Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #47093

Creating a Predictive Model of Innovation Self-Efficacy Based on Cognitive Dissonance Levels in Innovation-Based Learning Programs

Mercedes Terry, University of North Dakota

As a Ph.D. candidate enrolled in the University of North Dakota's Biomedical Engineering Program, I am actively engaged in an enriching Innovative-Based Learning (IBL) experience. Within this dynamic academic setting, I have undertaken a leadership role in groundbreaking research focused on Parkinson's disease, collaborating seamlessly with a diverse cohort of both online and in-person graduate and undergraduate students.

One of my greatest sources of satisfaction lies in leveraging my knowledge and skills to mentor undergraduate students, guiding them in the refinement of their research and professional capabilities. I take immense pride in fostering an inclusive and collaborative environment where students can thrive, encouraging their academic growth and contributing to the broader community of biomedical engineering scholars.

Abigail Tubbs, University of North Dakota

Ph.D. student and the Chief Technology Officer of MindMend Biotech LLC. Her research and entrepreneurial work focus on the intersection of biotechnology and engineering innovation. She is deeply committed to mentoring women in STEM and actively advocates for increasing diversity and inclusion within engineering education.

Brandon Fugger, University of North Dakota

I am a PhD student in Biomedical Engineering at the University of North Dakota, where I mentor undergraduate and graduate engineering students. My focus is on building a collaborative learning environment and supporting student growth in research and professional development.

Blair Dupre, University of North Dakota

Blair Dupre is a Ph.D. student in Biomedical Engineering at the University of North Dakota, focusing on developing diagnostic tools and strategies for Parkinson's disease. Blair brings extensive professional experience in biologics manufacturing, where he has optimized processes to enhance patient care globally. His passion for pharmaceuticals stems from their impact on patient's lives, driving his commitment to improving manufacturing and ensuring the availability of life-saving medications. His work impacts the lives of those with neurological disorders, with a focus on migraines, bipolar disorders, and synucleinopathies.

Dr. Enrique Alvarez Vazquez, University of North Dakota

Dr. Enrique Alvarez Vazquez is an assistant professor in the biomedical engineering program at the University of North Dakota (UND), with prior experience as a computer systems engineer at the Center for Visual and Cognitive Neuroscience (CVCN). He holds multiple advanced degrees, including a Ph.D. in Electrical Engineering from North Dakota State University (NDSU), along with expertise in telecommunications, software engineering, and college teaching.

Dr. Alvarez Vazquez specializes in biomedical engineering, with research interests spanning digital/analog communications, embedded systems, computer programming, and systems design. His work includes developing advanced devices for multisensory, psychophysical, and vestibular research. Recently, his focus has expanded to health informatics, digital health, and software engineering.

With an extensive publication record and proficiency in various software languages, Dr. Alvarez Vazquez is deeply passionate about advancing engineering education.

Ryan Striker P.E., University of North Dakota

Ryan Striker is a life-long learner. Ryan has two decades of professional experience designing embedded electronic hardware for industrial, military, medical, and automotive applications. Ryan earned his BS and PhD in Electrical Engineering and his MS in Systems Engineering. Ryan presently serves as the Director of Systems Engineering and Assistant Professor of Biomedical Engineering at the University of North Dakota.

Creating a Predictive Model of Innovation Self-Efficacy Based on Cognitive Dissonance Levels in Innovation-Based Learning Programs

Abstract

This study examines how cognitive dissonance (CD) affects innovation self-efficacy (ISE) in students enrolled in an Innovation-Based Learning (IBL) biomedical engineering program (BME). By exploring this relationship, this research aims to show how CD can be leveraged to enhance innovation skills in engineering education. IBL emphasizes applying engineering principles to solve real-world problems. IBL fosters creativity, critical thinking, and problem-solving skills through complex, open-ended projects that promote collaboration, iteration, and real-world application. This approach cultivates an innovation-driven mindset and leadership skills, essential for success in STEM fields, such as biomedical engineering.

CD, the psychological discomfort from encountering conflicting ideas or challenges that contradict one's knowledge, is common in IBL since norms differ from traditional education. This can initially amplify CD in students, particularly those accustomed to structured learning environments. IBL's focus on open-ended problem-solving and real-world applications challenges students' existing strategies and expectations. Rather than being merely a problematic side effect, CD is a natural consequence of engaging in IBL. When managed effectively, it fosters deeper understanding, enhances problem-solving skills, and strengthens ISE—confidence in one's ability to handle innovation tasks. Navigating and resolving CD helps students reconcile conflicting ideas, fostering creativity and resilience. However, if not addressed, CD can leave students feeling overwhelmed or disengaged. Therefore, managing CD help students successfully engage in innovation tasks.

This study was conducted within a BME program with an IBL framework. The participants included undergraduate and graduate students who completed surveys at the beginning and end of the semester to capture changes in CD and ISE. The CD survey was adapted from a validated scale to reflect IBL-specific scenarios, assessing students' psychological discomfort when confronting conflicting ideas or ambiguous challenges. ISE was measured using an established scale, which evaluates confidence in completing innovation-related tasks such as generating creative solutions and addressing complex problems. Data collection was facilitated through the MOOCIBL platform (a custom LMS) to ensure consistency. Spearman's rank correlation was used to explore initial relationships between the variables, while logistic regression modeling was implemented to predict ISE based on CD scores. These statistical approaches provided insights into the interplay between these constructs.

The results revealed a positive relationship between CD and ISE, indicating that as students reduced their levels of CD over the semester, their ISE increased. Logistic regression further demonstrated that decreased CD strongly predicted higher ISE, suggesting that as students managed CD, they grew more confident in their ability to innovate. These findings emphasize the importance of structured opportunities to help students navigate CD. The predictive model highlights practical pedagogical implications, showing that intentionally introducing CD while providing structured support strengthens students' problem-solving, adaptability, and confidence in generating innovative solutions, ensuring students are better equipped to tackle complex, real-world STEM challenges.

Introduction

Innovation-based learning (IBL) signifies a transformative change in engineering education, focusing on using engineering principles to address real-world issues in ways that extend past conventional project-based learning. IBL is an overall broad curriculum that includes many courses that are designed to equip students to confront intricate, open-ended challenges that demand innovative answers by promoting creativity, critical thinking, and problem-solving abilities. In IBL students engage in interdisciplinary projects that challenge them to identify real world problems, propose novel solutions and share their research outside of the classroom to create real world impact. A key component of IBL is fostering a culture where failure is not only accepted but seen as a natural and necessary part of the innovation process. Students are encouraged to iterate, refine, and learn from setbacks, reinforcing the idea that meaningful innovation often requires multiple attempts and adjustments. Assessments for students in these projects include milestone-based evaluations where students must successfully identify the gap they are trying to fill, the solution for that gap and how they are going to externalize their research. These assessments are used to ensure that students not only grasp engineering principles but can also apply them in a meaningful and innovative way. The increasing significance of innovation-oriented skills in STEM fields, particularly biomedical engineering, highlights the necessity to explore how teaching methods can improve students' innovative capabilities [1], [2], [3], [4], [5], [6].

In IBL environments, students often experience cognitive dissonance (CD)—a psychological discomfort arising from conflicting ideas or beliefs when faced with novel and ambiguous tasks. CD occurs when individuals encounter information or situations that challenge their knowledge, beliefs, or expectations. Transitioning to an IBL classroom, where norms differ significantly from traditional education, can amplify CD, particularly for students accustomed to structured learning environments. IBL emphasizes open-ended problem-solving and real-world applications, in contrast to the linear approaches of traditional education. This shift requires students to identify technical challenges, inefficiencies, and knowledge gaps while generating innovative solutions—tasks that may conflict with their prior learning strategies and assumptions. Additionally, the unfamiliarity of navigating ambiguity and the iterative nature of innovation can further intensify CD. This discomfort, however, can catalyze growth. It drives individuals to reconcile inconsistencies by adjusting their perceptions or changing their behaviors. When managed effectively, CD can lead to deeper learning, enhanced creativity, and the development of problem-solving skills [7]. For example, Adcock [7] discusses how CD, when properly addressed in learning environments, serves as a catalyst for deeper engagement, encouraging students to reconcile conflicting information, think critically, and refine their problem-solving abilities—aligning with the idea that effectively managed CD fosters enhanced learning and creativity. However, CD is complex. While it fosters intellectual growth and innovation, unresolved CD can result in frustration, disengagement, and decreased performance[8], [9], [10]. The ability to balance and manage this psychological phenomenon is critical to optimizing learning outcomes and ensuring students fully benefit from the IBL experience

Innovation self-efficacy (ISE), defined as confidence in one's ability to engage in innovation-related tasks, can be pivotal in determining students' success in an IBL program.

Based on Bandura's social cognitive theory, self-efficacy affects how people tackle challenges, remain resilient in overcoming obstacles, and ultimately reach their objectives [11], [12]. In the context of innovation, self-efficacy represents students' confidence in their ability to develop creative concepts, try out new solutions, and make significant contributions to innovation. High levels of ISE are associated with greater resilience, proactive problem-solving, and a willingness to take intellectual risks [13], [14], [15]. For example, Schar et al. [14],[15] further highlights that academic and life experiences play a critical role in shaping engineering students' ISE emphasizing that exposure to open-ended challenges, hands-on projects, and interdisciplinary collaboration enhances their confidence in tackling complex problems and driving innovation.

Previous research shows that developing ISE requires exposure to challenging tasks, opportunities for iterative learning, and experiences that build confidence in one's abilities and CD is essential in this process as it encourages students to face and address intellectual challenges. However, the relationship between CD and ISE has not been thoroughly investigated, highlighting a lack of insight into how these factors affect student outcomes in IBL settings.

This study aims to address this gap by examining how varying levels of CD impacts ISE among students in a biomedical engineering IBL program. We developed a predictive model that elucidates the dynamics between these variables by analyzing data collected from undergraduate and graduate students over a semester. Our research adds to the expanding body of literature on CD and self-efficacy within educational contexts, providing valuable insights for creating effective inquiry-based learning programs that bolster students' innovation abilities and self-assurance.

Methods

This study was conducted in a biomedical engineering program at XX University which is of R1 designation, utilizing an IBL framework. Participants included both undergraduate and graduate students enrolled in the program. Two surveys were administered, one to measure CD and a second to measure ISE, at the beginning and end of the Fall 2024 semester. The CD survey was adapted from the Al-Adamat & Atoum Cognitive Dissonance Scale [9] to fit IBL concepts and scenarios. This survey provides ten scenarios related to IBL problems. For example, Scenario 10 states "Your team project is being compared with another teams project that appears to be more advanced." Each scenario is followed up with two questions to assess how that student would respond. The participant is scored by giving them a one if they choose the most adaptable answer and a 0 if they do not with a possible score from 0-20. A higher score indicates that the participant is experiencing less CD, while a lower score indicates that the participant is experiencing greater CD. This was designed to assess the level of psychological discomfort students experienced when encountering conflicting ideas or ambiguous challenges in the IBL environment. Based on an established scale by Gerber et al., [18] the ISE survey evaluated students' confidence in engaging with innovation-related tasks, such as generating creative ideas and solving complex problems. In this survey, the first six questions collected demographic questions. This was followed by twenty-nine items where participants were to rate their degree of confidence that they can do that activity from 0-5 with 0 being not at all confident and 5 being extremely confident that they can do that activity. Both surveys were distributed via the MOOCIBL platform, an online learning management system tailored for IBL programs [16],[17],[18]. Students accessed the surveys through this platform, and their responses were exported into Microsoft Excel for subsequent data analysis. This method guaranteed uniformity in conducting the survey and promoted effective data gathering.

Statistical analyses such as correlation analysis, one tailed paired t-tests, and regression modeling were performed in Excel to investigate the connections between these variables and evaluate trends in the data [19]. Python was also used to develop a predictive model using logistic regression to determine the likelihood of students achieving high ISE scores based on their CD scores (Appendix A and B). We chose a one-tailed t-test because our hypothesis was directional, based on prior research and theoretical frameworks suggesting that as cognitive dissonance (CD) decreases, innovation self-efficacy (ISE) increases. This assumption is grounded in cognitive dissonance theory, which posits that individuals experiencing dissonance are motivated to resolve it, often leading to cognitive and behavioral adjustments that enhance confidence in problem-solving and innovation-related tasks. Given that IBL encourages students to navigate uncertainty and adapt to novel challenges, we expected that as students became more comfortable with the open-ended nature of IBL, their CD levels would decrease, leading to higher ISE. A one-tailed test was appropriate because we were specifically testing for an increase in ISE as CD levels dropped, rather than assessing whether any change—positive or negative—occurred. This aligns with our a priori expectation that lower dissonance facilitates innovation efficacy rather than inhibiting it. The results aim to elucidate how CD influences students' development of ISE within the context of an IBL biomedical engineering program. The University's Institutional Review Board (IRB) approved the current study (IRB protocol #IRB0005373).

Demographics	*Participants (n)*
UG	**50**
Fr	23
So	18
Jr	5
Sr	4
Grad	**18**
MS	9
Ph.D.	9
Online	28
In-Person	40

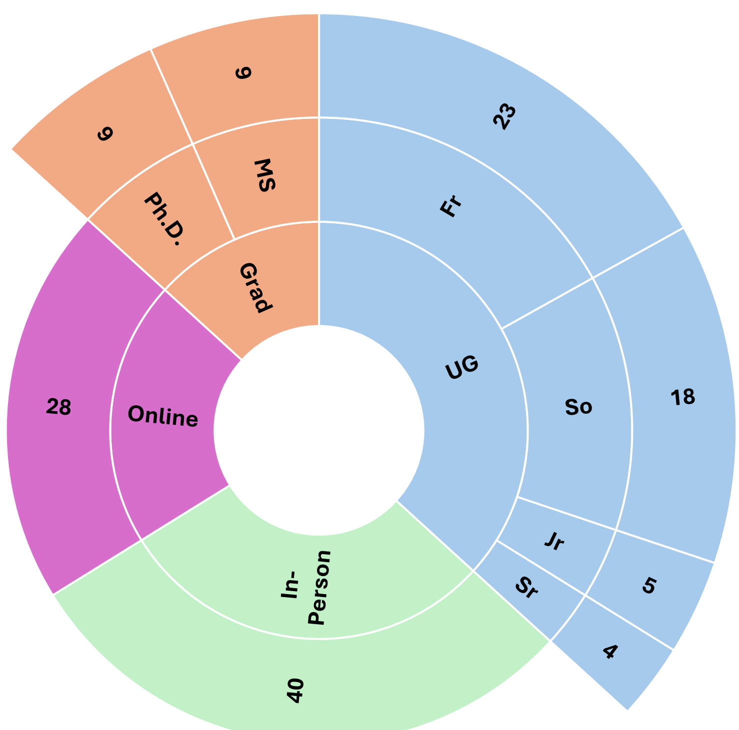

Figure 1: Demographics of participants with 68 total participants including Undergraduate (UG, n=50), and Graduate (Grad,n=18) students

Results

There was a total of 107 students who were invited to participate in the study, this includes all students taking and IBL BME class at the University of North Dakota (UND). A total of 87 participants completed ISE surveys and 86 for CD. Certain surveys were excluded from analysis because participants either did not complete both the pre- and post-surveys for each measure or failed to complete all four required surveys (two for ISE and two for CD). As a result, 68 participants who completed all four surveys were included in the final analysis. Out of the 68 total surveys, 50 were undergraduate (UG), and 18 were graduate (Grad) students. Of those students 28 identified as an online student and 40 identified as In-person students. Of the 28 online students, 16 online were UG and 12 were Grad. Figure 1 provides a full breakdown of the demographic distribution of the participants. The participants for this study were drawn from multiple classes across the IBL BME program. However, while UG and Grad students were enrolled in separate course sections, all IBL courses are designed to be interdisciplinary and are offered to both groups simultaneously. Importantly, students across these different levels actively collaborate on innovation projects, ensuring that graduate students are fully integrated with undergraduates throughout the course. This integration extends to the key learning assessments, including the gap, solution, and impact assessments, which remain consistent across all IBL courses, regardless of academic level. These assessments are centered around students' innovative projects and evaluate their ability to successfully apply engineering principles to real-world challenges. While the structure and expectations of these assessments remain uniform, the evaluation process considers the educational level of the student, ensuring that UG and Grad students are assessed based on appropriate academic rigor and depth analysis.

Additionally, prior research indicates that being in an online learning environment does not diminish a student's ability to innovate or make a meaningful impact. Studies have shown that when properly structured, online courses can foster the same levels of creativity, problem-solving, and collaboration as in-person settings. In the IBL program, online and in-person students engage in the same project-based curriculum, collaborate across modalities, and are provided with equal opportunities to externalize their research and create real-world solutions [20], [21].

By maintaining uniform expectations and interdisciplinary collaboration while adjusting evaluation criteria accordingly, the IBL framework ensures that all students, regardless of class standing, develop critical problem-solving and innovation skills in a shared learning environment. To address concerns regarding potential cohort effects, a separate subgroup analysis was conducted to assess whether undergraduate and graduate students exhibited significantly different patterns in cognitive dissonance resolution and innovation self-efficacy gains.

There is a notable contrast in the number of undergraduate participants (UG, n=50) versus graduate participants (Grad, n=18). This can be explained by the organization of the biomedical engineering program, which has a greater enrollment of undergraduates. Likewise, there is a higher number of freshmen (Fr, n=50) in comparison to sophomores (So, (n=18), juniors (Jr, n=5), and seniors (Sr, n=4). This imbalance in class size could be attributed to several things, such as students' progress through their academic careers, specialization, and other academic commitments, which may reduce participation in such surveys or courses. Additionally, some students may drop the program or switch majors as they progress, reducing the number of upperclassmen. Furthermore, this undergraduate program is new, which may explain the higher number of freshmen participants compared to upper-level students.

Innovation Self-Efficacy

The ISE survey results demonstrated minimal deviations from normality, supporting the use of a one-tailed paired t-test to analyze the pre- and post-survey scores. For the pre-survey, the kurtosis was -0.273, indicating a slightly platykurtic distribution with a flatter peak, while the skewness was -0.038, suggesting near-perfect symmetry in the data. Similarly, the post-survey results showed a kurtosis of -0.559, reflecting a slightly more platykurtic distribution, and a skewness of -0.225, indicating a minor negative skew with a slight tendency toward a longer left tail. These values demonstrate that the data approximated normality, making the paired t-test a robust and appropriate statistical method for significant differences to compare the pre- and post-survey scores. A one-tailed paired t-test showed a statistically significant difference between the pre- and post-survey scores, with a p-value of 6.99×10^{-5} and a 95% confidence interval. Figure 2 shows the descriptive statistics for the dataset. A subgroup analysis was done with just UG and

	Pre-Survey	*Post Survey*
Median	3.76	3.93
Mode	3.66	5
Min	2.48	2.48
Max	5	5
Kurtosis	-0.27	-0.56
Skewness	-0.04	-0.23

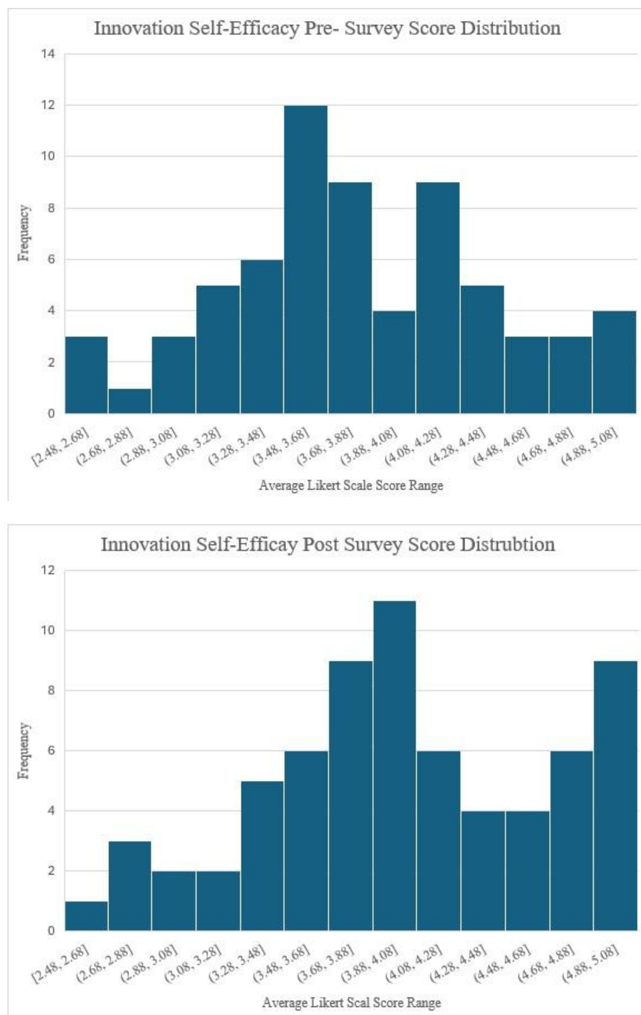

Figure 2: Distribution of Innovation Self Efficacy Pre- and Post Survey Scores showing normal distribution with kurtosis of -0.27 and -0.56 and skewness of -0.04 and -0.23

Grad students. The t-test showed a significant difference in ISE scored in UG students ($p=2.57 \times 10^{-5}$) but not for Grad students ($p=0.37$).

Cognitive Dissonance

The CD survey results demonstrated minimal deviations from normality, supporting using a one-tailed paired t-test to analyze the pre- and post-survey scores. For the pre-survey, the kurtosis was -0.383, indicating a slightly platykurtic distribution with a flatter peak, while the skewness was 0.198, suggesting near-perfect symmetry with a minor positive skew. Similarly, the post-survey results showed a kurtosis of -0.778, reflecting a slightly more platykurtic distribution, and a skewness of -0.007, indicating near-perfect symmetry in the data. These values demonstrate that the data approximated normality, making the paired t-test a robust and appropriate statistical method for significant differences to compare the pre- and post-survey scores. A one-tailed paired t-test showed a statistically significant difference between the pre-and post-survey scores, with a p-value of 8.80×10^{-5} and a 95% confidence interval. Figure 3 shows the distribution of scores for the pre- and post-CD surveys. A subgroup analysis was done with

	Pre-Survey	*Post Survey*
Median	9	10
Mode	12	8
Min	1	0
Max	19	19
Kurtosis	-0.38	-0.77
Skewness	0.198	-0.007

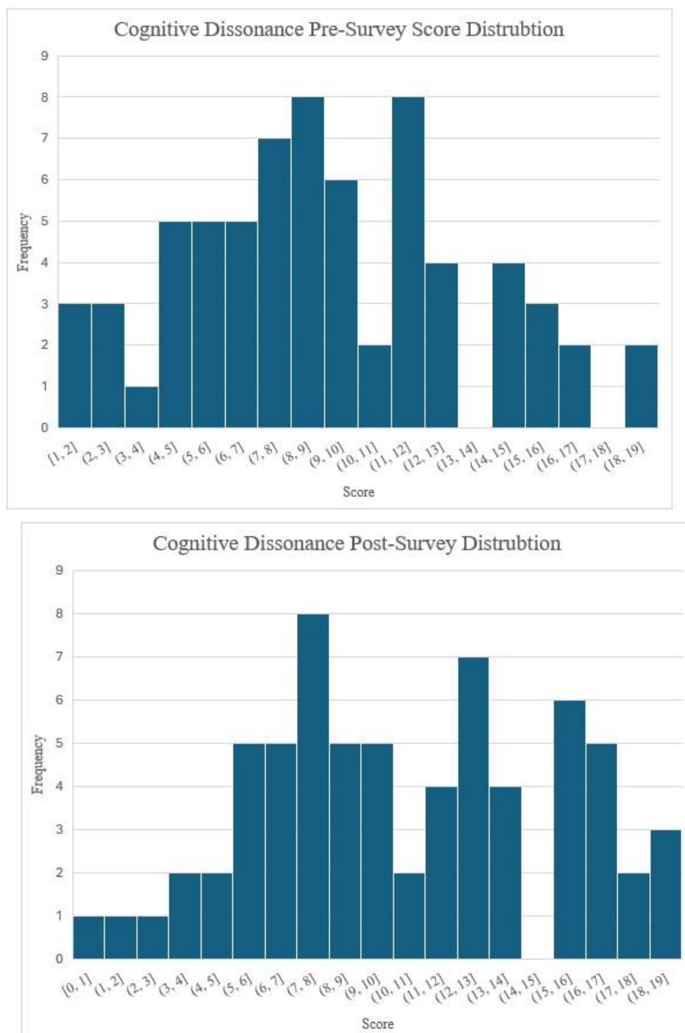

Figure 3: Distribution of Cognitive Dissonance Pre- and Post Survey Scores with kurtosis of -0.38 and -0.77 and skewness of 0.198 and -0.007

just UG and Grad students. The t-test showed a significant difference in CD scores in UG students ($p=0.00021$) but not for Grad students ($p=0.38$).

Relationship Between Cognitive Dissonance and Innovation Self Efficacy

A correlation analysis examined the relationship between CD and ISE. The Pearson correlation coefficient for the pre-surveys was 0.57, indicating a moderate positive relationship between the two variables. This suggests that students who experienced lower CD tended to have higher ISE at the beginning of the semester. The post-survey correlation coefficient was 0.63, indicating a positive relationship between cognitive dissonance scores and innovation self-efficacy, where higher survey scores (reflecting less CD) were associated with greater ISE after students completed the IBL program.

These results suggest that students who successfully resolved CD were more likely to see improvements in their ISE, supporting the theory that CD is crucial for developing ISE. The data indicates that all students experienced some level of CD during the semester, as reflected in their scores. Of the 68 students, 32 showed both a decrease in CD and an increase in ISE, suggesting that resolving CD played a significant role in fostering higher innovation confidence. Conversely, students who did not resolve CD or whose CD scores remained stable ($n=36$) were 19.4% less likely to see improvements in ISE. These findings highlight that managing and resolving CD can increase ISE in an IBL environment. These findings correspond with the wider positive trends noted in both datasets, emphasizing the interaction between these essential concepts in a learning setting focused on innovation. While correlation analysis established a general relationship between CD and ISE, it did not account for the extent to which CD levels could predict shifts in ISE or identify patterns beyond linear associations. To address this limitation, predictive modeling techniques were employed to quantify the likelihood that changes in CD would lead to measurable improvements in ISE, offering deeper insights into how cognitive dissonance influences innovation self-efficacy over time.

The initial logistic regression model, optimized using GridSearchCV, achieved an accuracy of 71.4%. GridSearch CV is a method used to check how well a predictive model will work on new data. It does this by splitting the data into multiple parts, training the model on some parts, and testing it on others, helping to ensure that the results are not just a coincidence but meaningful. The model's performance varied across the two classes. For Class 0 (low ISE), the model achieved a recall of 100% but had a low precision of 33%, leading to an F1-score of 0.50, indicative of a high false positive rate. For Class 1 (high ISE), the model performed more effectively, with a precision of 100%, a recall of 67%, and an F1-score of 0.80. These results highlight that the model is better at identifying high ISE cases but struggles to classify low ISE cases accurately. The macro-average F1-score of 0.65 and weighted F1-score of 0.76 reflect the imbalance in class distribution and the model's emphasis on Class 1.

Additional modeling techniques and optimizations were explored to improve the model results. Advanced machine learning algorithms, including Random Forest, Gradient Boosting, and XGBoost, were implemented to capture potential non-linear relationships and interactions in the data. Random Forest, Gradient Boosting, and XGBoost are advanced computer-based methods used to make predictions by combining multiple decision-making steps. Random Forest works by creating many small decision trees and averaging their results to improve accuracy. Gradient Boosting builds decision trees one at a time, learning from mistakes to get better with each step. XGBoost is an improved version of Gradient Boosting that is faster and more efficient, making it useful for finding patterns in large and complex datasets. These methods help make better predictions by reducing errors and improving reliability. The Random Forest model achieved the highest accuracy at 78.6%, with an AUC of 0.79. It demonstrated strong performance for Class 1 (high ISE) with a precision of 100%, a recall of 75%, and an F1-score of 0.86. However, for Class 0 (low ISE), while recall was perfect at 100%, precision was lower at 40%, reflecting a high false positive rate. Similarly, the XGBoost model achieved an accuracy of 78.6% with an AUC of 0.75, showing comparable performance to Random Forest, with identical precision and recall values for both classes.

In contrast, the Gradient Boosting model performed less effectively, with an accuracy of 64.3% and an AUC of 0.67. Gradient Boosting struggled particularly with Class 0, achieving a recall of 50% and a precision of only 20%, resulting in a macro-average F1-score of 0.52. Overall, Random Forest and XGBoost demonstrated superior performance, particularly in identifying high ISE cases. At the same time, further improvements are needed to address the imbalance and improve precision for low ISE predictions.

Discussion

This study demonstrates that lower levels of cognitive dissonance (CD) are associated with higher ISE in an IBL biomedical engineering program, highlighting that effectively reducing cognitive dissonance enhances students' confidence in their ability to innovate. The results indicate statistically significant advancements in resolving CD and ISE throughout the semester. Additionally, correlation analysis showed a moderate positive relationship between these two variables, which became more robust following the intervention, emphasizing the possible benefits of IBL approaches in enhancing ISE. The analysis of pre- and post-surveys demonstrated notable improvements in both areas, with the average ISE rising from 3.9 to 4.1 and CD scores increasing from an average of 9.5 to 10.9 (reflecting less experience of CD). These results support effectively managing CD, promote deeper learning, and boost students' confidence in their innovative capabilities. Moreover, the stronger correlation identified in the post-survey indicates that as students engaged with the open-ended, problem-solving elements of IBL, their ability to handle CD became more closely associated with their ISE.

The subgroup analysis revealed notable differences between UG and Grad students in both ISE and CD changes**.** A t-test showed a significant increase in ISE scores for UG students whereas no significant change was observed for Grad students. Similarly, UG students experienced a significant reduction in CD over the semester, while Grad students did not. These findings suggest that UG students, who may have less prior experience with open-ended, innovation-driven learning environments, undergo greater shifts in both CD and ISE when exposed to the IBL framework. In contrast, Grad students, who are likely to have more familiarity with self-directed problem-solving, may enter the course with a more stable level of ISE and CD, resulting in less measurable change. Future research should explore whether different instructional scaffolding approaches are needed to maximize ISE development across academic levels.

The predictive modeling efforts further emphasized the importance of this relationship. The initial logistic regression model provided a solid baseline with an accuracy of 71.4% but struggled to classify low ISE cases due to class imbalance. Advanced machine learning models, including Random Forest, Gradient Boosting, and XGBoost, achieved improved accuracy and

AUC scores, with Random Forest and XGBoost reaching 78.6% accuracy and AUC values of 0.79 and 0.75, respectively. These models effectively identified high ISE cases but continued to exhibit challenges in accurately classifying low ISE cases, as evidenced by lower precision for Class 0. The performance result highlights the critical need for balanced datasets and feature refinement to improve the robustness of these models. By leveraging machine learning, we gain insights into how CD levels contribute to ISE in ways that simple correlations cannot capture, particularly in identifying key features that influence student outcomes. The performance results further highlight the critical need for balanced datasets and feature refinement to improve the robustness of these models, ensuring they can better predict and support students who may struggle with innovation self-efficacy.

The results of this study highlight the importance of CD as an educational tool for improving ISE. Unlike traditional methods that primarily focus on technical skill development, this study demonstrates that actively managing cognitive dissonance within IBL environments can significantly enhance students' ability to innovate**.** Educators can promote deeper engagement and enhance critical thinking skills by creating learning environments that encourage students to confront and resolve opposing ideas. The moderate relationship between CD and ISE emphasizes the need to incorporate activities focused on creative problem-solving and iterative learning within engineering programs. Furthermore, this study is among the first to apply predictive modeling techniques to examine how cognitive dissonance impacts innovation efficacy in engineering education**,** offering a data-driven approach to optimizing instructional design. The effectiveness of these predictive models indicates that machine learning can serve as a powerful tool for identifying key factors that influence ISE, allowing for more targeted interventions. By integrating CD theory with engineering education and leveraging machine learning for deeper analysis, this research provides a new framework for fostering innovation mindsets, marking a significant advancement in how engineering programs approach student learning and development.

While this study supports the idea that resolving CD can contribute to ISE development, the findings also suggest that ISE growth can occur even in students whose CD levels remain stable. This indicates that while CD resolution may serve as a mechanism for enhancing ISE, it is not necessarily a prerequisite for its improvement. Other factors, such as increased exposure to innovation-based challenges, peer collaboration, and structured feedback within the IBL environment, may independently foster ISE. These factors are critical in understanding how engineering students develop confidence in their ability to innovate. Some students may experience growth through the resolution of CD, while others may benefit from repeated engagement in innovation-driven activities regardless of their CD levels. Future research should further investigate the different pathways through which ISE can develop, distinguishing between students who gain confidence through overcoming CD and those who build ISE through iterative learning experiences.

However, several limitations should be noted. First, the analysis was based on a relatively small dataset, including only 68 participants, which may have impacted the findings' generalizability and the predictive models' reliability. Second, the dataset demonstrated an imbalance in class distribution, with a notably higher number of cases showing high ISE. This likely affected the models' accuracy in identifying low ISE cases. Additionally, the study depended on self-reported survey data, which could introduce response bias.

To overcome these limitations, upcoming research should prioritize broadening the dataset by involving participants from various academic programs and institutions. A more extensive and representative dataset would enhance the applicability of the findings and elevate the effectiveness of predictive models. Moreover, employing advanced data augmentation methods like SMOTE or under-sampling could alleviate class imbalance and strengthen the robustness of the models. Future investigations might also assess different machine learning algorithms, such as Support Vector Machines, neural networks, and ensemble stacking, to better understand the complex relationships between CD and innovation effectiveness. Additionally, integrating qualitative data, like interviews or observational studies, could offer more significant insights into how students navigate and reconcile CD within IBL contexts.

Conclusion

This research explores the interaction between CD and ISE within an IBL biomedical engineering program, using both pre- and post-survey data to analyze changes over the semester. The results demonstrated a statistically significant improvement in CD and ISE among participants, with pre-survey and post-survey mean scores increasing from 9.5 to 10.9 and 3.9 to 4.1, respectively. Correlation analysis further revealed that lower levels of CD were associated with higher ISE, as indicated by a post-survey correlation coefficient of 0.63, suggesting a moderately strong positive relationship. These findings reveal that as students experience lower levels of CD, their confidence in their ability to innovate improves. The study highlights the critical role of structured pedagogical strategies in managing CD in fostering students' ISE. Specifically, within the IBL framework, strategies such as milestone-based assessments**,** and structured innovation project that generate real world impact and allow students to practical implement engineering concepts may support students in managing CD and build confidence in their innovation abilities. By addressing and reducing CD, students enhance their problem-solving skills and develop the resilience and creativity necessary for innovation.

The findings emphasize the importance of designing educational environments that challenge students to confront and resolve conflicting ideas, as these cognitive challenges directly contribute to building innovation-driven mindsets, which are essential for success in STEM fields. By embedding structured opportunities within the IBL framework—such as milestone-based assessments, interdisciplinary collaboration, and iterative problem-solving—educators can create learning experiences that not only help students navigate cognitive dissonance but also develop the adaptability, resilience, and problem-solving skills necessary for innovation. These findings contribute to engineering education by providing a deeper understanding of how CD can be intentionally leveraged to enhance ISE and highlight the need to create structured opportunities where students encounter and resolve conflicting ideas, enabling them to develop critical thinking, adaptability, and confidence in generating innovative solutions, which are skills that are essential for thriving in STEM disciplines.

References

[1] L. Singelmann, E. Alvarez, E. Swartz, M. Pearson, R. Striker, and D. Ewert, “Innovators, Learners, and Surveyors: Clustering Students in an Innovation-Based Learning Course,” in *2020 IEEE Frontiers in Education Conference (FIE)*, Oct. 2020, pp. 1–9. doi: 10.1109/FIE44824.2020.9274235.

[2] E. M. Swartz, M. Pearson, L. Singelmann, R. Striker, and E. A. Vazquez, “Innovation-based Learning: Enhancing Innovative Problem Solving and Higher-order Thinking in Education Through Multidisciplinary Collaboration,” presented at the 2020 ASEE Virtual Annual Conference Content Access, Jun. 2020. Accessed: Mar. 17, 2024. [Online]. Available: https://peer.asee.org/innovation-based-learning-enhancing-innovative-problem-solving-and-higher-order-thinking-in-education-through-multidisciplinary-collaboration

[3] M. Pearson, R. Striker, E. M. Swartz, E. A. Vazquez, L. Singelmann, and S. S. Ng, “Innovation-based Learning: A New Way to Educate Innovation,” presented at the 2021 ASEE Virtual Annual Conference Content Access, Jul. 2021. Accessed: Mar. 17, 2024. [Online]. Available: https://peer.asee.org/innovation-based-learning-a-new-way-to-educate-innovation

[4] L. N. Singelmann and D. L. Ewert, “Leveraging the Innovation-Based Learning Framework to Predict and Understand Student Success in Innovation,” *IEEE Access*, vol. 10, pp. 36123–36139, 2022, doi: 10.1109/ACCESS.2022.3163744.

[5] L. Montesinos, D. E. Salinas-Navarro, and A. Santos-Diaz, “Transdisciplinary experiential learning in biomedical engineering education for healthcare systems improvement,” *BMC Med. Educ.*, vol. 23, no. 1, p. 207, Apr. 2023, doi: 10.1186/s12909-023-04171-x.

[6] A. Santos-Díaz, L. Montesinos, M. Barrera-Esparza, M. del Mar Perez-Desentis, and D. E. Salinas-Navarro, “Implementing a challenge-based learning experience in a bioinstrumentation blended course,” *BMC Med. Educ.*, vol. 24, no. 1, p. 510, May 2024, doi: 10.1186/s12909-024-05462-7.

[7] A. Adcock, “Cognitive Dissonance in the Learning Processes,” in *Encyclopedia of the Sciences of Learning*, N. M. Seel, Ed., Boston, MA: Springer US, 2012, pp. 588–590. doi: 10.1007/978-1-4419-1428-6_5.

[8] L. Festinger, *A theory of cognitive dissonance*. in A theory of cognitive dissonance. Stanford University Press, 1957, pp. xi, 291.

[9] Ministry of Education, Mafraq, Jordan, O. A. Al-Adamat, A. Y. Atoum, and Yarmouk University, Irbid, Jordan, “Cognitive dissonance and its relationship to emotional intelligence,” *Cogn. Brain Behav. Interdiscip. J.*, vol. 26, no. 4, pp. 215–229, Dec. 2022, doi: 10.24193/cbb.2022.26.12.

[10] “Cognitive Dissonance Theory After 50 Years of Development | Zeitschrift für Sozialpsychologie.” Accessed: Jan. 14, 2025. [Online]. Available: https://econtent.hogrefe.com/doi/10.1024/0044-3514.38.1.7

[11] A. Bandura, “Self-efficacy: Toward a unifying theory of behavioral change,” *Psychol. Rev.*, vol. 84, no. 2, pp. 191–215, 1977, doi: 10.1037/0033-295X.84.2.191.

[12] A. Bandura, *Self-efficacy: The exercise of control*. in Self-efficacy: The exercise of control. New York, NY, US: W H Freeman/Times Books/ Henry Holt & Co, 1997, pp. ix, 604.

[13] M. Schar, S. K. Gilmartin, B. Rieken, S. Sheppard, S. R. Brunhaver, and H. L. Chen, “The Making of an Innovative Engineer: Academic and Life Experiences that Shape Engineering Task and Innovation Self-Efficacy,” presented at the 2017 ASEE Annual Conference &

Exposition, Jun. 2017. Accessed: Jan. 14, 2025. [Online]. Available: https://peer.asee.org/the-making-of-an-innovative-engineer-academic-and-life-experiences-that-shape-engineering-task-and-innovation-self-efficacy

[14] M. Schar, S. Gilmartin, A. Harris, B. Rieken, and S. Sheppard, "Innovation Self-Efficacy: A Very Brief Measure for Engineering Students," in *2017 ASEE Annual Conference & Exposition Proceedings*, Columbus, Ohio: ASEE Conferences, Jun. 2017, p. 28533. doi: 10.18260/1-2--28533.

[15] D. Verdín, A. Godwin, and B. Benedict, "Exploring First-Year Engineering Students' Innovation Self-Efficacy Beliefs by Gender and Discipline," *J. Civ. Eng. Educ.*, vol. 146, no. 4, Oct. 2020, doi: 10.1061/(ASCE)EI.2643-9115.0000020.

[18] E. Gerber, C. K. Martin, E. Kramer, J. Braunstein, and A. R. Carberry, "Developing an Innovation Self-Efficacy Survey".

[19] G. Norman, "Likert scales, levels of measurement and the 'laws' of statistics," *Adv. Health Sci. Educ. Theory Pract.*, vol. 15, no. 5, pp. 625–632, Dec. 2010, doi: 10.1007/s10459-010-9222-y.

[20] M. Pearson, L. Singelmann, R. Striker, E. A. Vazquez, and E. M. Swartz, "Benefits of Long-distance Collaboration in Higher Education Institutions to Train Students in Innovation Practices," presented at the 2020 ASEE Virtual Annual Conference Content Access, Jun. 2020. Accessed: Feb. 17, 2025. [Online]. Available: https://peer.asee.org/benefits-of-long-distance-collaboration-in-higher-education-institutions-to-train-students-in-innovation-practices

[21] M. Terry, E. A. Vazquez, D. Ewert, and R. Striker, "Bridging the Great Divide: A Strategy for How Online Graduate Students Can Participate and Enhance the Education of Undergraduate Students," presented at the 2024 ASEE Annual Conference & Exposition, Jun. 2024. Accessed: Feb. 17, 2025. [Online]. Available: https://peer.asee.org/bridging-the-great-divide-a-strategy-for-how-online-graduate-students-can-participate-and-enhance-the-education-of-undergraduate-students

Appendix A – Python Code for Predicting Innovation Self-Efficacy

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, accuracy_score

# Load the dataset
file_path = r'your.csv'  # Replace with the path to your csv
data = pd.read_csv(file_path)

# Feature Engineering
data['cd_change'] = data['cd_post'] - data['cd_pre']
data['ie_change'] = data['ie_post'] - data['ie_pre']
data['high_ie'] = (data['ie_post'] >= 3.5).astype(int)

# Define features and target
X = data[['cd_pre', 'cd_post', 'cd_change']]
y = data['high_ie']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Standardize features and define logistic regression model
scaler = StandardScaler()
log_reg = LogisticRegression(max_iter=1000, class_weight='balanced')

# Create a pipeline
pipeline = Pipeline([
    ('scaler', scaler),
    ('log_reg', log_reg)
])

# Define hyperparameter grid for optimization
param_grid = {
    'log_reg__C': [0.01, 0.1, 1, 10, 100],
    'log_reg__solver': ['liblinear', 'lbfgs']
}

# Use GridSearchCV to find the best model
grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Retrieve best parameters and evaluate the optimized model
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_

# Test set evaluation
y_pred_optimized = best_model.predict(X_test)
optimized_accuracy = accuracy_score(y_test, y_pred_optimized)
optimized_classification_report = classification_report(y_test, y_pred_optimized)

print("Best Parameters:", best_params)
print("Optimized Accuracy:", optimized_accuracy)
print("Classification Report:\n", optimized_classification_report)1.
```

Appendix B – Python Code with Random Forest, Gradient Boosting, and XGBoost

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE

# Load your dataset here
file_path = r'your.csv'  # Replace with the path to your csv
data = pd.read_csv(file_path)

# Feature Engineering
data['cd_change'] = data['cd_post'] - data['cd_pre']
data['ie_change'] = data['ie_post'] - data['ie_pre']
data['high_ie'] = (data['ie_post'] >= 3.5).astype(int)

# Define features and target
X = data[['cd_pre', 'cd_post', 'cd_change']]
y = data['high_ie']

# Add polynomial features
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X_poly, y, test_size=0.2, random_state=42, stratify=y
)

# Check class distribution before applying SMOTE
if y_train.nunique() > 1:
    # Handle class imbalance with SMOTE
    smote = SMOTE(random_state=42)
    X_train_balanced, y_train_balanced = smote.fit_resample(X_train, y_train)
else:
    print("SMOTE not applied as y_train contains only one class.")
    X_train_balanced, y_train_balanced = X_train, y_train

# Standardize features
scaler = StandardScaler()
X_train_balanced = scaler.fit_transform(X_train_balanced)
X_test = scaler.transform(X_test)

# Models
models = {
    'Random Forest': RandomForestClassifier(random_state=42, class_weight='balanced'),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'XGBoost': XGBClassifier(eval_metric='logloss', random_state=42)
}

# Hyperparameter grids
param_grids = {
    'Random Forest': {
        'n_estimators': [50, 100, 200],
        'max_depth': [None, 10, 20, 30],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4]
    },
    'Gradient Boosting': {
        'n_estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 5, 10],
```

```
        'subsample': [0.8, 1.0],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4]
    },
    'XGBoost': {
        'n_estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 5, 10],
        'subsample': [0.8, 1.0],
        'colsample_bytree': [0.8, 1.0]
    }
}

# Perform Grid Search for each model
results = {}
for name, model in models.items():
    print(f"Training {name}...")
    if y_train_balanced.nunique() > 1:
        grid_search = GridSearchCV(model, param_grids[name], cv=5, scoring='accuracy', n_jobs=-1, error_score='raise')
        grid_search.fit(X_train_balanced, y_train_balanced)
        best_model = grid_search.best_estimator_
        y_pred = best_model.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)

        # Conditional AUC calculation
        if len(best_model.classes_) > 1:
            auc = roc_auc_score(y_test, best_model.predict_proba(X_test)[:, 1])
        else:
            auc = None
            print(f"AUC for {name} cannot be calculated due to a single class in predictions.")

        report = classification_report(y_test, y_pred)
        results[name] = {
            'Best Params': grid_search.best_params_,
            'Accuracy': accuracy,
            'AUC': auc,
            'Classification Report': report
        }
    else:
        print(f"Skipping {name} as y_train_balanced contains only one class.")

# Print results
for name, result in results.items():
    print(f"\n{name} Results:")
    print(f"Best Params: {result['Best Params']}")
    print(f"Accuracy: {result['Accuracy']}")
    print(f"AUC: {result['AUC']}")
    print(f"Classification Report:\n{result['Classification Report']}")

```