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Student Preferences and Performance in Active Learning Online Environments

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Student Preferences in Active Learning Environments

The education environment is continually evolving to identify optimal learning environments tailored to student needs, especially in the instructional methodologies to engage students. One of the strategies proven effective in engineering education is active learning. This strategy, particularly defined by their student-centered approach and emphasis on higher-order thinking, has been associated with enhanced student performance across various disciplines in engineering education [1,2].

This research investigated the relationship between students' instructional mode preferences and academic performance across three educational modules: statistics, material jetting, and Python programming. By employing a ranking-based survey, students' preferences among four distinct modes of instruction including traditional, self-study, game, and VR were investigated to determine the correlations between these preferences and academic outcomes in the courses. Beyond that, we aim to understand the predictability of learner performance based on their mode preferences. More explicitly, this paper considers how students' learning mode rankings across different modules influence not just their post-module knowledge scores but also the broader metrics of content comprehension and delivery effectiveness.

Active learning and instructional modes in engineering education

Active learning is a student-centered educational paradigm that has transformed engineering education by fostering engagement and developing higher-order cognitive abilities [2]. This pedagogical shift is supported by evidence suggesting that active learning strategies can significantly enhance the performance of engineering students [1]. Such strategies are particularly well-suited to the applied nature of engineering, where practical problem-solving and the application of theoretical knowledge are dominant [3]. In this context, active learning has been a critical theme of curricular innovation, offering various instructional modes to enhance the academic and practical skills of students.

Over the last several decades, transitioning active learning experiences into online learning environments has been explored – especially with Universal Design for Learning (UDL) [4]. Many of the in-class active learning approaches require adapting and shifting to carry the same impact in an online course. With the transition to remote instruction during the COVID-19 pandemic, there has been an increase in the use of online educational environments and approaches, even as universities transitioned back to in-person instruction. For this study, we focused on four online instructional modes:

Traditional: The traditional mode (as described here) in online environments was framed to mirror in-person instruction with a common course schedule and recorded lectures. This approach is deeply rooted in the dissemination of complex theoretical knowledge, where instructors guide students through the intricacies of engineering [5]. Lectures provide a structured format that can efficiently cover extensive content and offer a foundational understanding that students can then apply in more practical settings. Despite the rise of more interactive approaches, the traditional mode remains relevant, particularly for introducing fundamental concepts that form the basis of engineering thought and practice [6].

Self-Study: Self-study is a mode that places the onus of learning squarely on the shoulders of students, empowering them with the autonomy to explore subjects independently. In engineering, this mode is crucial given the discipline's complex problem-solving nature [7]. Self-study allows students to absorb challenging content at a personalized pace and revisit difficult concepts, thus facilitating a deeper understanding. Additionally, it cultivates self-regulation and lifelong learning habits, skills indispensable to the modern engineer who must continually learn to keep pace with technological advancements [8].

Game-Based Learning: Game-based learning harnesses the engaging power of games to create an educational experience that is both interactive and enjoyable. In engineering education, games can simulate real-world challenges, offering a dynamic platform for students to apply theoretical knowledge in practical, problem-based scenarios [9]. This mode of instruction has the potential to bridge the gap between theoretical understanding and practical application, providing a safe space for experimentation, innovation, and the development of critical thinking and collaboration skills.

Virtual Reality (VR): Virtual Reality (VR) stands as a cutting-edge development in educational technology, particularly within engineering disciplines. VR offers immersive, three-dimensional simulations, allowing students to visualize and interact with spatial and physical systems in ways that traditional classroom settings cannot offer [10]. It provides an innovative means of experiential learning, where students can, for instance, walk through a virtual engine or manipulate simulated materials, thus fostering a deep understanding of engineering concepts. The use of VR in education not only enhances student engagement but also enables the application of complex theories in a tangible, interactive manner [11].

These modes represent a spectrum of instructional strategies that can cater to diverse learning preferences and educational needs in engineering. As the field continues to evolve, integrating and balancing these modes will be critical in developing curricula that prepare students not just for examinations, but for the multifaceted challenges of the engineering profession.

Instructional preferences and academic performance

In the engineering education, the relationships between students' instructional mode preferences and their academic performance have become a critical point for educators aiming to optimize learning outcomes. Freeman et al. [1] provides some evidence for the efficacy of active learning strategies, which have shown to significantly enhance student performance, particularly in STEM disciplines. This approach, which advocates for student engagement in the learning process, aligns well with the demands of engineering education, where application of knowledge is as crucial as its acquisition.

The instructional modes under examination in this study—traditional, self-study, game-based learning, and virtual reality (VR)—are distinct pathways within the active learning spectrum. Nguyen et al. [12] emphasize the critical role of student interaction, both with peers and teachers, in fostering engagement that can translate into improved academic performance. This underscores the potential benefits of game-based learning and VR, which are inherently interactive and have been gaining traction as powerful educational tools [13]. Graham et al. [14] utilize the TPACK framework to explore how the integration of technology influences instructional strategies and, by extension, student outcomes. This is particularly relevant when considering VR and game-based learning modes, which merge technological innovation with pedagogical content.

The shift toward digital learning environments has also prompted a reevaluation of self-study modes, which offer flexibility and cater to individual learning preferences. Awadhiya & Miglani [15] investigate the acceptance of e-learning, revealing a preference among students for online learning modalities that allow for autonomy and self-paced study, potentially leading to better academic performance. Moreover, the flipped classroom model, which often incorporates elements of self-study, has been examined across various fields of study. Zainuddin & Halili [16] assess the flipped classroom's effectiveness, noting that when students are given the opportunity to engage with content before class, they are better prepared to participate in active learning activities during face-to-face sessions, which could improve comprehension and test performance.

As engineering education continues to adapt to the changing landscape of learner preferences and technological advancements, understanding the interactions between instructional mode and academic outcomes becomes increasingly important. In the context of engineering education, the approach to instructional preferences becomes even more nuanced due to the field's inherent complexity. Overall, the literature suggests that while there is evidence to support the notion that instructional preferences can impact academic performance, the relationship is multifaceted and may be influenced by a variety of factors, including discipline, content complexity, and the instructional design itself. The goal for this work is to explore the relationship between student preference for different modes of instruction and student performance on online content modules.

Purpose of the study

This study is situated within a larger research study exploring the development of content modules related to advanced manufacturing and data science, both at the student level and industry professional level. This specific research investigated the relationship between students' instructional mode preferences and academic performance across a subset of three educational modules: statistics, material jetting, and Python programming. By employing a ranking-based survey, students' preferences among four distinct modes of instruction including traditional, self-study, game, and VR were investigated to determine the correlations between these preferences and academic outcomes in the courses. This exploration extends to understanding the impact of various factors on student outcomes when engaged with different instructional modes.

The research questions explored in this study are:

1. What are students' instructional mode preferences?
2. How do these preferences relate to their academic performance in engineering modules such as statistics, material jetting, and Python programming?

Methods

This study is part of a larger NSF project exploring the impact of educational modules on different populations (industry professionals and students) to gain knowledge that contributes to Additive Manufacturing and Data Science [17]. The overall research design is in Figure 1. The learning modules were developed using a learning design framework utilized by the primary university [18]. The pre- and post- assessment were developed by content knowledge experts in collaboration with an instructional designer. The focus for this study is the pre- and post-assessments included in each module and the post-all-module completion ranking survey of learning preferences.

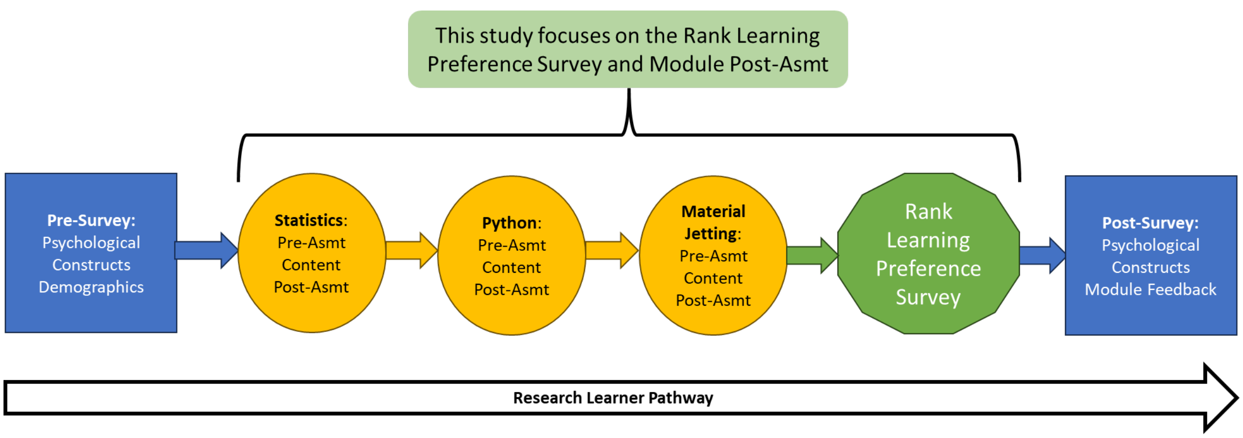

Figure 1. Overall Research Design and Learner Pathway.

After completing all three of the self-study learning modules, participants were asked four ranking questions with the same response options. The four questions were:

1. Overall, how would you arrange these designs according to your *general* learning preferences?
2. How would you rank these designs if you were taking a *Statistics* module?
3. How would you rank these designs if you were taking a *Material Jetting* module?
4. How would you rank these designs if you were taking a *Python* module?

The four responses that were ranked are listed below with the provided description of the learning mode:

Traditional: This is a more traditional learning experience. It would be asynchronously paced, so that every few days you have an assignment due. You would review a series of lectures and then have opportunities to practice the skills, receive feedback to refine the skills, and then complete a test to demonstrate what you mastered through the course. The instructor would engage with you across all of the assignments.

Self-Study: This would be a self-paced, self-study design. You would have a set of readings, video lectures, and guided tutorials to work through the content. You would determine the pace of the course for yourself. There would be weekly "office hours", when you can login for "live" help. Feedback across the assignments would be automated to guide you in real time.

Game Environment: In this version, you would engage in a game-like environment where you have challenges that grow in complexity as you move through the game. In each area, you would have access to tools, tutorials, and guides that help you master the content. Through the challenges, you would learn and demonstrate your mastery of the content.

Virtual Reality: This is an immersive experience that utilizes virtual reality (VR). You would visually experience a modern workplace where you would be apprenticed in the skills and content by a virtual mentor. There would be a storyline that guides you through the course to helps you master the content. The course wraps up with a project where you would demonstrate your mastery of the content.

Participants.

Data was collected between May 2022 and February 2023. Participants were recruited to complete the larger research study which required between two to three hours to complete. Participants were solicited from a 4-year STEM-focused institute in the Western US, 2-year community college in the Western US, STEM Alumni from the same 4-year institution, and local industry partners. Overall, 67 participants completed all (or a majority) of the data collection points within the overall research study. Within this sample, 33 identified students and 34 were professionals; 40 identified as male, 21 identified as female, and 6 chose not to respond; a majority of the sample identified as white (47), some identified as mixed race (8), with a few identifying as Hispanic (4) and Asian (4), with 4 preferring not to disclose.

Data Analysis

To analyze the relationship between students' instructional mode preferences and their test performance, descriptive and inferential statistical methods were employed. The descriptive statistics reveal variations in students' average preference scores for different instructional modes across modules and Spearman's rho correlation coefficients as a part of inferential statistical methods were calculated to examine the correlations between these ranks and the test outcomes which was chosen because of the non-parametric nature.

Results

The results section presents a comprehensive analysis of the intricacies between students' instructional preferences and their academic performance across three distinct modules: statistics, material jetting, and python programming. We explored how students' rankings of different instructional modes are related with their performance on post assessments.

RQ1. Student preferences for instructional modes

Table 1. Descriptive statistics on instructional modes

Module	Self-study M (SD)	VR M (SD)	Game-based M (SD)	Traditional M (SD)
General	2.62 (1.212)	1.92 (0.847)	2.58 (1.096)	2.88 (1.089)
Statistics	2.75 (1.119)	1.64 (0.792)	2.63 (1.085)	2.99 (0.977)
Material Jetting	2.03 (1.109)	3.00 (1.067)	2.50 (1.071)	2.47 (1.041)
Python	2.88 (1.066)	1.49 (0.766)	2.91 (1.011)	2.72 (0.966)

Note. 1 is the most preferred and 4 is least preferred.

The descriptive statistics (Table 1) reveal variations in students' average preference scores for different instructional modes across modules. For the Python module, VR was notably favored with a mean preference score of 1.49 (SD = 0.766), indicating a general student preference for VR over other modes. The lower standard deviation here suggests a consensus among the students. Conversely, game-based learning had the highest mean preference score of 2.91 (SD = 1.011) in Python, signaling it as the least favored mode with a wider spread in responses. In Material Jetting, VR was the least favored with the highest mean preference score of 3.00 (SD = 1.067).

Table 2. Friedman test results on instructional modes

Module	Self-study Rank	VR Rank	Game-based Rank	Traditional Rank	N	Chi-Square	df	Asymp. Sig.
General	2.38	3.08	2.42	2.12	66	19.618	3	< .001
Statistics	2.25	3.36	2.37	2.01	67	42.152	3	< .001
Material Jetting	2.97	2.00	2.50	2.53	66	18.673	3	< .001
Python	2.12	3.51	2.09	2.28	67	55.281	3	< .001

The Friedman test, a non-parametric test for detecting differences between groups when the dependent variable is ordinal, corroborates these preferences (Table 2). VR had the highest mean rank (3.51) for the Python module, significantly distinguishing it from other modes as evidenced by the Chi-Square value of 55.281 (df = 3, $p < .001$). In the general module, mean preference scores and ranks indicate that VR (M = 1.92, SD = 0.847; Mean Rank = 3.08) and traditional modes (M = 2.88, SD = 1.089; Mean Rank = 2.12) are on opposite ends of the spectrum, with VR being more favored. These differences are statistically significant, as shown by the Chi-Square value of 19.618 (df = 3, $p < .001$). For Statistics, VR is the most preferred (M = 1.64, SD = 0.792; Mean Rank = 3.36), and traditional instruction is the least (M = 2.99, SD = 0.977; Mean Rank = 2.01), with a Chi-Square value of 42.152 (df = 3, $p < .001$) confirming the significance. Material Jetting displays a preference reversal; self-study is most favored (M = 2.03, SD = 1.109; Mean Rank = 2.97), while VR is least (M = 3.00, SD = 1.067; Mean Rank = 2.00), although it had the lowest mean score. This suggests that while VR was less preferred on average, it was not ranked as the least within student preferences. The Chi-Square value of 18.673 (df = 3, $p < .001$) highlights significant differences in these rankings.

The analysis clearly demonstrates that student preferences for instructional modes are not uniform across different modules. VR stands out as a preferred mode in Python and Statistics, suggesting that the immersive nature of VR is particularly suited to these subjects. However, its less favorable standing in the Material Jetting module indicates that the appeal of instructional modes can be highly context-dependent. Traditional instructional methods exhibit a consistent preference across all modules, reflecting their enduring role in foundational education. These insights underline the importance of subject-specific considerations in instructional design and the necessity for educators to dynamically tailor their teaching strategies to align with the varied learning preferences.

RQ2. Relationships among students' instructional mode preferences and post-module assessment performance

We examined preferences for various instructional modes of students after they engaged in multiple self-study modules. By assessing these preferences against their performance in the post-module assessments for Statistics, Python, and Material Jetting, we aimed to discern potential patterns that might inform future instructional design. To understand these relationships, we calculated Spearman's rho correlation coefficients. It's important to note that due to the ranking system used for preferences (1 being the most preferred and 4 the least preferred), a negative correlation coefficient actually indicates a positive relationship where a preference for a particular instructional mode is associated with higher assessment performance.

In the Statistics module, a negative correlation was found between students' preference for Self-Study and their **post-test scores** ($r(67) = -.423$, $p < .001$), suggesting that students who achieve higher performance scores preferred self-study. This trend could imply that self-study might be particularly suited to the subject matter of statistics, even if students did not actually experience alternative instructional modes.

For Python, a positive correlation emerged between students' **pre-test scores** and preference for VR ($r(67) = .340$, $p = .005$). This may indicate that students with a stronger foundation in Python felt they would prefer VR, although they did not actually experience it. Additionally, a negative correlation was found between a preference for Self-Study and higher performance (post-test score) in Python ($r(67) = -.370$, $p = .002$), suggesting that students who performed well thought they would do well with self-study.

For Material Jetting, no significant correlations were found, indicating that for this module, preferences for instructional modes did not seem to be impacted by content knowledge.

Interestingly, within the Statistics module, strong negative correlations were observed between the preference for Traditional instruction versus Game-based learning ($r(67) = -.604$, $p < .001$) and Self-Study versus VR ($r(67) = -.508$, $p < .001$). This pattern was consistent in the Python module, where preference for Self-Study negatively correlated with preferences for Traditional instruction ($r(67) = -.379$, $p = .002$) and Game-based learning ($r(67) = -.539$, $p < .001$). In the Material Jetting module, preferences for Traditional instruction negatively correlated with Self-Study ($r(66) = -.533$, $p < .001$) and Game-based learning ($r(66) = -.541$, $p < .001$).

The findings suggest a relationship between students' preference for self-study and higher post-assessment scores, highlighting that students who performed better preferred the module the self-study module – where they already performed well. The positive correlation with VR in Python suggests that those with stronger academic foundations felt they would benefit from VR, despite not experiencing it. The distinct negative correlations between different preferences underscore the diversity in learning preferences and suggest the value in exploring various instructional modes to cater to different learning needs.

Limitation

This study has some limitations. The primary limitation is the nature of the data collected regarding student preferences in place of actually having students complete the modules using different instructional modes. Students were surveyed on their instructional mode preferences without having actual exposure to the instructional methods other than self-study. Therefore, their reported preferences are based on perception rather than experience, which could affect the reliability of these preferences as indicators of effective instructional design. Also, since all instruction was conducted through self-study, the study's results might reflect a bias towards this mode because of the familiarity, so the findings may not accurately represent the potential benefits or disadvantages of various instructional modes had they been applied in practice. However, the study provides valuable evidence supporting the need for adaptive instructional design although we have a clear limitation such as relying on students' preferences for instructional modes, without their actual experience with these modes. Future work implementing and comparing different instructional modes would greatly further this work.

Implication

The study's findings have implications for instructional design in educational settings. The observed correlations between students' preferences for certain instructional modes and their academic performance suggest that instructional design should not adopt a one-size-fits-all approach but rather should be tailored to include the diverse learning preferences of students. For example, the positive relationship between a preference for self-study and academic performance implies that instructional designs that foster autonomy and self-directed learning are highly preferred by high performing students. This may involve creating resources and assignments that encourage independent exploration and critical thinking, particularly for subjects where self-study is highly preferred as well as considering other engagement strategies for lower performing students.

Thus, instructional design should be responsive to the evolving needs and preferences of students. This may involve continuous feedback mechanisms to understand students' preferences and adapt the course design accordingly. Moreover, the design should incorporate a mix of instructional modes to provide a rich, multifaceted educational experience that aligns with different learning preferences. These insights underscore the need for dynamic instructional design that can accommodate the various ways students learn best and influence the strengths of different instructional modes to optimize academic outcomes.

Conclusion

This exploration into students' preferences for instructional modes offers initial insights in the educational design. The study provides valuable evidence supporting the need for adaptive instructional design although we have a clear limitation such as relying on students' speculative preferences for instructional modes, without their actual experience with these modes. It advocates a student-centered approach where educational strategies are not static but evolve in response to the diverse and changing needs of students. For instance, the data revealed an evident preference for self-study among high performers, suggesting that when students are given the autonomy to shape their learning journey, they can often achieve better outcomes. Conversely, the strong interest in VR for subjects like Python and Statistics suggests that innovative, immersive platforms could play a crucial role in enhancing student engagement and understanding in these areas.

The conclusion drawn from this study, therefore, is twofold: First, that educational experiences must be tailored to student preferences to maximize engagement and performance, and second, that further research is needed to explore the impact of these preferences when students are actively engaged in a variety of instructional modes. Future studies could benefit from a design where students experience each mode of instruction for different subjects to provide a more accurate measure of preference and performance. Such research would offer a deeper understanding of how different instructional modes influence learning outcomes and could potentially inform more effective educational practices.

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