control (M = 23.39, SD = 2.98) vs. treatment (M = 23.31, SD = 3.26, $t(43)$ = 0.1066, p-*value* = 0.9156) groups.

We also included a multinomial response question asking students whether the mechatronic project motivated them. Students were first presented with Meece, Clark, and Pintrich and Schunk's definitions of motivation (see 1.3 Student motivation subsection above), and then asked to answer "Yes", "No", or "Neither". These responses formed a single-item measure of student motivation.

2.4 Data collection

Pre/post surveys were collected during the spring (treatment) and fall (control) semesters of 2016. All surveys were administered through Qualtrics (Provo, UT), with the pre-survey collection occurring during week eight of the semester, and the post-survey collection occurring during week 16. Incentives, capped at 1% of the students' course grade, were awarded to participants who completed both pre/post surveys. The pre- responses were linked to post- responses via the unique last five digits of students' identification numbers. Once this data link was made, and before the results were analyzed, all identifying information was removed from our data set. Additionally, all students received an informed consent allowing them to "agree" or

Table 2. MSLQ sub-scale item questions used to measure student motivation

Subscale	Item	Questions
Value Components	Intrinsic Goal Orientation (IGO)	1, 16, 22, 24
	Extrinsic Goal Orientation (EGO)	7, 11, 13, 30
	Task Value (TV)	4, 10, 17, 23, 26, 27
Expectancy Components	Control of Learning Beliefs (CLB)	2, 9, 18, 25
	Self-Efficacy for Learning and Performance (SE)	5, 6, 12, 15, 20, 21, 29, 31

"not agree" to participate in the surveys. No students under 18 years of age, or who responded, "not agree", were included in the dataset. This collection methodology was approved by our institution's Institutional Review Board (IRB) as an exempt study under the human subject protections regulation, 45 CFR 46.101(b).

2.5 Data analysis

All statistical analyses were performed using R version 3.3.3 (R Foundation for Statistical Computing, Vienna, Austria) and RStudio (RStudio, Inc., Boston, MA). All quantitative variables met the assumptions of quasi-random sampling and independent observations. While our sample sizes were unequal (control $n = 23$; treatment $n = 63$), this did not negatively impact the homogeneity of variance, therefore satisfying this model assumption [36].

Decisions of statistical significance for our two-tailed hypothesis tests were based on Bonferroni adjusted α values, as shown by Equation 1,

$$\alpha = \frac{0.05}{n_{tests}} \tag{1}$$

where n_{tests} is the number of statistical tests performed per the research question. While the use of multivariate analyses (e.g., MANOVA) is often used in this scenario, repeated univariate analyses (e.g., ANOVA), with adjustments to guard against inflation of evidence, are an accepted statistical alternative that enables a simpler, more straight forward interpretation of the results [37]. Adjusted α values for each repeat test are included with our results. Furthermore, the effect of clustering (e.g., student groups, student interactions) was not considered in our analysis.

To answer the question of how student motivation and academic success were different following a mechatronic experience, we calculated descriptive statistics with the *psych* package [38] and one-way between-group Analysis of Covariance (ANCOVA) tests, using Type I Sums of Squares. Analyzing the effects on the multivariate dependent variable of student motivation, we used the categorical predictor variable of group assignment (treatment or control). To control for pre-existing differences between groups, we included the covariates of pre-survey student motivation, previous semester GPA, and composite ACT scores. Examining the effects on the multivariate dependent variable of academic success, we used the same predictor and covariate variables, less pre-survey student motivation scores. The assumptions of normality, linearity, homogeneity of variance, homogeneity of regression slopes, and reliability of covariate usage were satisfied once missing values (15%) of students' composite ACT scores were imputed (five datasets were generated using predictive-mean-matching) using the *Multivariate Imputation by Chained Equations (MICE)* package [39] and post-survey MSLQ results were square transformed for normality. One dataset was randomly selected, from the five imputed datasets of composite ACT scores, for use in our ANCOVA analysis. Where statistically significant differences were found, Cohen's d [31] was used to calculate the size of effect for ANOVA tests using the *effsize* package [40] and interpreted per Cohen's proposed small = 0.20, medium = 0.50, and large = 0.80 [31].

Our second research question asked students to select whether they had been motivated or not by the experience. To answer this, we analyzed the difference in the proportion ($\hat{\pi}$) of students who reported, "Yes" vs. those who reported, "No" or "Neither" (combined as "Not_Yes") using a Fisher's Exact test [41]. This consolidation was used due to the small low counts of aggregate responses for "No" (5, 6%) and "Neither" (6, 7%). We reported Cohen's h as a measure of the effect size (strength of association) of our odds ratio test, as appropriate (i.e., statistically significant results). Again, we interpreted values per Cohen's suggested small = 0.20, medium = 0.50, and large = 0.80 [31].

The third research question examined the relationship between student motivation and the level of academic success, for both control and treatment groups. To answer this, partial Pearson's correlations (r) were used to explore the relationship between academic success (final project scores) and student motivation (post-survey levels minus pre-survey levels), while controlling for students' previous semester GPA. We found no violations of the assumptions of normality, linearity, and homoscedasticity after missing values (14%) of students' previous semester GPA scores (e.g., first semester freshman) were imputed (five datasets were generated using predictive-mean-matching) using the *MICE* package [39], post-survey MSLQ results were square transformed for normality, and course grades were Box-Cox transformed using the *car* package [42]. One dataset was randomly selected, from the five imputed datasets of previous semester GPA scores, for use in our correlation analysis. We also used paired-sample t-tests to test whether there was a significant difference between the correlation coefficients of the control group compared to the treatment group (i.e., r_1 vs. r_2) for each subscale and item of student motivation. We used the *cocor* package [43] for this and reported z statistic for these tests, per Fisher [44]. Effect sizes for difference in group correlation coefficients were reported using Cohen's q (i.e., small = 0.10, medium = 0.30, and large = 0.50) [31].

Table 3. Unadjusted descriptive statistics of student motivation and academic success

	Control (n = 23)					Treatment (n = 61)				
Dependent Variable	**M**	**SD**	**M_{trim}**	**Min**	**Max**	**M**	**SD**	**M_{trim}**	**Min**	**Max**
Value/Expectancy	5.35	0.75	5.38	3.75	6.70	5.49	0.75	5.53	3.82	7.00
Value	5.37	0.68	5.39	4.00	6.58	5.46	0.83	5.48	3.58	7.00
Expectancy	5.33	0.89	5.38	3.50	6.81	5.53	0.75	5.57	3.69	7.00
IGO	5.20	0.80	5.17	4.00	6.50	5.40	0.91	5.42	3.50	7.00
EGO	5.66	0.66	5.67	4.25	7.00	5.46	0.98	5.49	2.75	7.00
TV	5.26	1.03	5.30	3.00	6.83	5.51	1.16	5.62	1.50	7.00
CLB	5.14	1.00	5.21	2.75	6.75	5.31	0.92	5.35	3.00	7.00
SE	5.52	0.82	5.57	3.75	6.88	5.74	0.77	5.76	3.88	7.00
Course Grade	0.87	0.07	0.88	0.64	0.97	0.90	0.08	0.91	0.56	0.99
Project Score	0.81	0.18	0.83	0.40	1.00	0.89	0.08	0.91	0.49	1.00
Quiz Score	0.83	0.08	0.84	0.67	0.98	0.82	0.10	0.83	0.55	0.94

3. Results

3.1 Levels of motivation and academic success

The objective of this study was to examine differences in student motivation and academic success in a treatment (robotic) vs. control (non-robotic) groups. To accomplish this, we first analyzed the influence of outliers and found no significant impact. This was based on a paired-sample t-test of post-survey student motivation means (M = 5.45, SD = 0.16) vs. 5% trimmed means (M = 5.48, SD = 0.16, $t(8) = -0.2849$, p-$value$ = 0.7830) and academic success means (M = 0.86, SD = 0.04) vs. 5% trimmed means (M = 0.87, SD = 0.04, $t(4) = -0.3308$, p-$value$ = 0.7575). Turning to descriptive statistics of unadjusted student motivation scores (Table 3), we found means for all subscales and items (except EGO and quiz scores) were higher in the treatment vs. control group. However, when we controlled for differences in pre-experience student motivation (i.e., pre-survey MSLQ scores) and prior academic achievement (i.e., GPAs and ACTs), we found no statistical evidence that these mean scores were higher in the mechatronic experience [$F(6,77)$ = 0.03, p-$value$ = 0.8630] (α = 0.0500). This was based on a one-way between-groups ANCOVA. Further testing the *value* and *expectancy* subscales separately, we again found no statistical difference between mean scores for either *value* [$F(6,77)$ = 0.13, p-$value$ = 0.7224] or *expectancy* [$F(6,77)$ = 0.38, p-$value$ = 0.5408] (α = 0.0167). Moreover, no evidence was found that mean scores for the individual items of IGO, EGO, TV, CLB or SE were higher following the mechatronic experience [all tests: $F(6,77) \leq 2.66$, p-$value \geq 0.1069$] (α = 0.0063). In short, we were not able to claim that the gains in mean student motivation in Table 3 were due to the mechatronic experience. The higher mean scores of student motivation in our treatment group could be due to confounding variables or chance. We would need a combined sample size of roughly 800 (*expectancy*) and 2,300 (*value*), to statistically claim a difference (with an 80% probability of being correct). To our knowledge, no previous literature has indicated the need for sample sizes of these magnitudes.

Next, we examined differences in academic success. While the means of course grades and project scores were higher in the treatment vs. the control group, the means of quiz scores were lower (Table 3). Controlling for GPA and ACT scores using a one-way between-groups ANCOVA, we found strong statistical evidence that mean course grades were higher in the mechatronic experience group [$F(5,78)$ = 7.76, p-$value$ = 0.0067, 1-β = 0.81] (α = 0.0500). This resulted in a medium effect size (d = 0.70, $d_{95\%CI}$ = 0.20 to 1.20). Statistical evidence was also found that project scores were higher in the mechatronic experience group [$F(5,78)$ = 6.51, p-$value$ = 0.0127, 1-β = 0.50] (α = 0.0167). This resulted in a small effect size (d = 0.48, $d_{95\%CI}$ = 0.00 to 0.98). In contrast, the mechatronic experience did not exhibit statistical evidence of an effect on quiz scores [$F(5,78)$ = 0.25, p-$value$ > 0.6150] (α = 0.0167). There were no appreciable interaction effects between academic success and GPAs or ACTs either [all tests: $F(5,78)<2.32$, p-$value$ > 0.1315].

3.2 Proportion of motivated students

Looking at Table 4, we see that 55 (90%) of the treatment group students reported that the mecha-

Table 4. 2 × 2 contingency table for whether students were motivated by the experience

	Response		
Group	**Not Motivated**	**Motivated**	**Total**
Control	5	18	23
Treatment	6	55	61
Total	11	73	84

Table 5. Within-group Pearson's partial correlations of student motivation and final project scores, while adjusting for previous semester GPA

	Control (n = 23)			Treatment (n = 61)			
	r	Statistic	*p-value*	r	Statistic	*p-value*	Adjusted α
Value/Expectancy	0.47	2.35	**0.0291**	0.07	0.52	0.6048	0.0500
Value	0.13	0.58	0.5679	0.08	0.64	0.5226	0.0167
Expectancy	0.27	1.26	0.2207	–0.01	–0.07	0.9444	0.0167
IGO	0.07	0.30	0.7702	0.14	1.07	0.2871	0.0063
EGO	0.07	0.33	0.7421	–0.02	–0.12	0.9016	0.0063
TV	–0.12	–0.55	0.5901	–0.07	–0.50	0.6169	0.0063
CLB	0.25	1.18	0.2531	–0.10	–0.79	0.4315	0.0063
SE	0.54	2.90	0.0089	0.08	0.62	0.5351	0.0063

Note: n = 84; H_0: r = 0.00.

tronic experience was motivating (per Meece, Clark, and Pintrich and Schunk's definitions). In comparison, 18 (78%) of the control group students felt that the non-mechatronic experience motivated them (per the same definitions of motivation). To test whether there was statistical evidence that these proportions were different, we used a Fisher's Exact test. We found no evidence that the proportion of motivated students in the treatment group [$\hat{\pi}$ = 0.90] was different than in the control group [$\hat{\pi}_1 - \hat{\pi}_2$ = 0.12, *p-value* = 0.1634, *OR* = 2.51, *h* = 0.33] (α = 0.0500). To be able to state statistical evidence of a difference (based on our data and 80% power), we would have needed a combined sample size of close to 300. To our knowledge, recommendations of this sample size have not previously been published.

3.3 Relationship between motivation and academic success

To understand the relationship between each subscale and item of student motivation, as well as final project scores, we calculated Pearson's partial correlation coefficients (r), while adjusting for students' previous semester GPA (Table 5). In the control group, every value of r was not significantly different from zero, except for the *value/expectancy* vs. final project score [r = 0.47, *p-value* = 0.0291] relationship. However, more interesting than the control's *value/expectancy* result was what we found for the treatment group. There was no significant relationship between students' final project scores and the value they placed on the final project or the belief(s) they held in their ability to effectively complete it. This result was true for each of the items within *value* and *expectancy* as well [all tests: *p-value*>α]. Using paired-sample t-tests, we statistically confirmed there to be no difference between our control and treatment group's r values [all tests: $r_1 - r_2 \leq 0.46$, *p-value*>0.0417]. This was true for all the student motivation subscales and items (Table 6). Even so, itis interesting to point out that, while not statistically significant (α = 0.0063), the relationship between SE and final project scores was below the common significance level for single hypothesis *a priori* research questions [control r = 0.54, treatment r = 0.08, *p-value* = 0.0417]. While we cannot claim a significant difference, there appears to be a meaningful relationship between self-efficacy and academic success (when adjusting for GPAs).

Table 6. Between-group t-tests of difference in Pearson's partial correlations of student motivation and final project scores, while adjusting for previous semester GPA

	r_1–r_2	*z-value*	*p-value*	Adjusted α
Value/Expectancy	0.40	1.68	0.0929	0.0500
Value	0.04	0.17	0.8619	0.0167
Expectancy	0.28	1.11	0.2663	0.0167
IGO	–0.07	–0.29	0.7741	0.0063
EGO	0.09	0.35	0.7261	0.0063
TV	–0.06	–0.22	0.8286	0.0063
CLB	0.36	1.40	0.1604	0.0063
SE	0.46	2.04	0.0417	0.0063

Note: n = 84; H_0: $r_1 \neq r_2$.

4. Discussion

Fig. 3 graphically represents the relationships found from our pilot experiment examining the differences and relationships between mechatronic experiences, student motivation, and academic success. A detailed discussion follows.

4.1 Levels of motivation and academic success

Our first research question asked whether there was a difference in student motivation and/or academic success in the treatment (robotic) vs. control (non-robotic) groups. Considering student motivation, we did not observe a difference (top left dashed line of Fig. 3). While this is in contrast to current literature that has stated improvements to student motivation following mechatronic experiences, we posit that the research designs undergirding these findings appeared to have been predicated on single

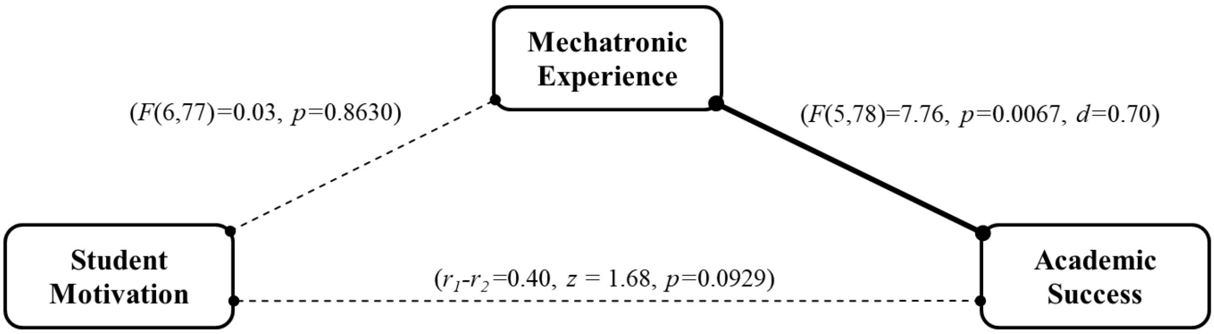

Fig. 3. Framework of the relationship between mechatronic experiences, student motivation and academic success, based on research findings. Solid lines indicated statistically significant relationships, while dashed lines indicated statistically insignificant relationships.

item questionnaires that were most often administered once [3–7]. Pre/post surveys and/or control vs. treatment group methodologies were not used. Therefore, we argue for two alternative explanations: (1) previously observed effects of mechatronic experiences on the *value* and *expectancy* dimensions may not be as drastic as thought, and (2) previously observed impacts on *value* and *expectancy* may not have been due to mechatronic experiences. Looking at more historic research, it is well documented that motivation has a tendency to decrease over time [45]. Additionally, interest (i.e., *intrinsic goal orientation*) has been found to peak during the middle of a project, and wane towards the end [46]. While these do not speak directly to the statistical similarity of mean scores observed in our study, they do indicate the dynamic nature of motivation that could be confounding a positive change in student motivation. Does motivation change at similar rates or degrees for mechatronic vs. non-mechatronic experiences? Are peaks in motivation the same, or do they occur at similar points in an experience? Future work is required to answer these questions. However, it is important to highlight that we did not observe a negative impact on student motivation in the mechatronic experience group. This would indicate that implementing this type of rigorous, domain spanning experience did not demotivate students.

Considering post levels of academic success between groups, we found significant differences in course grades and project scores (solid line of Fig. 3). Students who engaged in the mechatronic experience averaged three percentage points higher on course grades and eight percentage points higher on final project scores. This translated to an average course grade of A– in the treatment group vs. B+ in the control group, and an average final project score of a B+ in the treatment group vs. a B- in the control group. From a student's perspective, this is a practically significant difference, especially those applying for scholarships. This aligns with the concept that a medium effect is "likely to be visible to the naked eye of a careful observer" [31, p. 156]. While this does not prove causality (assignment to experimental groups was not random, thus no directional arrow in Fig. 3), it does reveal an association between mechatronic experiences and improved academic success in open-ended problem-solving projects and courses. This is not surprising, as these experiences require students to integrate divergent technical domains towards an effective solution. Harnessing this skill is central to authentic problem-solving. This aligns with various studies that have linked mechatronic experiences with motivation, or motivation with engagement, or engagement with academic success (as indicated by Fig. 1). More significantly, our findings make a strong connection between each end, thus supporting the link between the parts, as indicated by Duncan and McKeachie [32]. However, when considering quiz scores, academic success was not different for the treatment vs. control group. This would indicate that students' knowledge of content (specifically programming syntax) was not affected by the mechatronic experience. This is juxtaposed to research that found students' knowledge of content (specifically electronic sensors) to be higher following a mechatronic experience compared to the same students' levels after a baseline experience [5]. This study did not compare scores against a separate control group, possibly leading to differing results. Another explanation could be that mechatronic experiences impact knowledge retention differently for different content domains. As a note of comparison, the same grading rubrics and schemes were used to measure course grades, project scores, and quiz scores for the control and treatment groups. This was done to mitigate confounding variability when measuring these variables.

As an interesting side note, we did find a slight interaction (*p-value* = 0.0332) between previous semester GPA and group assignment, when considering the dependent variable TV. It appeared that, in the treatment group, higher-achieving students placed less value on the mechatronic experience vs. lower-achieving students. While we cannot claim statistical evidence of a difference in TV (*p-value* $> \alpha$), this does parallel the inverse relationship often found between students' prior level of knowledge and the level of effort exerted towards a goal [17]. Could it be that the value placed on a mechatronic experience is mediated by students' previous level of academic achievement (i.e., higher achieving students are less motivated by mechatronic experiences)? Again, future research is needed to understand these relationships.

4.2 Proportion of motivated students

Our second research question looked at differences in the proportion of students who reported being motivated in the treatment vs. control group. We found no difference (again, top left dashed line in Fig. 3). This corroborates the results found for our first research question. Just as we did not find a difference in reported levels of student motivation, we did not find a difference in the proportion of students that were motivated. The hands-on, multidisciplinary, technical nature of mechatronic had no significant impact on motivation. Therefore, wise consideration is called for when deciding to implement these experiences, especially if the purpose is to impact student motivation, as defined by Meece, Clark, and Pintrich and Schunk (see Motivation subsection above).

4.3 Relationship between motivation and academic success

Looking at research question three, we asked if there was a relationship between student motivation and academic success (bottom dashed line in Fig. 3). Limited correlations were found. The only exception was a positive relationship between *value/ expectancy* and final project scores in the control group. This indicated that, in the control group, students who reported higher levels of student motivation earned higher final project scores. This is not surprising, as these subscales are considered adaptive motivational beliefs and have been positively linked to academic success [45]. However, this positive relationship did not hold true for the individual subscale items or in the treatment group. Moreover, we found no difference in the relationship between students' *value choices* or *expectancy beliefs* and final project scores when comparing the control vs. treatment groups. This would indicate that the mechatronic experience had no impact on the relationship between students' level of motivation and academic success. While much literature has found a positive relationship between these variables (e.g., the more a student is motivated towards an academic goal the higher the level of achievement they attain for that goal) [47], we concluded that the mechatronic experience had no effect, positive or negative, on the strength of relationship between student motivation and academic success. This was not surprising, as this again confirms results found from our first two research questions.

4.4 Limitations

While we strove for rigor in our study, limitations still existed. First, our measures of motivation were based on students' self-reported responses. While one can argue that the use of this type of data is limiting, there is a well-established record of literature that has used the same instrument and methods to measure motivation [32]. Therefore, we did not feel it was unreasonable to inform our conclusions based on self-reported responses.

Next, we did not consider the limitations due to our non-random quasi-experimental design unrealistic. This is a common scenario found in educational research [28], and only encumbers how broadly one can generalize our findings.

Another limitation was the non-equivalent sample size of the control and treatment groups. While this is often considered an issue for ANOVA/ ANCOVA, it is only an issue when it adversely affects the assumption of homogeneity of variance [36]. Our data did not violate this assumption. However, this did add to our inability to find a statistically significant difference in student motivation, even though this was beyond our control (sample size needs have not been previously published for this topic area).

Finally, the same instructor taught the control and treatment groups. While this consistency was used to mitigate confounding variability of instructor differences, it did not account for the instructor's engagement level. The instructor was highly motivated to engage with and motivate the students, regardless of the content being taught (e.g., mechatronic or non-robotics). While we felt this removed variability of instructor differences, instructor engagement may still have overshadowed the effect of the mechatronic experience on student motivation results.

4.5 Recommendations

From the results of our pilot experiment, we recommend further research that examines the following:

- Effects size of mechatronic experiences on student motivation.
- Change in student motivation in mechatronic experiences vs. change in time.

- Interaction effects of Task Value and academic preparedness in mechatronic experiences.
- Impact of major, age, class level, previous technical experience, ethnicity, and/or gender identification on student motivation and academic success.
- Impact of instructional quality and motivation on student motivation in mechatronic experiences.

Expanding on the above, we did not find statistical differences in motivation orientation between the control vs. treatment group. While higher mean scores were observed in the treatment group, our sample or effect sizes were not large enough to find statistical significance. As previously noted, current literature lacks empirical sample and/or effect sizes for similar mechatronic experiences. Furthermore, motivation has been found to be dynamic throughout a project, peaking during the middle and dropping at the end. This raised several questions: Does motivation change at similar rates for mechatronic vs. non-mechatronic experiences? Do peaks in motivation have the same magnitude, and occur at the same time, for mechatronic vs. non-mechatronic experiences? When examining Task Value, we found slight interactions between GPA and group assignment. While we cannot claim statistical significance, this may indicate that higher-achieving students find less value in mechatronic experiences vs. lower-achieving students (*vice versa* for the control group). Put another way, does academic achievement mediate students' motivational *value* of mechatronic experiences? While we did find statistical differences for academic success, GPA and ACT scores were the only covariates included in the ANCOVA model. Future analyses could extend this model to include variables of major, age, class level, previous technical experience, ethnicity, and/or gender identification. Finally, we recommend that future research be conducted to examine the affect that instructor variability (e.g., instructional quality) has on student motivation and academic success. Literature has found that students with engaged instructors have higher levels of student motivation and academic success [48]. Therefore, including this covariate could improve our model's sensitivity to discerning differences in student motivation.

5. Conclusions

This pilot experiment empirically quantified the differences in undergraduate student motivation and academic success for a mechatronic experience (treatment) vs. a non-mechatronic (control) experience. Considering the first research question, we found no statistical differences in reported motivation. In contrast, there were differences in academic success, with the treatment group scoring an average of three percentage points higher on course grades. Answering the second research question, we found that the proportion of students motivated by the course project was not different for the treatment vs. control group. Furthermore, there was no association between students' level of motivation and their level of academic success, which answered our final research question. Synthesizing these results, we are encouraged: students in the more rigorous mechatronic experience did not have lower levels of student motivation. Even more encouraging, project scores and final course grades were higher in the mechatronic experience group. Not only do these findings provide empirical evidence explicating differences in student motivation and academic success in mechatronic experiences, but they also encourage further investigation into the nuances of these constructs.

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