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Mechatronics and Academic Success: Towards Understanding the Impacts of Age, Major, and Technical Experience

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Abstract

This study built on previous research that found significant differences in the mean level of academic success (i.e., course grades) for students who participated in a mechatronic experience (i.e., integrating mechanical, electronic, and computer systems) vs. those who did not. This paper further examined this variation in course grades by conducting a two-way Analysis of Covariance to understand the impact academic major (i.e., technology major vs. non-technology major) and group assignment (i.e., control vs. treatment) had, while controlling for pre-study covariates of GPA, ACT, age, and technical experience. When adjusting for differences in ACT and GPA scores, we found significant main effects for group assignment (expected), but not for major (unexpected). Furthermore, no interaction effects where found between academic major and group assignment. When analyzing age and previous technical experience level (i.e., mechanical, electrical, and computer systems), we found age to be a significant predictor of course grades, while previous experience (in any area) was not. This would indicate that younger students performed better in the course, while, contrary to education theory, previous technical experience had no impact on course grades. This study used a quasi-experimental, nonequivalent group design with a convenience sample of n = 84 students in a first-year technology course. It looks to expand the empirical foundations supporting the impacts of mechatronic experiences on academic success.

Keywords: academic success, mechatronics, engineering education

1. Introduction

Academic success is often directly related to the level of academic engagement a student exhibits [1]. This engagement is contextual and can be strongly impacted by a students' motivation within the given context [2], [3]. In this study, we defined academic success as a combination of *academic achievement* (e.g., grades and GPAs), *attainment of learning outcomes* (e.g., student engagement and proficiency profile), and *acquisition of skills and competencies* (e.g., critical thinking and problem solving) [4]. We defined student motivation to include *expectancy beliefs* (i.e., *self-efficacy*, *attributions*, and *control beliefs*), *value choices* (i.e., *goal orientation*, *interest*, and *importance*), and *meta-cognition* (i.e., *self-regulated* learning) [5]. This motivation-cognition-learning model takes the perspective that these constructs form a symbiotic and dynamic relationship. A student continually evaluates intrinsic and extrinsic feedback to dynamically adjust their motivation towards learning [6]. 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* [6, p. 306].

In this paper, we focused on the construct of academic achievement – course grades – and assumed it to be influenced by students' motivation in the classroom. This perspective is supported by Pintrich *et al.* [3] and Linnenbrink-Garcia [7], who indicate real-world technical projects and course activities to influence and improve students' motivation. Specifically, we found significant differences in mean course grades for students who participated in a mechatronic experience (i.e., one that require students to integrate mechanical and electronic systems that are controlled by a software system) vs. those who did not [8]. While others [9], [10] indicate similar improvements in learning following mechatronic experiences, there is limited published evidence describing the impact that age, experience, and major can have on academic success, within a mechatronic experience [11]. In a broad learning context, Clark [12] stated that prior knowledge effects the level of effort (motivation) directed toward a goal. Similarly, Kamphorst *et al.* [13] cited Astin [14] and Tinto [15] as indicating students' prior experiences can influence their level of academic success. Examining learning profiles, Nelson *et al.* [1] found that a student's major – as related to a course's content – was significantly associated with their learning profile. They found major students predominantly exhibited adaptive learning profiles and achieved higher levels of academic success vs. non-major students within a computer science course.

Based on the literature above, we hypothesized that students with a major related to mechatronics would exhibit higher levels of academic success vs. non-major students. The context of this hypothesis was a mechatronic experience conducted in a core first-year course within our department's undergraduate technology curricula. We tested this hypothesis while controlling for the variables of ACT scores, previous semester GPA, age, and previous technical experience. This allowed us to remove sources of confounding variation and better understand the impact these variables had on students' academic success. Explicitly, we asked the following research questions to help guide our research:

1. Did the treatment group have different levels of academic success vs. the control group when considering major vs. non-major status?
2. Did past academic success impact future academic success?
3. Did age and/or previous experience impact academic success?

2. Materials and Methods

2.1. Study Design

A quasi-experimental, non-equivalent control vs. treatment design was used in our study, as described by [16], and commonly used in educational research [17]. Both groups came from students enrolled in a freshman-level problem-solving course offered at a large Midwest land grant university. Our treatment group mechatronic experience was conducted as the final project during the last four weeks of the spring 2016 semester (excluding the final exam week), as illustrated by Table 1. This project asked students to integrate the mechanical and electrical hardware of a robot with original software program code. The software code was required to autonomously control the robot through a predefined maze using sensor inputs and motor outputs. The administration of this project was significantly informed by the methods and lessons learned from others [9], [10], [17]–[22] and was preceded by four weeks of course content fundamental to successful completion. The hardware and software used in this project was an Arduino UNO microcontroller (Arduino, USA), ZUMO v1.2 robot (Pololu, Las Vegas, NV), and the Arduino 1.6.10 integrated development environment (Arduino, USA).

Table 1
Treatment group semester schedule.

Week	Week Topic	Project Requirements
8	Introduction, IDE, Structure Variables, Data Types	Complete five Mechatronic Activities
9	Arithmetic, Constants Flow Control, Switch Case, Break	
10	Digital & Analog I/O, Time	
11	Motor & Sensor Functions	
12	Challenge Task Development	Complete one of the Mechatronic Project challenge tasks in teams of four students 1. Manufacturing Part Delivery Task 2. Agricultural Harvesting Task 3. Animal Science Health Monitoring Task
13	Challenge Task Development & Testing	
14	Challenge Task Testing	
15	Challenge Task Completion/Presentation	
16	Finals Week	

Our control group received instruction by the same instructor, during the fall 2016 semester. At week 10 of the semester the control group’s instruction differed. The instructor presented serial communication and character string parsing content and required students to complete a final project focused on data analysis problems within the Arduino programming environment and computer hardware (e.g., determine the number of significant figures in a user defined number, sort user defined numbers in numeric order, and perform three predefined calculations while allowing the user to input unique variable values). No functionality was expected of the students beyond the bounds of the microcontroller board (i.e., the sequential functionality of the project was largely hidden from the students). Furthermore, the instructor did not present any mechatronic related content with the control group.

All students in the study received an informed consent allowing them to “agree” or “not agree” to participate in the study. No students under 18 years of age, or who responded, “not agree”, were included in our dataset. This study was approved as an exempt study under the human subject protections regulation, 45 CFR 46.101(b) by our Institutional Review Board (IRB).

2.2. Survey Sample Population

Our study was conducted using a convenience sample of n=84 undergraduate students across the control (n=23) and treatment (n=61) groups (Table 2). Further demographic information for our survey population can be found in Table 2. Gender and ethnicity splits favored women (3%) and underrepresented students (2%) slightly more than our department’s population percentages. Students were predominately within the 18 – 20 year range (M=19.62, SD=1.57), as expected for a freshman level course. Also, the majority of students in our study were departmental majors (75%). Students indicated more previous mechanical experience compared to electrical or computer. Furthermore, many did not envision computer programing to be an important skill to acquire during their education.

Table 2

Survey sample demographics with departmental population comparison.

	Study (n=84)		Department (N=475)	
Variable	Count	%	Count	%
Male	77	92	451	95
Female	7	8	24	5
White/Caucasian	74	88	427	90
Non-White/Caucasian	10	12	48	10
18 – 20 years	67	80	–	–
21 – 23 years	14	17	–	–
Over 23 years	3	3	–	–
Major	63	75	–	–
Non-Major	21	25	–	–
Control	23	27	–	–
Treatment	61	73	–	–

	Likert Scale Distribution						
Variable	None (0)	A Little (1)	Some (2)	A Lot (3)	M	Mdn	SD
Mechanical Experience	9	30	36	9	1.54	2	0.83
Electrical Experience	21	43	17	3	1.02	1	0.78
Computer Experience	28	34	21	1	0.94	1	0.80

2.3.Measures

Academic success was measured using final course grades using a 0.00 to 1.00 scale. These 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 (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. Grading of these quizzes were assessed using close-ended answer keys.

The variables of GPA and ACT were collected from the Institutional Research unit of our university. GPA values, on a 0.00 – 4.00 scale, represented students' scores earned in the semester prior to participating in our study. ACT values, on a 1 – 36 scale, represented students' composite scores across all testing areas. Missing GPA and ACT data were imputed using the Multivariate Imputation by Chained Equations (MICE) package [23] in the R software application, version 3.3.3 (R Foundation for Statistical Computing, Vienna, Austria) and RStudio (RStudio, Inc., Boston, MA).

Previous experience was self-reported by students. They were presented with descriptions of mechanical, electrical, and computer systems, per the National Center for Education Statistic's Classification of Instructional Programs (CIP) taxonomy of mechanical (14.1901), electrical (14.1001), and computer software engineering (14.0903) [24]. Respondents were given four Likert Scale level options (e.g., "None", "A Little", "Some", and "A Lot") for each area. These levels were recoded for analysis as follows: None = 0, A Little = 1, Some = 2, and A Lot = 3.

Age was measured in years for each student at the time of the study. However, in accordance with human subject regulation (45 CFR 46.101(b)), participants under 18 years old were not included in our study. Additionally, students 25 and above were combined as ≥ 25 years old, due to limited counts.

2.4.Data Analysis

To answer our research questions, we calculated descriptive statistics with the psych package [25] and used two-way between-group Analysis of Covariance (ANCOVA) tests, using Type I Sums of Squares. Analyzing the effects on academic success, we used the categorical predictor variables of group assignment (treatment vs. control) and major (major vs. non-major). To control for pre-existing differences between groups, we included the covariates of previous semester GPA, composite ACT scores, age, and previous experience. Assumptions of normality, linearity, homogeneity of variance, homogeneity of regression slopes, and reliability of covariate usage were satisfied after course grades were Box-Cox transformed [26] and GPA and ACT scores were square transformed. Decisions of statistical significance for our two-tailed hypothesis tests were based on a Type I error rate of $\alpha = 0.05$. Where statistically significant differences were found, Cohen's f [27] was used to calculate the size of the effect for our ANCOVA tests using the effsize package [28] and interpreted per Cohen's proposed small = 0.10, medium = 0.25, and large = 0.40 [27].

3. Results and Discussion

First, we analyzed the influence of outliers in our dataset and found no significant impact. This was based on a paired-sample t-test of academic success means (M=0.86, SD=0.04) vs. 5% trimmed means (M=0.87, SD=0.04, $t(4)$=-0.3308, p=0.7575). Examining descriptive statistics of unadjusted course grades per the predictor variables of group assignment and major (Table 3), we found means to be higher in the treatment vs. control group and for majors vs. non-majors. To answer the research questions of how students' major, past academic success, age, and experience impacted course grades, we used a two-way ANCOVA model to control for previous GPA and ACT scores, as well as age and experience level. However, because our response variable was non-normally distributed (A=4.3147, p<0.0001), we transformed course grades in our analyses. In the following subsections we present our findings for each research question.

Table 3
Unadjusted descriptive statistics of course grades per category.

Group Assignment	Degree Option	n	M	SD	Mdn	Min	Max
Control	Major	12	0.86	0.07	0.88	0.64	0.91
	Non-Major	11	0.89	0.05	0.89	0.81	0.97
Treatment	Major	51	0.90	0.008	0.92	0.56	0.98
	Non-Major	10	0.91	0.08	0.93	0.74	0.99

3.1. Research Question 1: Majors vs. Non-majors

Analyzing students' major and group assignment, we found no statistical evidence of interaction effects on mean course grades [F(1,74)=0.02, p=0.8871]. This is supported graphically in Figure 1, which illustrates no intersection in the effect slopes. Simply put, a student's major did not influence how their group assignment effected course grades (and *vice versa*).

Looking at effects of group assignment on course grades, we found statistically significant differences [F(1,74=6.03, p=0.0164, $1\text{-}\beta$=0.69], as previously published [8]. This had a "medium" effect (f=0.29) on course grades so that students in the treatment group had higher course grades than students in the control group. Furthermore, group assignment accounted for 5% of the variation in course grades (model with vs. without GPA: ΔR^2=0.05). Practically speaking, this was a 3%-point higher grade average for students who engaged in the mechatronic experience vs. students who did not engage in the mechatronic experience. This aligns with the concept that a medium effect is "likely to be visible to the naked eye of a careful observer" [27, p. 156]. While we did find statistical difference between treatment and control group course grades, we cannot claim statistical evidence that the difference was caused by our mechatronic experience. This is because of our research design's non-random assignment. However, we made every effort to reduce confounding differences in the groups by controlling for the previously stated covariates and maintaining identical grading rubrics and graders for both groups. Even though we were hamstrung by the non-random nature of our real-world educational research, we can claim that the difference was not due to chance.

Examining students' major, we did not find statistical evidence of main effects on course grades [F(1,74)=0.11, p=0.7466]. Students not majoring in our department did not achieve any better or worst course grades than students within our department. This was interesting, as the mechatronic experience was more technically rigorous and considerably removed from many of the non-major students' programs of study (e.g., agronomy, agricultural business, food science). This is encouraging, as our findings indicate we were able to increase the rigor [11] without negatively impacting non-majors. The weight of this finding is magnified when considering that the course in question serves as a technical elective for many non-departmental majors at our university. Even so, our findings are juxtaposition to other's research that found non-major students predominately adopted maladaptive learning profiles which lead to lower course grades compared to major students who adopted adaptive learning profiles and earned higher grades [29]; others support this, indicating student engagement to be positively correlated to academic success [1], [30]. When considering the divergence of our findings, we suggest that our study illustrate the ability of a highly rigorous educational experience to "beat the odds" and positively impact students academically. Even if they are not majoring in a program related to the technical content of the experience.

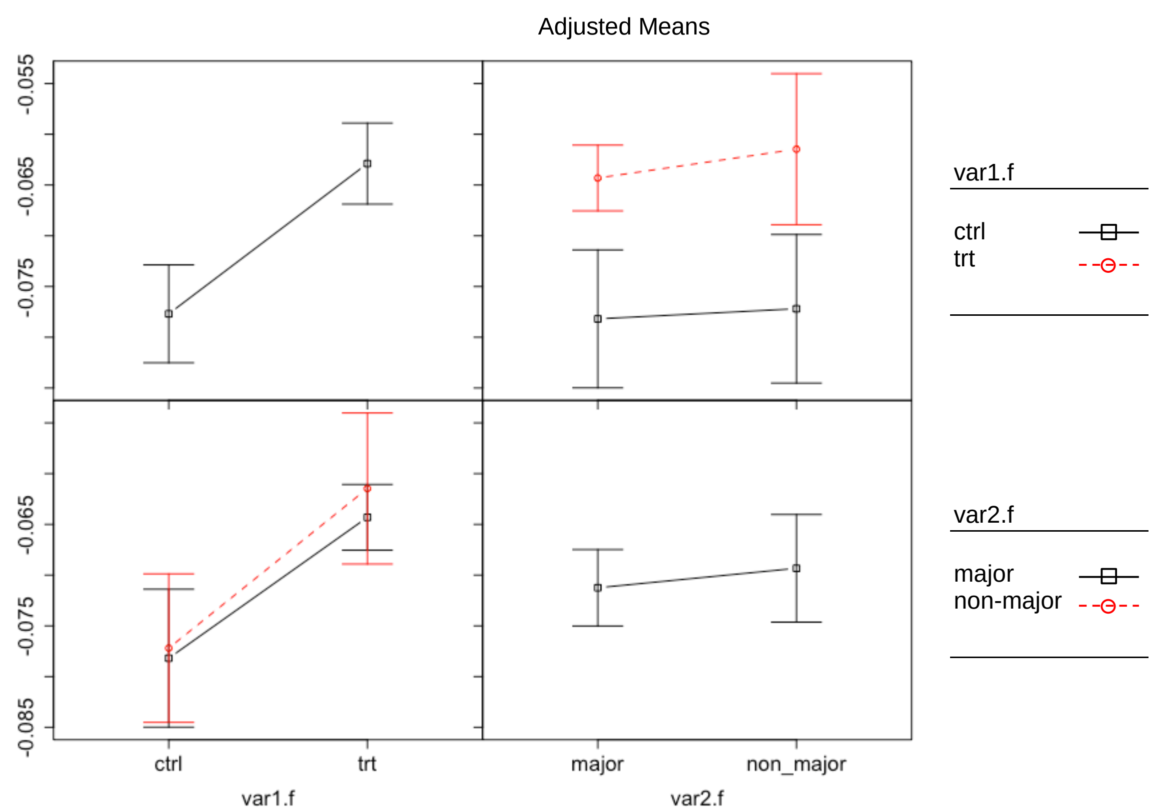

Figure 1
Main effects of group assignment and student major on adjusted mean course grades.

3.2.Research Question 2: Impact of previous GPA and ACT scores

Answering our second question, we found previous semester GPA to be significantly related to course grades [$F(1,74)=22.70$, $p<0.0001$, $1\text{-}\beta=0.99$, $f=0.55$). These scores accounted for 19% of the variation in course grades (model with vs. without GPA: $\Delta R^2=0.19$) and exhibited a "large" effect size. Plainly speaking, students with higher GPAs finished the course with higher grades ($r=0.45$, $t(82)=4.58$, $p<0.0001$). This was expected. We used GPA scored earned by students one semester prior to the study. The latent effect was much reduced compared to that of ACT scores, which were earned multiple semesters prior. Consequently, ACTs were not a significant predictor of course grades [$F(1,74)=0.07$, $p=0.7882$]. While ACT scores are commonly used to predict academic success in college [31], [32], our study looked at a course that students took in their second or third (if not more) semester of college. Students' ACT scores coming out of high school may have been a good predictor of first-semester academic success, however their GPAs proved to better predict success given the situational aspects of our study. Again, this does not come as a surprise. It does indicate the diminishing value of ACT scores as a variable in predicting collegiate academic success.

3.3. Research Question 3: Impact of age and previous experience

In our ANCOVA model, age had a significant influence on course grades [$F(1,74)=7.28$, $p=0.0086$, $1\text{-}\beta=0.77$, $f=0.31$). Age accounted for 4% of the variation in our dependent variable ($\Delta R^2=0.04$). Furthermore, age was negatively correlated with course grades ($r=-0.25$, $t(82)=-2.36$, $p<0.0206$). This indicated that younger students had higher grades compared to older students. This is juxtaposed to the theory that older students (i.e., above 20 years old) earn higher levels of academic success compared to younger students [33], [34]. We did not find this to be the case in our study. Moreover, our findings validated the intentionality of developing the mechatronic experience for a younger student majority (e.g., 18–20 year olds) vs. an older student minority (e.g., 22 – 23 year olds. In that respect, our mechatronic experience was a success.

In contrast to age, we found students' previous experience in mechanical, electrical, and computer systems were not significant factors in determining course grades [all tests: $F(1,74)\leq 0.63$, $p\geq 0.4314$]. This does not align with research that suggests previous technical experience is negatively associated with effort levels [12], and research that positively correlates effort with academic success [1]. Given the low levels of previous experience (e.g., nearly 75% of respondents had a little to some mechanical and electrical, while nearly 75% had none to some computer experience), it is surprising that this did not significantly impact course grades. Even more interesting, computer programming was an integral requirement of our study's experience, yet students' experience in this area was the lowest of the three (Table 2 illustrates that students' averaged between "None" to "A Little" computer system experience). Because this variable was not a significant predictor of course grades, it would follow that the level of previous experience, especially computer programming, did not negatively impact course grades in our programming rigorous experience. That is significant. We were able to bridge students' experience gap and enable them to succeed academically separate from the low experience levels they brought with them.

3.4. Limitations

While the study was conducted with an eye to rigor and objectivity, there are still limitations. First, our non-random, non-equivalent design poses philosophical issues with being able to claim cause and effect relationships in our model. Consequently, we are only able to claim associated relationships. This kept us from being able to state that mechatronics increased grades. However, our quasi-experimental design methodology is commonly used in educational research. It would be nearsighted to discredit these types of studies as invalid or non-rigorous. They represent real-world scenarios that educators practice in and real students are engaged in. Second, the insignificance of ACT and technical experience found in our study may have been impacted by our sample size. Given a larger sample, we may have found these variables to be significant. And this is the crux of sample size vs. effect size calculations. In our case, we were not aware of any published studies to date that have given effect size of mechatronic experiences and course grades. Lastly, the variable of experience level was subjectively self-reported. This has the potential to impose some systemic errors into our model. Therefore, generalizations of our results for this variable should be carefully interpreted. We offer that our study was based on the state of the art of our topic and employed realistically rigorous methods.

4. Conclusion

This paper examined how course grades differed in a mechatronic experience group vs. a non-mechatronic experience group for major vs. non-major students. We found that course grades were significantly different between the two groups, while course grades were not different for majors vs. non-majors. We also analyzed covariates of ACT, GPA, age, and technical experience and found that GPA and age were significantly associated with higher grades. Interestingly, technical experience had no impact on students' grades (good or bad). A few interesting implications can be drawn from our study, as follows:

- Non-major students were able to perform to the same academic level as major students, when given a technically rigorous experience that was significantly removed from many of the non-major's career goals.

- Students who were given a more hands-on, technically rigorous project did better academically in the course.

- Age was an important factor in students' academic success, with younger students earning higher grades compared to older students.

- Students were able to "beat the odds" and succeed academically, regardless of limited technical experience.

- GPA scores, compared to technical experience, was a better predictor of academic success in a technically rigorous project.

4.1. Acknowledgements

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