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Research Article

Effects of flipped teaching on entrepreneurship professional student' learning motivation, self-directed learning, and learning outcome

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ABSTRACT

Flipped instruction has garnered significant interest in higher education for its potential to enhance student motivation and self-regulated learning. This quasi-experimental study examined the impact of flipped teaching on motivation and self-directed learning attributes among 106 entrepreneurship students at universities in Taiwan. Students completed pre- and post-intervention surveys measuring intrinsic motivation, extrinsic motivation, and facets of self-directed learning. Bayesian paired samples t-tests revealed that flipped instruction significantly increased both intrinsic and extrinsic motivation. Self-directed learning attributes including internal processes, behavioral approaches, and environmental preferences also improved following the flipped teaching intervention. Additionally, machine learning models were developed to predict students' final exam scores based on pre-intervention motivation, self-directed learning, and learning expectations. A linear regression model accounted for 59.1% of variance in exam scores, with pre-learning expectations emerging as the strongest positive predictor. However, pre-intervention intrinsic motivation intriguingly showed a negative relationship with predicted exam performance. Overall, this study provides preliminary evidence that flipped instruction can increase student motivation and self-directed learning capabilities. The predictive modeling also suggests complex interactions between attributes in influencing academic achievement. Further research with larger, more diverse samples is recommended to validate the motivational and self-regulatory benefits of flipped teaching for higher education students.

Keywords: flipped teaching, learning motivation, self-regulated learning, learning expectation

INTRODUCTION

Flipped teaching and instruction is an increasingly popular pedagogical approach in which the traditional in-class lecture and out-of-class homework elements are reversed (Martínez-Jiménez & Ruiz-Jiménez, 2020; Sohrabi & Iraj, 2016). In a flipped classroom, students gain first exposure to content via pre-recorded video lectures and other materials outside of class. Then, in-class time is used for activities that reinforce and apply that knowledge, such as discussions, collaborative projects, and problem-solving exercises (Akcayir & Akcayir, 2018). Proponents of flipped teaching argue that this model can increase student motivation and engagement by promoting active learning during class time (Abeysekera & Dawson, 2015). Flipped instruction also has the potential to encourage self-directed learning, as students take greater responsibility for their initial acquisition and comprehension of course material (Ceylaner & Karakus, 2018; Leatherman & Cleveland, 2020).

The flipped classroom model has the potential to increase student motivation in higher education settings. By moving lectures outside of class time and dedicating in-person hours to active learning, flipped instruction emphasizes student engagement over passive listening (Steen-Utheim & Foldnes, 2018). According to self-determination theory, active learning activities that allow for autonomy, competence building, and peer collaboration can satisfy students' basic psychological needs. Meeting these needs enhances intrinsic motivation (Ryan & Deci, 2020). Studies have found positive impacts on motivational outcomes when flipping college courses. For example, Gross et. al. (2015) saw increased student engagement, enjoyment, and interest levels in an introductory biology course after flipping the curriculum. Similar motivational improvements were reported across flipped courses in electronics, statistics, and programming (Yilmaz, 2017).

However, research suggests that to fully realize motivational benefits, careful course design is required when flipping the classroom. In particular, in-class activities should connect to real-world contexts, provide an optimal challenge, and give students choice over their learning pathways (Abeysekera & Dawson, 2015). Professors also play a key role in promoting student buy-in and perceptions of autonomy with flipped instruction (Cheng & Weng, 2017). When these best practices are followed, flipped classrooms can increase student motivation through need-satisfying active learning experiences. More research is still needed to refine flipped teaching methods that maximize engagement in higher education contexts.

Flipped instruction's impact on self-regulated learning is particularly noteworthy (Sun et al., 2017, 2018). By requiring students to access and assimilate instructional content independently before class, flipped instruction fosters proactive learning habits, nudging students towards self-directedness (Long et al., 2017). As students navigate through the content at their own pace, they are compelled to develop skills in setting learning goals, planning their study sessions, and monitoring their comprehension, all hallmarks of self-regulated learning (Santos & Serpa, 2020). In the classroom setting, the emphasis shifts from passive content reception to active application, collaboration, and discussion, which further refines their metacognitive awareness, evaluative strategies, and capacity for reflection (Akcayir & Akcayir, 2018; Steen-Utheim & Foldnes, 2018). Through this iterative process, flipped instruction cultivates a learning environment, where students are not just recipients but active agents, continually calibrating and advancing their learning trajectories.

Research has demonstrated a clear link between students' learning expectations and their academic performance in college courses. According to a study by Greene et al. (2004), students' forecasts of their final exam scores at the beginning of a college course positively predicted their actual exam performance. Additionally, Hopkins et al. (2020) found that students' self-efficacy beliefs regarding a course significantly influenced the final grades they received. Students who entered a course with higher confidence in their ability to learn and master the material tended to achieve higher grades in the course. These findings align with models of self-fulfilling prophecy and self-efficacy in which students' beliefs shape their academic behaviors and outcomes (Andrade, 2019; Zimmerman, 2000) . Institutions of higher education may benefit from assessing incoming students' expectations for their courses and helping students foster positive yet realistic beliefs in their learning abilities. This could increase motivation and ultimately translate into better course performance.

Students pursuing entrepreneurship require particular motivations and skills to succeed in their learning and future careers. According to Price and Walker (2021), entrepreneurship students with strong learning motivation tend to have keen observation abilities, rich imagination, and exploration skills. These attributes enable them to thoroughly analyze problems, constantly improve solutions, and adeptly apply knowledge. Therefore, educators should identify entrepreneurship students' motivations and learning needs, facilitate in-depth discussion of relevant issues, and boost students' willingness to learn (Collins et al., 2004). Once students' learning motivation is enhanced, their ability development as entrepreneurs is multiplied (Obschonka et al., 2019). After sparking students' motivation, instructors must sustain engagement by continually improving teaching methods, providing incentives and inspiration, and maintaining motivation at consistent levels (Ahn et al., 2019). This promotes active learning and helps students evolve beyond previous learning approaches. Overall, tailored instruction and motivation techniques can empower entrepreneurship students to gain the skills and mindsets needed for enterprising careers.

The flipped classroom model, where traditional homework and lecture are reversed, presents several challenges for both teachers and students. According to research by O'Flaherty and Phillips (2015), one major challenge is the large amount of time and effort required by teachers to create high-quality video lessons and activities for students to complete outside of class. Teachers must learn new technologies and presentation styles to produce engaging videos. Another significant challenge is the increased demand on students' self-motivation and self-discipline. Students are expected to engage with the material independently before coming to class, which can be difficult for those who struggle with self-directed learning or lack the necessary digital literacy skills (Bishop & Verleger, 2013). Additionally, there is often an increased workload for educators in preparing the materials and activities for the flipped classroom (Abeysekera & Dawson, 2015). This model also assumes that all students have equal access to technology and the internet outside of the classroom, which may not be the case for students from low-income families or rural areas (Schiller & Herreid, 2013). Some students may lack motivation if pre-class work is not compelling or mandatory. Despite these challenges, studies indicate the benefits of the flipped classroom model often outweigh the difficulties (O'Flaherty & Phillips, 2015).

Research is the bedrock of innovation and progress in education. It allows educators to systematically analyze and refine pedagogical strategies, tailoring them to the evolving needs of diverse learners. This study, in particular, delves into the world of flipped instruction, an educational method that has gained traction in recent years due to its potential for fostering both student motivation and self-regulated learning.

Building on the established foundation, our research is anchored on several key hypotheses. Firstly, we posit that flipped teaching plays a substantial role in boosting learning motivation. Secondly, we believe that this instructional method also notably heightens self-regulated learning among students. Lastly, our study contends that a combination of a student's learning motivation, their propensity for self-directed learning, and their initial learning expectations can be indicative of their eventual final exam outcomes.

LITERATURE REVIEW AND HYPOTHESES

The rapid advancement of information technology in recent years has propelled the evolution of learner-centered teaching methodologies, with the flipped classroom emerging as a prime exemplar. Long et al. (2017) highlights the flipped classroom as a pivotal shift from traditional pedagogical techniques, positioning it as an emphatically student-centric approach.

The essence of the flipped classroom is not novel. Its roots can be traced back to the 1990s when Eric Mazur, a Harvard physics professor, revolutionized the teaching landscape. Instead of one-directional knowledge impartation, Mazur introduced a model, where students would preview content before lectures, paving the way for engaging in-class discussions and collaborative problem-solving (Mohan, 2018). The concept gained widespread traction after Khan Academy's online platform introduced an array of educational videos, further democratizing access to flipped content (Zengin, 2017). The modern interpretation, however, often credits Bergmann and Sams for crystallizing the idea. In 2007, these educators uploaded their lectures to YouTube to aid students who had missed classes, inadvertently laying the foundation for a model wherein students prep before class and then collaborate and deliberate in the classroom (Abdullah et al., 2019).

At its heart, the flipped classroom turns the traditional teaching model on its head. Lopes and Soares (2018) elucidate that students engage with lectures and content at their own pace, often through videos, and then apply and discuss this knowledge interactively in class. This paradigm shift fosters a more individualized learning experience, acknowledging that learners assimilate knowledge at varied speeds (Martínez-Jiménez & Ruiz-Jiménez, 2020). In fact, flipped teaching gives educators a unique opportunity: rather than merely transmitting information, they can focus on facilitating comprehension and addressing challenges students face in real-time (Akcayir & Akcayir, 2018).

While the flipped classroom presents promising results, its implementation requires careful planning. As Hwang and Chen (2019) indicate, the true merit of this model lies not just in the content provided but in its integration with in-class discussions and problem-solving sessions. Therefore, teachers need to be adept at guiding these interactions and ensuring the content aligns with classroom activities.

Intrinsic and extrinsic motivations are fundamental constructs in understanding human behavior, particularly in academic settings (Ryan & Deci, 2000). Intrinsic motivation refers to engaging in an activity for the inherent satisfaction derived from the activity itself, without any external rewards or pressures. It is driven by personal interest, curiosity, or the pleasure of mastering a task (Diseth et al., 2020). On the other hand, extrinsic motivation is driven by external factors such as rewards, punishments, or other tangible outcomes. For instance, a student might study hard to receive praise from a teacher (an extrinsic motivator) rather than out of genuine interest in the subject (intrinsic motivator) (Serin, 2018). The hierarchical model provides a framework to organize the literature on these motivations, emphasizing the psychological mechanisms underlying motivational changes (Ryan & Deci, 2020). Another perspective posits that while intrinsic motivation can be undermined by external rewards, it can also coexist with extrinsic motivators, depending on the context and individual perceptions (Cheng, 2019). In the realm of education, it is crucial to strike a balance between these motivations to foster genuine interest and ensure positive outcomes.

It is essential to recognize the underpinning motivations that drive students. Lee (2018) posits that motivation acts as an internal compass, guiding and maintaining activity towards achieving learning objectives. This sentiment is echoed by Havwini and Wu (2019), who suggest that a drive to learn can significantly influence academic outcomes. The flipped classroom model, by its design, engages and kindles this motivation. By empowering students to take charge of their learning journey, it fosters deeper engagement and commitment. Zheng et al. (2020) present a tangible example of this.

H1. Flipped teaching has significant positive effects on learning motivation.

One potential benefit of the flipped approach is its positive impact on self-regulated learning. Self-regulated learning refers to the degree to which students are metacognitively, motivationally, and behaviorally active participants in their own learning (Zimmerman, 2008). Research suggests that flipped instruction may enhance self-regulated learning by giving students more autonomy over their initial learning process and providing opportunities to monitor comprehension, such as through pre-class quizzes (Sun et al., 2017). The interactive classroom activities also allow students to clarify misconceptions and practice applying knowledge. According to Zimmerman's social cognitive model, these opportunities for monitoring, feedback, and adjustment are critical components of developing self-regulatory skills (Lee et al., 2022).

Multiple studies provide empirical support for a connection between flipped teaching and self-regulated learning. In one study of an undergraduate technology course, students in the flipped sections reported higher levels of metacognitive self-regulation, including greater goal-setting, planning, monitoring, and strategy use (Lai & Hwang, 2016). The researchers propose that having to independently watch lecture videos helped activate these metacognitive processes. Enhanced metacognitive self-regulation has also been documented in K-12 flipped math classes, along with increased motivation and use of learning strategies (Sun et al., 2018).

While promising, some researchers argue that flipped teaching does not automatically increase self-regulated learning without directly incorporating activities meant to develop metacognition and study skills (Rasheed et al., 2020). However, structure can be built into pre- and post-class activities to scaffold self-regulatory skill building. For example, Yoon et al. (2021) used guided reflection questions and self-assessments before, during, and after recorded lectures to positively impact medical students' regulation of motivation and learning strategies. Careful integration of metacognitive development into the flipped model may amplify its benefits.

In conclusion, emerging evidence largely supports the hypothesis that flipped teaching can positively impact self-regulated learning. By shifting more active cognitive processing into individual pre-class work and devoting class time to knowledge application and discussion, flipped instruction may aid students in goal-setting, progress monitoring, help-seeking, and other self-regulatory processes. More research is still needed to refine best practices for flipped teaching to maximize its potential to develop independent and self-directed learners.

H2. Flipped teaching has significant positive effects on self-directed learning.

Several studies have examined the relationship between student motivation, self-directed learning, expectations and academic achievement. Intrinsic motivation, or the internal drive to learn and succeed, has been linked to better learning outcomes and higher grades (Claver et al., 2020; Taylor et al., 2014). Students who are intrinsically motivated to learn tend to be more engaged in the learning process, put in more effort, and use more self-regulated learning strategies (Shin & Bolkan, 2021).

In addition to motivation, a student's self-directed learning abilities and skills have been associated with academic success. Self-directed learning refers to the degree to which students are able to take responsibility for their own learning by setting goals, planning their learning, using different strategies, and self-evaluating (Ceylaner & Karakus, 2018). Students with greater self-directed learning capabilities exhibit higher achievement and obtain higher grades (Jansen et al., 2019; Sadiq & Ali, 2020). Enhancing students' self-directed learning skills through training may lead to improvements in their academic performance.

Finally, students' expectations about their potential achievement or grades has an influence on their actual outcomes. According to expectancy-value theory, if students have high expectations for success and place a high value on excelling, they are more likely to be motivated to put in the effort to succeed (Steinmayr et al., 2019; Wigfield & Eccles, 2000). Studies show that students' expectancy of their grade is associated with their actual grade, even when controlling for previous achievement (Brown et al., 2008; Talsma et al., 2018). Therefore, supporting students in developing positive and realistic expectations may improve their academic performance.

Machine learning techniques like regression, decision trees, and neural networks can analyze student data to identify key predictors of academic performance. These algorithms handle large datasets well, uncovering complex patterns and interactions (Rastrollo-Guerrero et al., 2020). Studies using machine learning have determined engagement, past performance, demographics, and other factors strongly predict student grades and GPA (Enughwure & Ogbise, 2020; Kovacic, 2012). Machine learning models tend to outperform traditional statistics, yielding accurate predictions (Abu Saa et al., 2019). Though focused on undergraduates so far, machine learning shows promise for identifying drivers of achievement at all educational levels (Huang & Fang, 2013). Overall, machine learning represents an impactful methodology for uncovering the drivers of academic success.

In summary, existing research indicates that student motivation, self-directed learning abilities, and expectations seem to be positive predictors of academic achievement and grades. Further research is still needed to determine the relative influence of each factor and how they interact in influencing achievement outcomes.

H3. Learning motivation, self-directed learning, and learning expectation are predictors of final exam score.

METHODOLOGY

This study utilized a quasi-experimental design to examine the effects of flipped teaching on student learning motivation and self-regulated learning. Additionally, it investigated how learning motivation, self-directed learning, and learning expectations predict final exam performance.

Participants of the Study

A total of 106 entrepreneurship professional student from the universities in Taiwan participated in the study. Demographic information about the students was not collected in the study.

Data Collection Tools and Process

In the quasi-experimental study, "learning motivation scale", "self-regulated learning scale" and "learning expectation scale" scales were applied to the participants before the training. At the end of the training, "learning motivation scale" and "self-regulated learning scale" scales were applied, and a multiple choice test was also applied.

Learning Motivation Scale

Motivated strategies for learning questionnaire (MSLQ) developed by Pintrich et al. (1991) has been widely utilized in educational research (Zheng et al., 2020). In this study, the intrinsic and extrinsic motivation subscales of MSLQ were implemented using a 5-point Likert scale, with responses ranging from one ("not at all true of me") to five ("very true of me"). The intrinsic motivation subscale contains four items assessing students' inherent interest and internal drive to learn, such as "in a class like this, I prefer course material that really challenges me so I can learn new things." In the original validation study, Pintrich et al. (1991) reported an internal reliability coefficient alpha of .74 for this subscale.

The extrinsic motivation subscale includes four items measuring external motivators, such as grades, evaluations, and recognition from others. An example item is "the most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade." Pintrich et al. (1991) found an alpha of .62 for this subscale.

Confirmatory factor analysis (CFA) was performed. Calculated as $\chi^2/df=1.2$, CFI=.995, TLI=.990, SRMR=.0284, and RMSEA=.0429. Since $\chi^2/df<3$, CFI and TLI>.90, SRMR and RMSEA<0.8 (Brown, 2015; Hu & Bentler, 1999), the two-factor structure scale was validated by CFA. The study calculated reliability for intrinsic (Cronbach's α=.870 and McDonald's ω=.874) and for extrinsic (Cronbach's α=.830 and McDonald's ω=.840). MSLQ motivation subscales provide valid and reliable measures of students' internal motivations (IMs) and EMs (EMs) in academic contexts.

Self-Regulated Learning Scale

For self-directed learning, the scale items of which validity and reliability were made by Fisher et al. (2001) were taken as a basis. Scale items were examined by experts. A scale pool of 13 items was created. Since the item structure of the scale was changed, Exploratory Factor Analysis was performed again. Bartlett's Test of Sphericity (χ^2=1,177, df=78, p<.001) and KMO (.813). A four-dimensional scale has been formed. Then, the overlapping items were removed, and the process was repeated. Varimax rotation is used in the principal axis method. Bartlett's Test of Sphericity (χ^2=813, df=35, p<.001) and KMO (.783). As a result, a three-factor structure was obtained. In factor 1, the items were examined and named as "I am confident in my ability to search out information", "I have high belief in my abilities", "I want to learn new information" and internal process. The items in factor 2 were reviewed and named as behavioral approach, "I like to gather the facts before I make a decision", "I set specific times for my study", and "I evaluate my own performance". The items in the last factor "when presented with a problem I cannot resolve, I will ask for assistance", "I critically evaluate new ideas" and "I am aware of my own limitations" were examined and named as environmental preference.

Then CFA was applied. Calculated as $\chi^2/df=1.23$, CFI=.994, TLI=.989, SRMR=.0329, and RMSEA=.0470. Since $\chi^2/df<3$, CFI and TLI>.90, SRMR and RMSEA<0.8 (Brown, 2015; Hu & Bentler, 1999), the three-factor structure scale was validated by CFA. The study calculated reliability for internal process (Cronbach's α=.930 and McDonald's ω=.935), for behavioral approach (Cronbach's α=.602 and McDonald's ω=.643) and for environmental preference (Cronbach's α=.892 and McDonald's ω=.896). As a result, a valid and reliable self-directed learning scale was created.

Learning Expectation

The learners' expectation of success at the end of the course instruction was used to scale. Pintrich et al. (1991) items related to control of learning beliefs were used in the expectancy component. Scale items "if I study in appropriate ways, then I will be able to learn the material in this course", "it is my own fault if I do not learn the material in this course", "if I try hard enough, then I will understand the course material", and "if I do not understand the course material, it is because I did not try hard enough". In the original study, the reliability was calculated as alpha (.68).

Then CFA was applied. Calculated as $\chi^2/df=0.938$, CFI=1.0, TLI=1.0, SRMR=.0120, and RMSEA=.0. Since $\chi^2/df<3$, CFI and TLI>.90, SRMR and RMSEA<0.8 (Brown, 2015; Hu & Bentler, 1999), the factor structure scale was validated by CFA. The study calculated reliability Cronbach's α=.842 and McDonald's ω=.846). As a result, a valid and reliable learning expectation scale was created.

Final Exam

A multiple-choice exam was created to measure the final performance of the students. The test consists of 30 questions. An experiment was carried out on the group of students who had attended the course before. The discrimination power of the questions ranged from .30 to 0.85. The difficulty level of the questions varies between 0.34 and 0.74. Since the questions were appropriate, students' performances were used to scale at the end of the study.

Table 1. Course outline for each week

Week	Topic	Pre-class	In-class
1	Evolution of entrepreneurship in business education	Readings on history of entrepreneurship in business academia	Analysis of role business schools have played in shaping entrepreneurial thought
2	Advanced entrepreneurial mindset & leadership	Harvard Business Review articles on leadership in entrepreneurship	Leadership self-assessment & peer reviews
3	Opportunity recognition & blue ocean strategy	Reading on 'Blue ocean strategy' by W. Chan Kim & Renée Mauborgne	Workshop on blue ocean strategy canvas
4	Business model Canvas & value proposition	Introduction to business model Canvas	Hands-on workshop creating a business model canvas
5	Competitive analysis in EdTech	Analysis of various EdTech competitors	SWOT analysis workshop
6	Advanced market research techniques	Reading on conjoint analysis & advanced market research techniques	Workshop on designing market research for niche sectors
7	Financial modeling & projections	Tutorials on creating financial models	Hands-on workshop on projecting finances
8	Intellectual property, patents & trademarks	Case studies on IP battles in startups.	Mock IP strategy creation
9	MVP, prototyping & feedback mechanisms	Deep dive into rapid prototyping techniques	Prototyping lab
10	Growth hacking & digital marketing strategies	Introduction to growth hacking	Digital marketing campaign workshop
11	Advanced sales techniques & CRM tools	Reading on account-based marketing & advanced B2B sales	CRM tool workshop
12	Global networking & cross-cultural entrepreneurship	Case studies on startups expanding internationally	Cross-cultural communication workshop
13	Scaling strategies & organizational structure	Organizational theories relevant to scaling startups	Workshop on organizational design for growth
14	Venture capital, angel investors & crowdfunding	Deep dive into different funding methods	Mock investor meetings & negotiations
15	Mergers, acquisitions & exit strategies	Case studies on startups that underwent M&As	Roundtable discussions on exit strategy considerations
16	Resilience, failure & pivoting in entrepreneurship	Reading on psychology of failure & resilience	Workshop on strategies for pivoting a business idea
17	Advanced pitching, storytelling & stakeholder management	Techniques for crafting compelling narratives in business	Mock pitches with a panel of 'investors'
18	The future of entrepreneurship & innovation	Predictions & trends in entrepreneurship for next decade	Scenario planning workshop & course wrap-up

Instructional Design

The experimental teaching was conducted for 18 weeks. The learning motivation pre-test was implemented before the experimental teaching. The course, grouping method, and evaluation standards were explained in the first week. Course outline is listed in **Table 1**.

The course integrated various technology tools to enhance the learning experience. Learning management systems like Moodle hosted course materials, videos, quizzes, forums, and other resources. The interactive video platform, PlayPosit, was employed to embed questions and interactive elements directly into videos. Communication tools such as Microsoft Teams facilitated team-based projects, idea sharing, and regular communication, while Google Meet was utilized for video conferencing, guest lectures, and virtual office hours. Collaboration and brainstorming tool Miro served as a digital whiteboard platform for collaborative brainstorming, business model canvas creation, SWOT analysis, etc., and Trello was employed for project management and task tracking. Feedback and peer review tools like Peergrade enabled students to submit assignments and receive peer feedback. Digital marketing and growth hacking tools such as HubSpot and Mailchimp were used for email marketing and CRM, and SEMrush and Ahrefs for SEO and competitor analysis. Financial modeling tools like Excel and Google Sheets were essential for financial projections and modeling. E-portfolios on Portfolium allowed students to document and showcase their learning journey, projects, and achievements over the course and prepare them for professional networking. Gamification tools Kahoot! and Quizizz made quizzes and assessments more engaging.

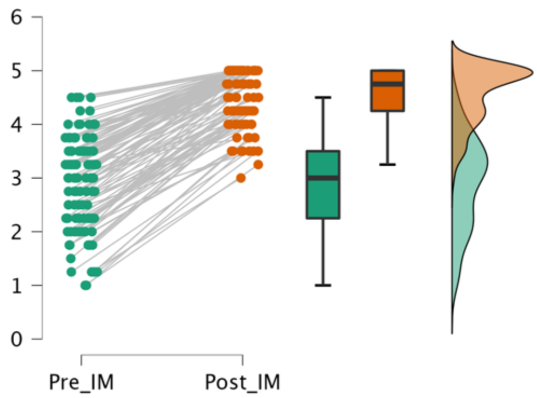

Figure 1. Raincloud chart for pre- & post-internal motivations (Source: Authors)

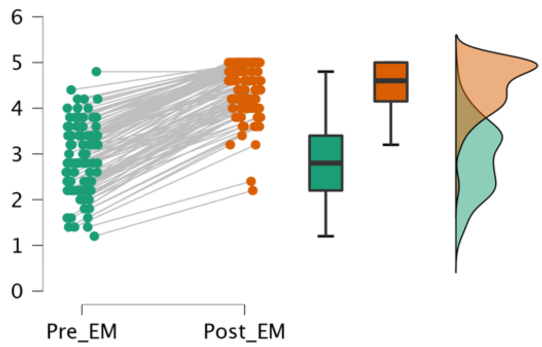

Figure 2. Raincloud chart for pre- & post-external motivations (Source: Authors)

Data Analysis

For a meticulous examination of the data, a combination of statistical tools and machine learning algorithms were employed, utilizing JASP and Python via Google Colab, respectively. Initially, we turned to JASP to implement a Bayesian t-test. Bayesian statistics offer an advantage over classical methods by providing a direct probability measure that can be interpreted more intuitively. Our aim was to understand whether flipped instruction has an effect on students' motivation and self-directed learning attributes. The results highlighted significant evidence in favor of the alternative hypothesis, indicating a profound impact of flipped instruction on both IM and EM. This was complemented by the observed change in behavioral attributes of self-directed learning and the students' environmental preferences pertaining to their learning experiences. Subsequent to the Bayesian analysis, we utilized Python programming in the Google Colab environment to delve into predictive modeling. The objective was to discern if student motivation and self-directed learning attributes could predict their final exam scores. The chosen model was a Linear Regression, owing to its efficiency in predicting continuous outcomes based on predictor variables.

FINDINGS

An investigation of the impact of flipped instruction on student motivation and self-directed learning was conducted. The findings, produced through machine learning analysis, present predictions regarding students' final course grades based on these pedagogical approaches.

Effect of Flipped Instruction on Internal and External Motivation

A visual analysis of the raincloud plot reveals intriguing shifts in both IM (**Figure 1**) and EM (**Figure 2**) scores following the intervention. For IM, the median score post-intervention exceeds that of the pre-intervention baseline. This upward shift is further reflected in the condensed interquartile range and clustering of individual data points for the post-intervention distribution. Collectively, these results are suggestive of an enhancement in IM subsequent to the intervention. A similar trend emerges for EM, with the post-intervention median and interquartile range surpassing their pre-intervention counterparts. The post-intervention jitter

Table 2. Descriptive & Bayesian factor for internal & external motivation

Variables	n	Mean	SD	95% credible interval		BF_{10}	Error %
				Lower	Upper		
Pre-IM	108	2.921	0.850	2.759	3.083	$1.881*10^{+53}$	$6.937*10^{-57}$
Post-IM	108	4.556	0.521	4.456	4.655		
Pre-EM	108	2.893	0.753	2.749	3.036	$4.183*10^{+59}$	$2.457*10^{-62}$
Post-EM	108	4.459	0.571	4.350	4.568		

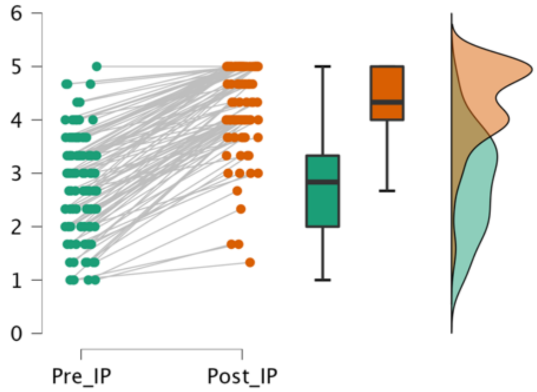

Figure 3. Raincloud chart for pre- & post-internal processes (Source: Authors)

plot also shows individual data points skewed higher relative to baseline. Taken together, the graphical elements imply a potential augmentation of both IM and EM after the intervention was introduced. However, while these visual cues offer preliminary evidence of motivational changes, statistically rigorous analyses are imperative before drawing definitive conclusions regarding the intervention's impact. Collectively, these visual cues hint at an overall enhancement in IM and EM post-intervention. However, to solidify these observations, a rigorous statistical analysis would be prudent. To achieve this, Bayesian paired sample t-test was applied.

Table 2 offers insight into the changes in IM and EM before and after a specific intervention, event, or treatment. A sample of 108 participants was evaluated in each case. Before the intervention, the average IM score stood at approximately 2.921, with a slight variation highlighted by a standard deviation (SD) of 0.850. Post-intervention, this score saw a considerable increase, averaging around 4.556, with a more consolidated SD of 0.521. A similar trend was observed for EM scores. Before the intervention, the average score was approximately 2.893, with an SD of 0.753. This average climbed to about 4.459 after the intervention, alongside a tighter SD of 0.571. Furthermore, the 95% credible intervals assure us of the reliability of these averages. For IM, the interval pre-intervention lies between 2.759 and 3.083, and post-intervention between 4.456 and 4.655. For EM, it is between 2.749 and 3.036 pre-intervention and 4.350 to 4.568 post-intervention. A Bayesian paired samples t-test further solidifies these observations. The Bayes Factor offers overwhelmingly strong evidence of a significant increase in both IM (approximately 1.881*10+53) and EM (approximately 4.183*10+59) following the intervention. The negligible error percentages further emphasize the precision of these findings. In summary, the data robustly suggests that the intervention under study has fostered a pronounced positive effect on the motivation levels of the 108 participants.

Effect of Flipped Instruction on Self-Directed Learning

Analysis of the graphical data reveals intriguing pre-post shifts across the three motivational domains of internal process (**Figure 3**), behavioral approach (**Figure 4**), and environmental preference (**Figure 5**). For internal process, the post-intervention distribution shows a higher median and more condensed interquartile range compared to baseline. This upward shift is further reflected in the jitter plot, with post-intervention data points predominantly exceeding their pre-intervention counterparts. A similar trend emerges for behavioral approach, with the post-intervention median and data point cluster surpassing the pre-intervention distribution. These graphical cues imply potential enhancements in both the internal processes and behavioral approaches to self-directed learning following the intervention. Finally, examination of environmental preference uncovers a comparable pre-post shift, with the median, interquartile range, and individual data points elevated after the intervention.

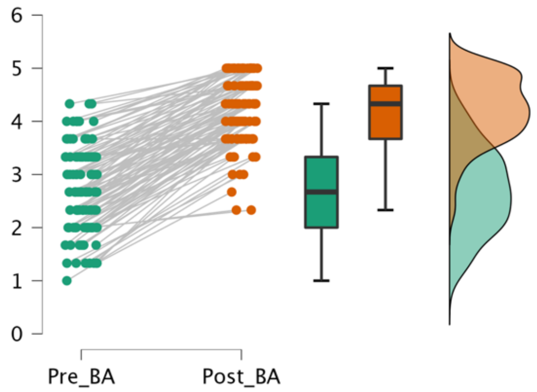

Figure 4. Raincloud chart for pre- & post-behavioral approaches (Source: Authors)

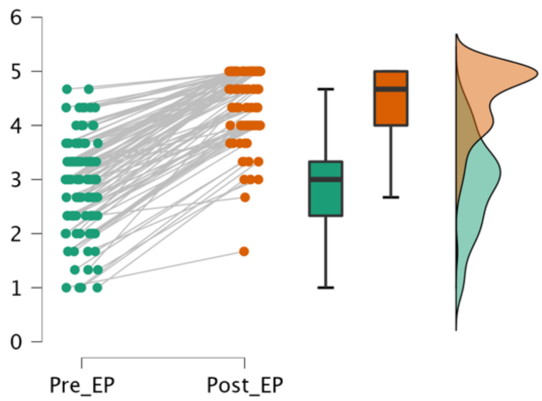

Figure 5. Raincloud chart for pre- & post-environmental preferences (Source: Authors)

Table 3. Descriptive & Bayesian factor for self-directed learning

Variables	n	Mean	SD	95% credible interval		BF_{10}	Error %
				Lower	Upper		
Pre-IP	108	2.790	0.938	2.611	2.969	$8.157*10^{+44}$	$4.439*10^{-50}$
Post-IP	108	4.297	0.791	4.146	4.447		
Pre-BA	108	2.697	0.782	2.548	2.846	$1.741*10^{+47}$	$4.014*10^{-50}$
Post-BA	108	4.210	0.621	4.092	4.329		
Pre-EP	108	2.913	0.859	2.749	3.077	$1.230*10^{+48}$	$3.571*10^{-51}$
Post-EP	108	4.482	0.648	4.358	4.605		

Collectively, the visual elements suggest the intervention may have enriched participants' internal processes, behavioral approaches, and environmental preferences related to self-directed learning. However, while these preliminary observations point to post-intervention improvements across domains, statistically testing the apparent pre-post differences is essential for substantiating any intervention effects.

The Bayesian paired samples t-test provides a comparative analysis of two paired measurements by assessing the strength of evidence for a difference between them, conveyed through the Bayes factor (BF_{10}) (**Table 3**).

Generally, a Bayes factor larger than one indicates evidence supporting the alternative hypothesis. Specifically, values greater than three suggest moderate evidence, those exceeding 10 indicate strong evidence, and those surpassing 100 are indicative of very strong evidence. Moving on to the descriptive statistics, it provides detailed insights into each measure. All measures had a consistent sample size of 108 participants. When examining the average (or mean) values, it is evident that the post-measurements (around 4.2-4.5) are consistently higher than their pre-counterparts (around 2.7-2.9). This trend denotes an observable increase from the pre- to the post-phase across all categories. SD offers insights into the variability of these measures. While the pre-measures have SDs generally around 0.7-0.9, the post-measures tend to be more consistent with slightly reduced SDs in the range of 0.6-0.8. This suggests that the post-measurements demonstrate a bit more uniformity in comparison to the pre-measurements.

Table 4. Machine learning model comparation for final exam

Machine learning model	MAE	R^2	MSE	RMSEA
Support vector machines	3.911	0.45991	23.938	4.893
Light GBM	4.195	0.35930	28.397	5.329
Ada boost regressor	4.33	0.42721	25.387	5.039
Linear regression	3.632	0.59096	18.130	4.258
Ridge regression	3.659	0.58437	18.422	4.292
Lasso regression	4.246	0.39757	26.701	5.167
Elastic net	4.475	0.29932	31.056	5.573
K Neighbors regressor	4.491	0.33914	29.291	5.412
Bayesian ridge	3.815	0.54173	20.312	4.507
XGB regressor	3.742	0.50962	21.735	4.662
Gradient boosting regressor	4.547	0.32802	29.784	5.457

Further reinforcing these findings are the 95% Credible Intervals, which provide a probability-based range wherein the true parameter is likely to be found. For all measures, the absence of overlapping intervals between the pre- and post-phases is consistent with the strong evidence from the Bayesian t-test about the distinctiveness of the means of the pre- and post-measures.

In the case of the comparison between pre- and post-IP measurements, BF_{10} is a staggering 8.157*10+44, pointing towards an incredibly strong evidence of a difference between these two measures. A similar pattern is observed in the other comparisons. BF_{10} for pre-BA versus post-BA is 1.741*10+47 and for pre-EP versus post-EP, it is 1.230*10+48. Both of these figures similarly indicate extremely strong evidence for a difference. Furthermore, the accompanying error percentages for these Bayes factors are exceptionally small, suggesting that these estimations are highly precise.

In conclusion, the results robustly suggest significant differences between the pre- and post-measures for IP, BA, and EP. The descriptive statistics corroborate this by highlighting the rise in mean values from pre- to post-phases, with the post-measurements also exhibiting slightly enhanced consistency.

Final Exam Results Prediction

We constructed a predictive model to forecast students' final exams based on measurements of their motivation, self-directed learning, and learning expectations at the beginning of their education. To validate the efficacy of our model, we employed a series of machine learning algorithms. Subsequently, based on the performance of the most accurate predictive model, we analyzed and compared the influence of the independent variables.

In evaluating the performance of various machine learning models, four key metrics were considered, as shown in **Table 4**: mean absolute error (MAE), R-squared (R^2), mean squared error (MSE), and RMSEA. MAE provides insights into the average absolute difference between observed and predicted values, with lower values signifying better model performance. R^2, on the other hand, offers a perspective on the proportion of variance in the dependent variable that the model can explain, with values closer to one being ideal. MSE measures the average squared difference between observed and predicted values, with lower values indicating better accuracy. Lastly, RMSEA (or potentially RMSE in some contexts) is the square root of MSE, which also favors lower values for optimal performance.

Upon analyzing the results, the linear regression model emerged as the standout performer. It boasts the highest R^2 value of 0.59096, suggesting it accounts for approximately 59.1% of the variance in the target variable. Additionally, it achieved the lowest MSE value of 18.13 and the lowest MAE value of 3.632. Its RMSEA, at 4.258, was also the most favorable among the evaluated models.

In summary, based on the metrics provided, linear regression appears to be the most efficient model among the given options. However, while these metrics are pivotal in gauging model performance, it is essential to ground the final model choice in the context of the specific business problem, model assumptions, and other external considerations.

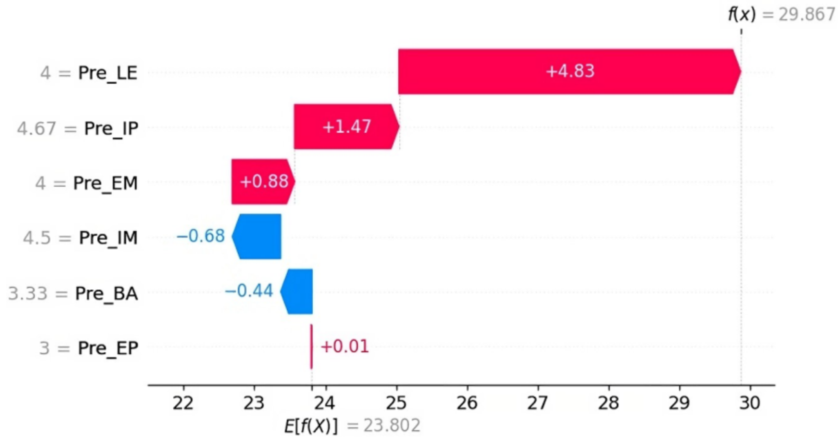

Figure 6. SHAP chart related to importance of independent variables (Source: Authors)

Feature Importance

Based on SHAP values analyzed through the graph, the impact of each independent variable on the model has been assessed. The variable with the most significant influence on the model is "pre-learning expectation". This variable has demonstrated a positive impact of +4.83, which prominently emerges among high-scoring students (**Figure 6**). Following this, the second most influential variable is "self-directed learning pre-internal process", contributing to a score increase of +1.47. In third place, we find the "pre-external motivation" variable, accounting for a positive shift of +0.88 in the score. The fourth in line, "pre-internal motivation", interestingly has a negative influence, leading to a decrease of -0.68 in the predicted score. This negative value signifies that its presence might result in a score drop. The fifth influential variable, "pre-behavioral approaches", also showcases a negative impact of -0.44 on model's outcome. Lastly, "pre-external preference" variable has an almost negligible positive effect of +0.01, suggesting its minimal contribution to the model.

In summary, while variables like "pre-learning expectation" and "self-directed learning pre-internal process" significantly enhance the model's prediction, others like "pre-internal motivation" and "pre-behavioral approaches" have shown to potentially decrease it. This analysis provides valuable insights into the relationships between independent variables and the dependent outcome, helping in understanding the nuances and intricacies of the model's predictions.

DISCUSSION

Flipped instruction refers to a pedagogical approach, where traditional teaching elements, such as lecture and homework, are reversed. Students are introduced to new content at home and practice working through it at school (Martínez-Jiménez & Ruiz-Jiménez, 2020; Sohrabi & Iraj, 2016). The introduction of flipped instruction appears to have a significantly positive effect on both IM and EM. Visual analysis, supported by the Bayesian paired sample t-test, evidences a pronounced increase in motivation post-intervention. The results of this study provide compelling evidence that flipped instruction can enhance student motivation, aligning with previous research. The substantial increase in both intrinsic and extrinsic motivation after introducing the flipped model supports Havwini and Wu's (2019) assertion that drive to learn strongly influences academic outcomes. Further, the motivational boost aligns with Zheng et al.'s (2020) study demonstrating heightened engagement and commitment in a flipped environment.

Understanding the reasons behind the motivational improvements is crucial for harnessing the full potential of flipped instruction. The marked motivational improvements can be attributed to core elements of the flipped approach. The self-paced nature provides flexibility and autonomy, which are key pillars of intrinsic motivation (Ryan & Deci, 2000). This enables students to tailor the learning journey to their needs and abilities. Additionally, active learning inherent in the flipped model compels students to apply their knowledge through discussions and collaborative problem-solving. This mastery of content and skills is a source of intrinsic satisfaction (Diseth et al., 2020). The interactive classroom also allows instant clarification of doubts, preventing demotivation.

While the flipped approach provides the necessary framework for enhanced motivation, it also requires a proactive attitude from the students. For students, being proactive is key to success in the flipped model. Seeking clarification on unclear content, asking for learning strategy guidance, and collaborating with peers activates intrinsic motivation (Ryan & Deci, 2000). Self-monitoring progress and proactively adjusting approaches also prevents demotivation (Zheng et al., 2020). Students should leverage instructor feedback and peer support while finding an optimal study environment. A proactive attitude, coupled with a well-balanced mix of intrinsic and extrinsic motivational drivers, can lead to optimal engagement. Critically, results reveal the synergistic motivational effects of intrinsic and extrinsic drivers when balanced well (Cheng, 2019). The flipped approach augments intrinsic interest while providing positive reinforcement through peer collaboration, educator guidance, and a sense of achievement. This fulfills the need for both autonomy and competence (Ryan & Deci, 2020). Therefore, the flipped model demonstrates how harnessing multifaceted motivations can optimize engagement.

The findings of this study hold significant implications for educators and policymakers alike. Given the importance of motivation in driving learning behaviors and outcomes, these findings are paramount. Notably, the pedagogical approach seemingly elevated not only intrinsic drivers but also extrinsic factors, suggesting a broadened appeal and engagement of learners. However, the study sample was limited, so further research across diverse cohorts is recommended. Additionally, long-term studies should track how motivational changes influence academic performance over time. A nuanced analysis of specific elements driving motivation could also provide actionable insights for educators. Nonetheless, the marked motivational improvements evidenced in this study underscore the merits of learner-centric flipped instruction.

Besides its impact on motivation, the intervention also had a positive effect on various domains of self-directed learning. The intervention seemed to bolster various domains of self-directed learning. Visual cues indicate enhancements in internal processes, behavioral approaches, and environmental preferences. The Bayesian t-test further reinforces this, with the post-measures substantially outperforming their pre-counterparts across the board. Given that self-directed learning is crucial in facilitating deeper understanding and better retention, the positive shifts in these domains provide an encouraging outlook on the flipped instruction's potential benefits. The results of this study provide preliminary evidence that flipping instruction can have a favorable impact on components of self-directed learning. The increases across goal-setting, learning strategies, motivation, and environment preference align with existing research highlighting the benefits of flipped teaching for self-regulated learning (Lai & Hwang, 2016; Sun et al., 2018). The autonomy inherent in pre-class content delivery appears to activate metacognitive processes like planning and monitoring comprehension. Additionally, the interactive in-class activities allow for feedback and adjustment, honing self-regulatory skills (Lee et al., 2022). However, it is important to note that some studies have argued against the sole efficacy of flipped teaching in increasing self-directed learning. The findings contrast with some studies arguing flipped teaching alone may be insufficient to increase self-directed learning without explicit training (Rasheed et al., 2020). This discrepancy highlights that merely providing videos and group discussions may not automatically enhance regulation; structured guidance can amplify the model's potential. For instance, incorporating pre-class self-assessments and post-class reflections could further boost metacognitive development (Yoon et al., 2021).

Overall, the findings showcase the merits of flipped instruction if implemented considerately. Instructors should provide autonomy support, interactive peer learning, and metacognitive guidance to activate self-determined motivation and self-directed competencies (Lai & Hwang, 2016). With structure and support, flipped classrooms can be springboards for persistent, lifelong learning skills. Nonetheless, the broad-based improvements across self-directed learning domains are encouraging. The flipped approach seems to compel students to engage more actively in their learning process. By combining autonomous content review with collaborative knowledge application, it appears to nurture competencies like goal-setting, strategy selection, help-seeking, and environmental structuring. Developing these skills could ultimately translate to deeper, lifelong learning. However, as a pilot study with a limited sample, further research is imperative. Longitudinal data tracking long-term academic performance would provide greater insight. Comparisons between flipped classrooms with and without metacognitive scaffolding could also elucidate best practices. While promising, more work is required to determine how self-directed learning enhancements might catalyze tangible learning gains. But this initial evidence helps cement the flipped model's potential as a student-centered, self-regulatory building approach if implemented thoughtfully.

A particularly intriguing aspect of the predictive models is the negative feature importance for pre-intervention motivation. The construction of predictive models showcases the potential interplay between initial metrics and final exam performance. The standout performance of the linear regression model indicates its robustness in predicting the outcome variable based on the independent factors. However, the real intrigue lies in understanding the feature importance, revealing the nuanced effects each independent variable has on predictions. For instance, while pre-learning expectations and pre-internal processes of self-directed learning elevate predicted scores, pre-IM presents an unexpected negative influence. These intricate relationships might indicate the importance of balancing various facets of the learning experience to achieve optimal outcomes. The machine learning models developed in this study provide new insights into how pre-intervention metrics may interact to predict final exam performance. Aligning with previous research, higher pre-intervention self-directed learning and expectations appear associated with increased exam scores (Ceylaner & Karakus, 2018; Talsma et al., 2018). This reinforces their positive influence on academic achievement.

However, the negative feature importance for pre-intervention motivation seems contradictory to studies linking motivation and academic success (Claver et al., 2020; Taylor et al., 2014). A possible explanation is that students with initially high motivation may have reduced effort assuming their motivational drive alone will yield results. This underscores the need to nurture multidimensional learning processes, not just motivation in isolation (Shin & Bolkan, 2021). A nuanced analysis of the negative relationship between pre-intervention motivation and predicted performance is warranted. A possibility is that students with initially high motivation became overconfident in their abilities. Without developing metacognitive skills, their motivation alone was insufficient to excel. This underscores the importance of cultivating multifaceted learning processes (Shin & Bolkan, 2021). For instance, boosting motivation along with goal-setting and help-seeking may better enable achievement (Ceylaner & Karakus, 2018). Alternatively, students with moderate motivation levels may have been compelled to enhance their self-regulation to succeed (Talsma et al., 2018). For optimal growth, nurturing motivation must go hand-in-hand with strategy development. Further research should explore this complex interplay between motivation, self-direction, and achievement.

The predictive power of the models supports the value of machine learning approaches in education. As demonstrated extensively, techniques like regression can uncover complex predictor relationships hidden in student data (Abu Saa et al., 2019; Rastrollo-Guerrero et al., 2020). The field would benefit from applying these methods to larger, more diverse datasets. Cluster analysis could reveal student subtypes based on profiles of attributes. Neural networks may also better capture nonlinear interactions.

Nonetheless, the findings provide a foundation. Instructors could consider assessing key measures early on, and then adapt their approach to optimize predicted outcomes. For instance, supplementing motivation with metacognitive strategy instruction could support students strong in motivation but lacking in self-regulation. Alternatively, reinforcing positive expectations along with motivation boosting may help other students. Ultimately, predictive insights allow personalized targeting of key areas to enhance achievement.

In light of these findings, it is evident that the models developed in this study provide valuable initial insights into the interplay between student attributes and exam performance. In conclusion, the models developed offer initial evidence that student attributes interact in nuanced ways to predict exam performance. While promising, further validation is required to determine generalizability and refine predictive accuracy. Additionally, research should explore how adapted instruction based on predictive insights impacts actual academic results. This could unlock a data-driven method for nurturing the factors underlying success.

CONCLUSIONS

The comprehensive analysis conducted in this study shed light on the profound influence of flipped instruction on several facets of student learning and motivation. Post-intervention scores demonstrated that flipped instruction significantly enhances both IM and EM towards coursework. In addition, it was evident that flipped instruction positively impacts not just the intrinsic motivational attributes but also the behavioral aspects of self-directed learning. Furthermore, it influences students' environmental preferences concerning learning. A pivotal part of the study was the attempt to predict student performance in final exams based on their motivation and self-directed learning attributes. Here, the linear regression model was notably adept, accounting for approximately 59.1% of the variance in final exam scores. 'Pre-learning expectation' and 'self-directed learning pre-internal process' emerged as key positive predictors of performance, while intriguingly, 'pre-intrinsic motivation' appeared to negatively influence outcomes. This suggests that while flipped instruction presents numerous advantages, there are intricate layers to the student learning experience that warrant deeper exploration in future research.

Limitations of the Study

The sample size was relatively small at 106 students from universities in Taiwan. A larger and more diverse sample would improve the generalizability of the findings. The study relied entirely on self-report survey measures for assessing motivation, self-directed learning, and expectations. More objective measures could validate and supplement students' perceptions. As a quasi-experimental rather than randomized controlled trial, confounding variables related to student characteristics or instructor effects could influence results. A randomized control trial would better isolate the impact of flipped instruction. The absence of a control group without flipped instruction makes it difficult to definitively attribute observed changes in motivation and self-directed learning to the flipped classroom intervention. The study's duration was fairly short at 18 weeks. Longer-term studies could provide insight into how motivation and self-regulatory skills evolve over time.

Recommendations

Apply experimental or quasi-experimental designs with larger sample sizes and control groups to further validate the effects of flipped instruction on motivation and self-directed learning. Collect data on academic performance like test scores, grades, and subject mastery to complement survey measures and evaluate predictive modeling. Conduct longitudinal studies over a semester or multiple semesters to assess the long-term motivational and self-regulatory impact of flipped teaching. Compare flipped classrooms with and without structured support for metacognitive skill development to pinpoint effective strategies. Expand predictive modeling using machine learning approaches like cluster analysis and neural networks on bigger datasets to uncover complex relationships with academic achievement.

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Ethics declaration: The authors declare that the study, which utilized questionnaires, was conducted in Taiwan and received approval from Prof. Dr. Shieh, Chich-Jen of Tung Fang Design University, Taiwan with code TW260223. Data was collected through these questionnaires, and participation was voluntary. Informed consent was obtained from all participants.

Declaration of interest: The authors declare no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

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