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Research Article

Enhancing business students' self-efficacy and learning outcomes: A multiple intelligences and technology approach

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ABSTRACT

This research investigates the effect of multiple intelligences (MIs) teaching strategy with technology-enriched environments on business administration students' self-efficacy, confidence, and learning outcomes. The study involved 276 participants from a university's business administration department, undergoing an international business course. A range of technology-based activities incorporating MI strategies was employed, exploring key topics such as globalization, corporate social responsibility, and market segmentation. Hypothesis testing revealed that high expectations and changes in viewpoints positively impacted self-concept, ability, and motivation, contributing to improved learning outcomes. The integration of technology in teaching facilitated these transformations, demonstrating how digital tools like virtual reality, interactive platforms, and online tutorials can enhance learning experiences. However, the effect on learning gain varied when viewpoints changed, indicating a need for further research into the differential impact of technology on learning outcomes. Despite some limitations, the study offers compelling evidence supporting the integration of MIs teaching strategy with technology-enriched environments in business administration education. Future studies should further explore the role of emerging technologies in this context.

Keywords: multiple intelligences teaching strategy, technology-enriched environments, technology education, motivation in learning, technology integration in teaching

INTRODUCTION

The ways in which students are instructed are consistently undergoing change in this age of increased globalization and technological development. To adequately educate students for the global business world, higher education, and notably the field of business administration, needs to adapt to the changes that are occurring. The integration of multiple intelligences (MIs) (Gardner, 1983) teaching techniques into contexts that are rich in technology is a relatively new strategy that is gaining popularity. In 1983, Howard Gardner came up with the notion of MIs, which postulates that individuals have varying types of intelligences and approaches to learning (Gardner, 1983). On the other hand, technology offers a wide variety of new tools and platforms that can accommodate several different learning styles.

Alhadabi and Karpinski (2019) emphasized that embracing the teaching philosophy grounded in Multiple Intelligences Theory prioritizes a learner-centric approach, where each student is considered uniquely gifted with varying potential. It's incumbent upon educators to fully comprehend each learner's strengths and traits, serving as the foundation for instructional design. Integrating technology into this educational framework enhances the execution and potential of multiple intelligences theory. In the 21st century's digital learning environment, technology offers a variety of platforms and tools. These cater to each student's unique intelligence type, enhancing the overall learning experience (Shonfeld et al., 2021). For instance, virtual reality can be used to bolster spatial intelligence, while online forums can stimulate interpersonal intelligence.

Multiple intelligences theory provides a model through which educators can identify critical factors in learning, thereby designing beneficial learning scenarios and minimizing obstacles to learning. This can be further amplified by the use of technology, such as adaptive learning systems that can customize the learning experience according to the individual strengths and weaknesses of each student (Hwang et al., 2013).

Nguyen (2019) expanded upon the concept of MIs, identifying nine distinct 'capacities' or types of intelligence. These include linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, naturalistic, and existential intelligences (Armstrong, 2009; Davis et al., 2019). Each of these intelligence types can be cultivated and honed using targeted technological tools and platforms, further enriching the learning landscape. In practice, the implementation of multiple intelligences theory in classrooms has demonstrated positive impacts on students' learning self-efficacy, as revealed by Alghamdi et al. (2020). This effect is potentially intensified with the addition of technology-enriched environments that provide diverse avenues for students to explore and express their distinct intelligence types.

In the dynamic realm of business administration, it has become imperative to embrace diverse learning styles and leverage the potential of technology, as opposed to being optional (Irgang dos Santos et al., 2022; Zhou, 2020). The integration of a pedagogical approach that utilizes multiple intelligences teaching strategy in conjunction with technology-enriched environments is of utmost importance within this setting. This methodology customizes the educational process to accommodate various types of intelligence, ranging from logical-mathematical and linguistic intelligence, which are fundamental to domains such as financial management and corporate communication, to interpersonal and intrapersonal intelligence, which are critical to leadership and team dynamics (Vincent et al., 2002). Through the implementation of this pedagogical approach, instructors can guarantee a comprehensive advancement of prospective corporate managers, empowering them to excel in diverse facets of their professional responsibilities.

Moreover, the incorporation of technology-enhanced settings offers tangible opportunities for hands-on experience with digital tools and platforms that hold growing significance in the contemporary business setting (Allen, 2020). In the digital age, students have the opportunity to interact with various technological tools such as big data analytics (Attaran et al., 2018), virtual collaboration tools (Müller & Wulf, 2020), and digital marketing platforms (Gómez Sierra, 2020). This engagement not only promotes self-efficacy and confidence but also contributes to the development of digital literacy, a crucial skill in today's society (Ahamad et al., 2021). The implementation of a multiple intelligences teaching strategy within a technology-enriched environment can effectively enhance the educational encounter in the field of business administration, resulting in the development of versatile and technologically proficient experts who are equipped to excel in the worldwide business arena.

"Perceived self-efficacy", another variable examined in the study, is defined by Bandura (1977) as how people think about whether they can plan and perform actions to achieve their goals. Individual anticipation of self-efficacy was also thought to be related to effort and individual willingness to exert effort toward a certain purpose (Schunk, 1991). When an individual presented proper skills and was given appropriate stimulation, self-efficacy was the determinative factor in taking actions, willing to pay efforts under pressure, and supporting the effort in frustration (Marino & Crocco, 2020). Gunning and Mensah (2011) indicated that high self-efficacy could predict higher confidence in learning. Students who were able to apply self-efficacy and develop suitable self-directed learning strategies would be more likely to acquire greater confidence in learning. An individual with lower self-efficacy would be more prone to negative thought and would choose to complete easier, less-challenging assignments that did not present a personal threat. Luka (2019) argued that factors in mathematics learning did not simply include anxiety and negative attitudes, while low self-efficacy was a factor in math anxiety that resulted indirectly in low math performance. Teachers who were able to positively affect students' learning effectiveness and reduce math anxiety would enhance students' confidence in learning. Moreover, students' goals, motivations, and academic outcomes would affect learners' beliefs in acquiring greater confidence in learning. Hassan (2020) regarded confidence as an individual being confident of the behavior, i.e., individual positive attitude to deal with general affairs. Confidence referred to a person, according to the past experience, confirming the efficacy to deal with certain specific work or affair

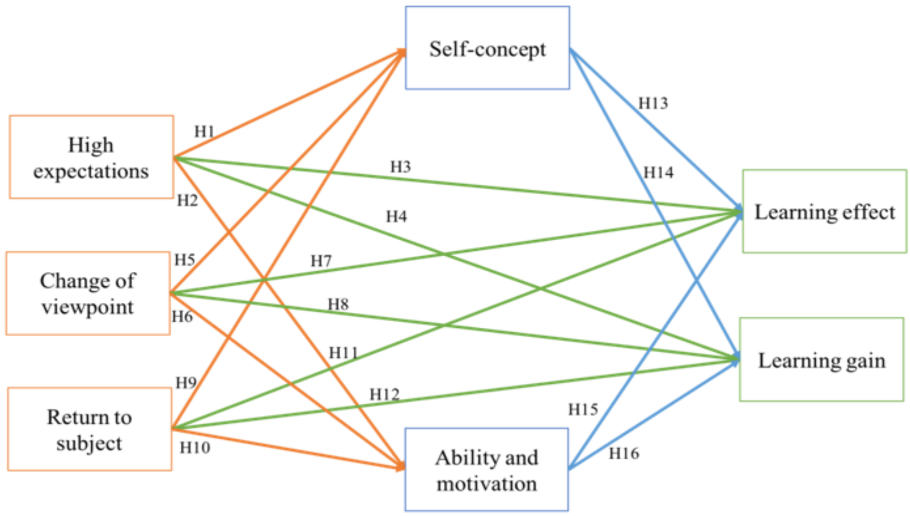

Figure 1. Conceptual structure (Source: Authors)

after several times of success and failure. A person who has self-confidence is one who believes in themselves or herself, is confident in what he or she has learned and is capable of and is unwavering in his or her assessment of the work they have done (Perry, 2011). MIs were popular in education because they assisted students in identifying their personal strengths and weaknesses and determining their optimal learning style (Barrington, 2004; Gul & Rafique, 2017). Each intelligence is diverse and distinctive, and intelligences in a variety of scenarios integrate operations with complex ways to boost students' confidence in their ability to learn. Each intelligence is diverse and distinctive, and intelligences in a variety of scenarios integrate operations with complex ways to boost students' confidence in their ability to learn (Hernández-Barco et al., 2021). Teacher who know their students' advantaged intelligences can help them learn by emphasizing those intelligences. Students who know their own strengths can use different strategies to feel more confident when learning (Fadilloh et al., 2021).

Few studies (Ahamad et al., 2021; Wen et al., 2019) have looked at the combined effect of multiple intelligence teaching strategy with technology-enriched environments, especially in the field of business education. This study aims to bridge this gap by investigating their combined impact on business administration students' self-efficacy, confidence, and learning outcomes. The aim of this study is to explore the effect of combining multiple intelligence teaching strategy and technology-enriched environments on the self-efficacy, confidence, and learning outcomes of business administration students in an international business course. These variables are crucial in the overall learning experience of students and have been linked to better academic performance and career success.

In light of the dynamic educational environment influenced by technological advancements and global interconnectedness, there arises a pressing imperative to reexamine conventional pedagogical approaches within the realm of business education. The introduction highlights the potential advantages that can be derived from integrating Howard Gardner's theory of MIs with environments that are abundant in technology (Gardner, 1983). The recognition of diverse student intelligences in the field of business administration prompts the consideration of integrating technology as a means to effectively accommodate these varied learning approaches. However, there is a significant gap in research regarding the collective influence of teaching MI and technology in the field of business education, which has not been thoroughly investigated. This could potentially have a significant impact on students' self-efficacy, confidence, and overall learning outcomes. From a pragmatic standpoint, comprehending this interplay can result in enhanced efficacy of business education, thereby cultivating individuals equipped to navigate the complexities of the international business arena.

METHODOLOGY

Following the above literature review and hypotheses, the conceptual structure of this study is shown in **Figure 1**. The details are explained below.

Based on the theoretical model created, the following hypotheses will be tested:

H1: High expectation has an effect on self-concept.

H2: High expectation has an effect on ability and motivation.

H3: High expectation has a direct and indirect effect on the learning effect.

H4: High expectation has a direct and indirect effect on learning gain.

H5: Change of viewpoint has an effect on self-concept.

H6: Change of viewpoint has an effect on ability and motivation.

H7: Change of viewpoint has a direct and indirect effect on the learning effect.

H8: Change of viewpoint has a direct and indirect effect on learning gain.

H9: Return to subject has an effect on self-concept.

H10: Return to subject has an effect on ability and motivation.

H11: Return to subject has a direct and indirect effect on the learning effect.

H12: Return to subject has a direct and indirect effect on learning gain.

H13: Self-concept has a direct effect on the learning effect.

H14: Self-concept has a direct effect on learning gain.

H15: Ability and motivation has a direct effect on the learning effect.

H16: Ability and motivation has a direct effect on learning gain.

In the study, there was only one group of participants (referred to as a "sample"). Because these participants interacted with one another during the course of the research, the study's design was centered around analyzing the interactions and outcomes within this single group. Due to this approach, the study did not utilize a traditional experimental design, which typically involves multiple groups (such as a control group and a treatment group) to compare results. Instead, the focus was solely on the single sample provided.

Data Collection Tools

Multiple intelligences teaching strategies

Before developing multiple intelligences teaching strategies, the necessary criteria for teaching based on the notion of MIs (Barrington, 2004; Davis et al., 2019; V & AHM, 2017) must be established. Expert opinion was solicited for a total of 19 items to ensure validity. Curriculum and instruction specialists (three), educational psychology specialists (two) and education technologist (two) make up a total of seven individuals. Each item's I-CVI was computed. I-CVI ranges from 1 to 0.86. According to Yusoff (2019), the minimum should be 0.83 when seven experts are present. No items are below 0.83, hence all of them were included in the other analysis. Three dimensions and 19 pieces make up the scale.

High expectations: Each student should be viewed as a talented student at the outset of a teacher's teaching assumptions and instructional design because each individual has a high level of intelligence.

Change of viewpoint: It is an established reality that pupils exhibit individual variances and that they exhibit clearly advantageous intelligence tendencies and disadvantageous intelligence tendencies. It is consequently vital to understand kids according to their strengths rather than their limitations.

Return to subject: MIs training emphasizes leading students through multiple channels to pique their interest in discussing subject matter and its impact on learning in depth.

Self-efficacy

The study items were changed according to the practice course in the Ng and Stillman (2007) scale. Then, exploratory factor analysis was performed. Since Bartlett's test of sphericity (χ^2=1,558, p<.001) and KMO measure of sampling adequacy (.898), it was determined that it was suitable for the factor structure. Items with a loading factor of .40 and above were included. Varimax was preferred for the rotation method. Scale items were collected in two factors. There were eight items left in the self-concept dimension and 6 items in the "ability and motivation" dimension. Factor loads vary between .472 and .758.

Confidence in learning

As a result of the literature review (Fogarty et al., 2001; Sadler, 2013) on learning confidence, 12 items were included in the pool. Validity control was ensured by expert evaluation of 12 items. Five experts took part in the Validity process. I-CVI value was calculated for each item. Three items with an I-CVI value of less than one were excluded from the scale. Explanatory factor analysis was performed for the remaining nine items. Since Bartlett's test of sphericity (χ^2=612, p<.001) and KMO measure of sampling adequacy (.811), it was decided that the sample was suitable for factor analysis. Varimax method is used for rotation. A two-factor structure was supported. The first factor was named the "learning effect" and consisted of four items. The second factor was named "learning gains" and consists of four items.

Participants and Procedure

This research involves the students registered for the international business course within the business administration department at a university in Taiwan. The total number of participating students is 276.

First, a team was initiated to organize the course contents. The team is composed of three experts (course instructor, technology expert, and curriculum development specialist). The team examined the course contents of International business. For each topic, which activities can be done based on MIs and/or technology were determined (**Table 1**).

Table 1. International business course content & activities

Topic	Key concept	Activities
Introduction to globalization & international business	Definition, importance, & scope of international business & impact of globalization on international business	Multiple intelligences activity: Group discussions on various aspects of globalization (interpersonal intelligence) Technology-enriched activity: Online quiz using interactive platforms (logical-mathematical Intelligence)
Understanding multinational corporations (MNCs)	Introduction to MNCs & their role in international business & advantages & disadvantages of MNCs	Multiple intelligences activity: Role-play as CEOs of MNCs, discussing their strategies (bodily-kinesthetic intelligence) Technology-enriched activity: Online presentations using digital presentation tools (visual-spatial intelligence)
Global business environment & cultural clusters	Influence of political, economic, & socio-cultural factors on international business & understanding cultural clusters: their role & impact on international business	Multiple intelligences activity: Interactive class discussion on different cultural clusters (verbal-linguistic intelligence) Technology-enriched activity: Virtual tour of different cultural clusters using virtual reality (VR) technologies (visual-spatial intelligence)
Cultural dimensions & technological environment	Hofstede's cultural dimensions & impact of technology on international business	Multiple intelligences activity: Case studies analysis & interpretations (logical-mathematical intelligence) Technology-enriched activity: Online brainstorming sessions using collaborative digital platforms (interpersonal intelligence)
Business ethics, corporate social responsibility (CSR), & sustainability	Understanding business ethics & its importance in international business, CSR in international business, & role of sustainability in international business	Multiple intelligences activity: Essay writing on various ethical issues in international business (verbal-linguistic intelligence) Technology-enriched activity: Online seminars on sustainability & CSR featuring guest speakers (interpersonal intelligence)
Big data & business analytics in international business	Role of big data in decision making & understanding business analytics & its implementation in international business	Multiple intelligences activity: Hands-on data analysis using datasets (logical-mathematical intelligence) Technology-enriched activity: Online tutorials on various data analytics tools (visual-spatial intelligence)
International business theories & frameworks	Internationalization process model & linkage-leverage-learning (LLL) framework	Multiple intelligences activity: Group projects on applying these theories in real-life scenarios (interpersonal intelligence) Technology-enriched activity: Webinars with industry experts discussing their experiences with these models (intrapersonal intelligence)

Table 1 (Continued). International business course content & activities

Topic	Key concept	Activities
Strategies in international business	Product-market strategies, competitive strategies, & understanding PCN, HCN, & TCN in international business	Multiple intelligences activity: Strategic decision-making games (logical-mathematical intelligence) Technology-enriched activity: Virtual reality (VR) business simulations (bodily-kinesthetic intelligence)
Market selection, segmentation, & targeting	Understanding market selection in international business & international segmentation & targeting	Multiple intelligences activity: Analyzing market reports and demographic data (logical-mathematical intelligence) Technology-enriched activity: Interactive digital maps to study geographical market segmentation (visual-spatial intelligence)
Adaptation & standardization in international business	Role of adaptation & standardization & case studies of successful & failed adaptation & standardization	Multiple intelligences activity: Debates on adaptation vs standardization (verbal-linguistic intelligence) Technology-enriched activity: Collaborative online platforms for group discussions (interpersonal intelligence)

Students can use smartphones during the course implementation process. Students can bring their own computers to the classroom if they wish. In the classroom environment, the computer and presentation device to be used by the instructor are ready. Also, students are provided with free Wi-Fi. At the end of the course, students are filled with the questionnaires of “teaching with multiple intelligences approach scale”, “self-efficacy scale”, and “learning confidence scale” for analyzing students’ changes in learning. 269 complete surveys were included in the study.

Data Analyses

Before beginning the examination of the data, it was determined that the data did not have a normal distribution. Shapiro-Wilk test for normality was done. Partial least squares structural equation modeling (PLS-SEM) method was chosen for data that lacked a normal distribution on the basis of the item. In R (4.2.2) and RStudio (2021.09), the “SEMinR” (2.3.2) (Ray & Danks, 2020) and “stats” (4.2.2) packages were utilized for data analysis. PLS-SEM combines PLS regression and structural equation modeling (SEM). It analyzes latent (unobserved)-observed relationships using multivariate methods. PLS-SEM excels in analyzing complicated data structures with several latent variables that are non-linearly related to each other and the observable variables. In cases with strong multicollinearity, it might be used instead of SEM (Hair et al., 2021).

RESULTS

In reflective measurement models, each indicator represents the effect of the underlying construct, causality flows from the construct to its indicators, the relationship between each indicator and the construct (factor loading) is the indicator’s absolute contribution to the construct, and the indicators are assumed to be highly correlated (Ghasemy et al., 2020; Hair et al., 2021) (**Table 2**).

Items with a loading factor having less than .70 have been eliminated. Each dimension has at least 3 items. The lowest calculated loading factor for the goods was .702, while the highest was .834. It anticipates the Cronbach’s alpha value to be at least .60. The lowest computed alpha value was .652, while the highest was .825. The rhoC and rhoA value should be more than or equal to .70 and less than .95 (Ghasemy et al., 2020). Also, between .60 and .70 are acceptable reliability ratings for exploratory research (Joseph F. Hair et al., 2021). Evaluate each construct’s convergent validity. The construct’s convergent validity explains its indicators’ variance. The average variance extracted (AVE) for all indicators on each construct determines convergent validity. AVE value is anticipated to exceed .50 (Hair et al., 2019). It has a value greater than .50 in every dimension.

Discriminant validity measures the extent to which a construct is empirically distinct from other constructs in the structural model. In order to determine discriminant validity, we checked Fornell-Larcker cross loading and heterotrait–monotrait ratio (HTMT).

Table 2. Factors loading, Cronbach's alpha, rhoC, AVE, & rhoA for each dimension

Dimension	Items	Loading	C. alpha	rhoC	AVE	rhoA
High expectation	MI_2	.753	.762	.848	.582	.766
	MI_3	.792				
	MI_4	.747				
	MI_7	.760				
Change view	MI_9	.716	.763	.840	.513	.764
	MI_10	.702				
	MI_11	.704				
	MI_12	.706				
	MI_13	.752				
Return subject	MI_14	.745	.759	.847	.581	.763
	MI_15	.749				
	MI_16	.805				
	MI_17	.747				
Self-concept	S_E_1	.774	.822	.875	.585	.826
	S_E_2	.795				
	S_E_4	.812				
	S_E_5	.731				
	S_E_7	.707				
Ability motivation	S_E_12	.811	.825	.877	.589	.826
	S_E_13	.753				
	S_E_14	.790				
	S_E_15	.753				
	S_E_19	.727				
Learning effect	C_I_1	.789	.725	.845	.645	.729
	C_I_2	.785				
	C_I_3	.834				
Learning gain	C_I_7	.793	.652	.810	.587	.693
	C_I_8	.749				
	C_I_9	.758				

Table 3. Fornell-Larcker cross loading

	High expectation	Change view	Return subject	Self-concept	Ability motivation	Learning effect	Learning gain
High expectation	.763	.	.	.	.	.	.
Change view	.691	.716	.	.	.	.	.
Return subject	.760	.707	.762	.	.	.	.
Self-concept	.725	.705	.734	.765	.	.	.
Ability motivation	.607	.593	.610	.611	.768	.	.
Learning effect	.598	.507	.613	.564	.578	.803	.
Learning gain	.628	.588	.584	.671	.545	.498	.766

When the Fornell-Larcker values are examined, it is expected to be smaller than the square root of AVE in the diagonal dimension (Hair et al., 2019). According to the table data, the lowest value varies between .498 and .760. All values are less than the square root of the corresponding AVE value (**Table 3**).

High HTMT values cause discriminant validity issues. Henseler et al. (2017) suggest a .90 threshold for structural models with conceptually related dimensions including cognitive satisfaction, affective satisfaction, and loyalty. In this case, an HTMT value of .90 indicates no discriminant validity. It is possible to conclude that there is discriminant validity when the Fornell-Larcker cross loading and HTMT tables are assessed combined (**Table 4**).

Formative Measurement

The quality of the formative measurement models is evaluated by looking at collinearity issues within the formative indicators.

VIF values were checked for collinearity among latent variables (**Table 5**). VIF values among the latent variables are expected to be below 10 (Hair et al., 2021). The lowest VIF values were calculated as 1.851 and the highest as 3.241. As a result, it can be stated that there is no collinearity in formative model (**Figure 2**).

Table 4. Heterotrait-monotrait ratio (HTMT)

	High expectation	Change view	Return subject	Self-concept	Ability motivation	Learning effect	Learning gain
Change view	.897						.897
Return subject	.897	.866					.897
Self-concept	.805	.812	.924				.805
Ability motivation	.756	.743	.769	.739			.756
Learning effect	.808	.679	.824	.726	.747		.808
Learning gain	.868	.828	.810	.894	.730	.707	.868

Table 5. VIF values

	Self-concept	Ability motivation	Learning effect	Learning gain
High expectation	2.602	2.602	2.93	2.930
Change view	2.403	2.403	2.742	2.742
Return subject	2.974	2.974	3.241	3.241
Self-concept			2.916	2.916
Ability motivation			1.851	1.851

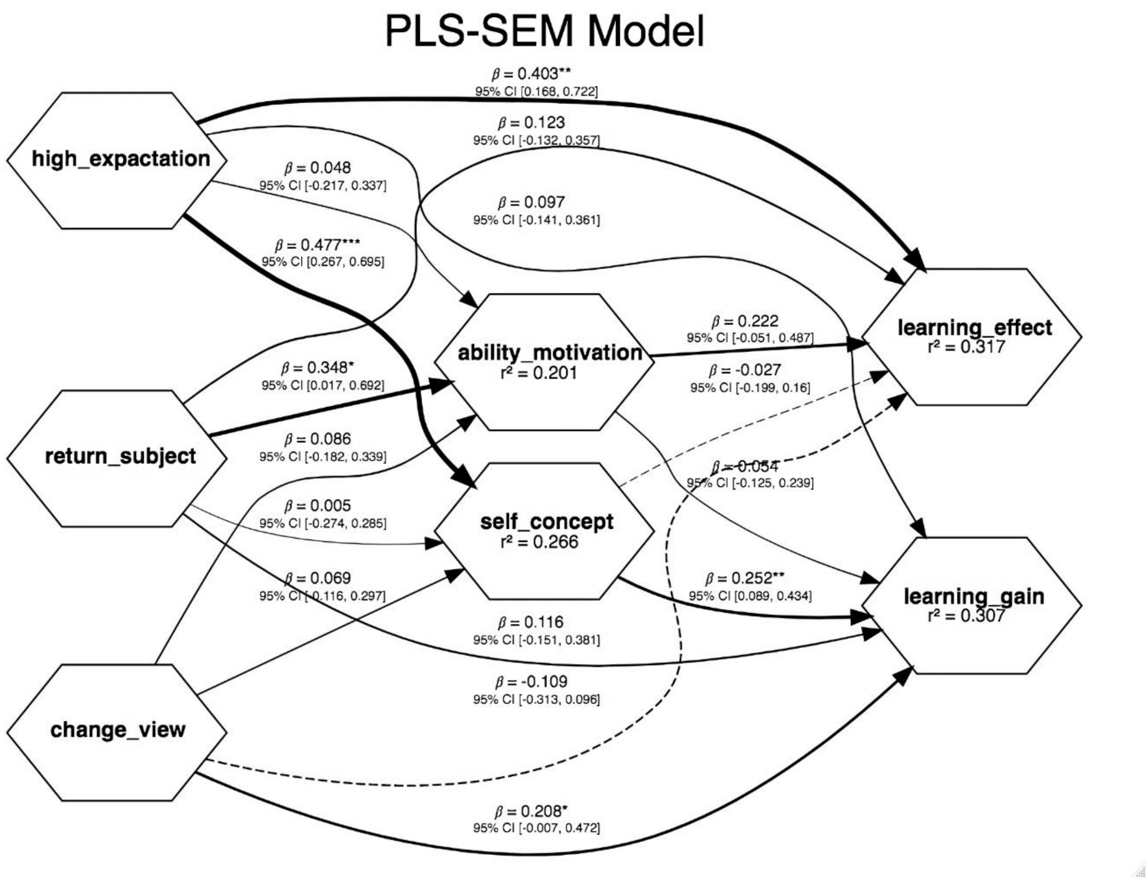

Figure 2. Final model (Source: Authors, using RStudio)

Significance of Path Coefficient

According to the path analysis result (**Table 6**), if the t-value is greater than 1.96 in the 5% confidence interval, the result is considered to be at the level of significance. In addition, the confidence interval range should not contain the value zero.

Accordingly, it can be said that high expectation has an effect on self-concept, ability motion, learning effect, and learning gain. It can be stated that while the change view variable has an effect on self-concept and ability motion, it has no direct effect on the learning effect and learning gain.

Table 6. Path coefficients

	Original estimated	Bootstrap mean	Bootstrap SD	t-stat	2.5% CI	97.5% CI
High expectation->self-concept	.299	.297	.073	4.105	.15	.438
High expectation->ability motivation	.266	.264	.093	2.874	.075	.439
High expectation->learning effect	.199	.204	.087	2.293	.039	.379
High expectation->learning gain	.218	.214	.093	2.331	.028	.395
Change view->self-concept	.318	.320	.075	4.253	.171	.464
Change view->ability motivation	.237	.241	.089	2.664	.066	.415
Change view->learning effect	-.063	-.065	.087	-.723	-.236	.106
Change view->learning gain	.096	.104	.091	1.065	-.066	.289
Return subject->self-concept	.272	.275	.082	3.311	.114	.434
Return subject->ability motivation	.232	.235	.091	2.546	.055	.416
Return subject->learning effect	.269	.271	.098	2.738	.074	.457
Return subject->learning gain	.000	-.002	.109	.001	-.22	.212
Self-concept->learning effect	.105	.104	.083	1.262	-.054	.272
Self-concept->learning gain	.359	.363	.092	3.91	.186	.548
Ability motivation->learning effect	.267	.265	.083	3.212	.104	.428
Ability motivation->learning gain	.137	.135	.078	1.741	-.019	.287

Table 7. Path coefficients for total effect

	Original estimated	Bootstrap mean	Bootstrap SD	t-stat	2.5% CI	97.5% CI
High expectation->learning effect	.301	.305	.085	3.533	.138	.474
High expectation->learning gain	.361	.359	.094	3.830	.163	.534
Change view->learning gain	.243	.251	.097	2.511	.065	.448
Return subject->learning effect	.359	.361	.092	3.908	.177	.539
Self-concept->learning gain	.359	.363	.092	3.910	.186	.548
Ability motivation->learning effect	.267	.265	.083	3.212	.104	.428

Table 8. R square & adjusted R square values

	Self-concept	Ability motivation	Learning effect	Learning gain
R^2	.647	.444	.466	.509
Adjusted R^2	.643	.437	.455	.500

In the return subject variable, it can be expressed that while it has an effect on self-concept, ability motion, and learning effect, it has no direct effect on learning gain. It can be said that while the self-concept variable has an effect on the learning effect, it has no effect on the learning gain. It can be articulated that while the ability motion variable has an effect on the learning effect, it has no effect on the learning gain.

As a result, the learning effect variable is affected by high expectation, return subject, and motivation variables, while the learning gain variable is affected by high expectation and self-concept variables.

As a result of calculating the total effect value (**Table 7**), it has high expectation, return subject, and ability motion effect values for the learning effect. According to beta values, the biggest effect value was the return subject variable with .359, then the high expectation variable with .301, and the ability motion variable with .267 value. In the learning gain variable, it has high expectation, change view, and self-concept effect values. While the direct effect was not at the level of significance in the change view variable, it reached the level of significance when the total effects were calculated. When compared according to beta values, the high expectation has the highest total effect value with a value of .361. Then, self-concept comes with .359, and lastly, change view affects the variable with .243.

When the calculated R square and adjusted R square values were reviewed, ability motivation had the lowest disclosure rate at 43.7%, while self-concept had the highest disclosure rate at 64.2% (**Table 8**). The model effect for the learning effect and learning gain aspects that were attempted to be tested was 50.9% and 50%, respectively. In numerous social science disciplines, R^2 values of .75, .50, and .25 are regarded substantial, moderate, and weak, respectively (Hair et al., 2011). Consequently, our model can be described as moderate.

Table 8. F square values

	Self-concept	Ability motivation	Learning effect	Learning gain
High expectation	.097	.049	.025	.035
Change view	.119	.043	.003	.005
Return subject	.070	.031	.041	.000
Self-concept			.007	.085
Ability motivation			.072	.021

Table 10. Supporting of hypotheses

Hypotheses	Results
H1: High expectation has an effect on self-concept.	Accepted
H2: High expectation has an effect on ability and motivation.	Accepted
H3: High expectation has a direct and indirect effect on the learning effect.	Accepted
H4: High expectation has a direct and indirect effect on learning gain.	Accepted
H5: Change of viewpoint has an effect on self-concept.	Accepted
H6: Change of viewpoint has an effect on ability and motivation.	Accepted
H7: Change of viewpoint has a direct and indirect effect on the learning effect.	Rejected
H8: Change of viewpoint has a direct and indirect effect on learning gain.	Partially Accepted
H9: Return to subject has an effect on self-concept.	Accepted
H10: Return to subject has an effect on ability and motivation.	Accepted
H11: Return to subject has a direct and indirect effect on the learning effect.	Accepted
H12: Return to subject has a direct and indirect effect on learning gain.	Rejected
H13: Self-concept has a direct effect on the learning effect.	Rejected
H14: Self-concept has a direct effect on learning gain.	Accepted
H15: Ability and motivation has a direct effect on the learning effect.	Accepted
H16: Ability and motivation has a direct effect on learning gain.	Rejected

f^2 values for each possible combination of endogenous and exogenous (predictor) components (**Table 9**). The effect size of .02 has a small impact on the structural level, while .15 has a moderate impact, and .35 has a big impact (Ghasemy et al., 2020). High expectation has small effect size on self-concept, ability motion, learning effect and learning gain. Change view small effect size on self-concept and ability motivation. Return subject has small effect size on ability motion and learning effect. Self-concept has small effect on learning gain. Ability motion has small effect size on learning effect and learning gain (**Table 10**).

DISCUSSION

The purpose of this study is to explore how integrating a multiple intelligence teaching style with technologically advanced learning settings affects the self-efficacy, confidence, and learning outcomes of business administration students enrolled in an international business course. In accordance with the multiple intelligence theory, the course contents have been transformed into in-class and out-of-class activities in which students and instructors can use technology effectively. In the study, the discussion will be constructed in the context of the effect of technology on possible outcomes.

The digital revolution has brought an array of tools and platforms that are adept at fostering high expectations within the classroom environment (Dvoretskaya et al., 2020). In fact, technology, when properly implemented, can greatly contribute to enhancing students' self-concept, ability and motivation - key determinants of successful learning outcomes (Latorre-Cosculluela et al., 2022). Simultaneously, these engaging activities used in the course can also stimulate student motivation, making learning more intriguing and less of a chore. According to the result of the study (Sandybayev, 2020) in business education, the employment and engagement of interactive features as technology-aided activities heighten motivation, thereby yielding superior learning outcomes. Within the scope of our study, it was noted that digital resources such as online collaboration tools, intelligent tutoring systems, and data-driven adaptive learning platforms had a noteworthy impact on enhancing learning outcomes. This observation serves to reinforce the efficacy of technology in establishing elevated educational standards and promoting learning.

The use of technology in education can significantly aid in changing perspectives or viewpoints (Pate, 2016). It provides students with a myriad of different resources, information, and tools that allow them to explore various facets of a subject, thereby fostering a more well-rounded understanding (Bedenlier et al., 2020). Online discussions (Eid & Al-Jabri, 2016), virtual tours (Chin & Wang, 2021), simulations (Ahamad et al., 2021), and a plethora of digital resources can expose students to a diverse range of ideas and viewpoints, effectively broadening their horizons and fostering a richer understanding of the subject matter.

According to results, multiple Intelligence strategy has an effect on self-efficacy (self-concept, ability and motivation). It is expressed in the study findings that there is a relationship between MIs and self-efficiency (Green, 2021; Hernández-Barco et al., 2021). Zarei and Taheri (2013) found that learners' MIs helped predict their self-efficacy, and some types of intelligence were better predictors of self-efficacy than others. Based on Mahasneh's (2013) study of university students, it was found that MI profiles have an effect on the student's self-efficacy.

The results of the study provide valuable insights that could guide the design and implementation of the multiple intelligences teaching strategy in technology-enriched environments. One of the crucial findings is the significant role of high expectations in shaping self-concept, ability, motivation, and subsequently, learning outcomes. Therefore, digital activities could be leveraged to create an environment that encourages students to meet high academic standards (Wekerle et al., 2022). This could involve using technology to provide personalized feedback, track progress, and set challenging yet achievable goals.

In relation to self-efficacy, technology can greatly enhance a student's confidence in their abilities (Latorre-Cosculluela et al., 2022; Zhang, 2022). For instance, through the use of digital tools, students can create and share their own content, participate in online discussions, and showcase their knowledge in various ways. This can lead to a stronger sense of self-efficacy and a positive self-concept. Further, the use of technology can contribute to improvements in ability and motivation (Kaur et al., 2020; Müller & Wulf, 2020). The diverse range of online learning tools and resources allows for the personalization of learning, catering to each student's unique learning style and pace. This can enhance their learning ability and sustain their motivation, as they can see tangible progress in their learning journey.

For business administration education, there is a need to make the use of technology more effective. This could involve incorporating more hands-on digital activities that mimic real-world business scenarios, such as virtual business simulations or data analysis using business intelligence tools. Additionally, digital tools that foster collaboration, such as online brainstorming platforms, could be used more extensively to enhance interpersonal skills, crucial in the business field.

CONCLUSIONS

The amalgamation of numerous intelligences teaching strategy in technology-enhanced environments offers a significant opportunity to revolutionize business administration education. The findings of this study demonstrate the efficacy of this pedagogical approach, with technology and MIs serving as catalysts for augmenting students' self-concept, abilities, and motivation, and ultimately increasing learning outcomes. The findings demonstrate the crucial role that high expectations and perspective shifts play in nurturing a positive self-concept and enhancing students' motivation and abilities. With its extensive array of digital tools and resources, technology played a crucial role in facilitating these changes. Virtual tours, online exams, digital presentations, and collaborative digital platforms were among the successful tools used to broaden students' perspectives and improve their comprehension of complex business concepts. However, the study also revealed that the impact of technology varies depending on how it is implemented, emphasizing the need for the effective integration of digital tools with traditional teaching methods in order to maximize learning outcomes. The contradictory findings regarding the learning effect and learning gain underscore the need for cautious consideration when designing and implementing technological interventions. Although the results of this investigation are promising, they are only the beginning. Future research has an abundance of opportunities to investigate the role of technology in education, particularly in the field of Business Administration, due to the rapid evolution of technology and pedagogical practices. The impact of various digital tools, the influence of emergent technologies such as artificial intelligence and virtual reality, and the role of technology in reinforcing learning and enhancing self-concept, ability, and motivation are all suitable for investigation. This study illuminates the transformative potential of integrating multiple intelligences teaching strategy with technology-enhanced environments in business administration education. It has provided compelling evidence to support the continued adoption and refinement of this approach, with the ultimate objective of enhancing the educational experience and providing future business executives with the skills, knowledge, and perspective they need to succeed in the global business landscape.

Given the findings of some hypotheses, there are a number of prospective areas for future research on the role of technology in improving learning outcomes. Exploring the influence of various digital tools or platforms could be one area of study. This could involve contrasting the efficacy of various technologies in enhancing particular aspects of learning, such as motivation, self-concept, and learning gain. The influence of emergent technologies, such as artificial intelligence and virtual reality, on learning experiences is another intriguing topic to investigate. These technologies offer intriguing opportunities for developing personalized, immersive learning environments. Within the context of business education, research could be conducted to examine their potential benefits and difficulties.

While this study provides valuable insights into the impact of the multiple intelligences teaching strategy with technology-enriched environments in business administration, it is important to acknowledge its limitations. The study was conducted among 276 students from a single business administration department at one university. Therefore, the results may not be representative of all students studying international business, particularly those from different universities, countries, or cultural backgrounds. The study relies on self-reported measures for constructs such as self-concept, ability, and motivation. These measures, while useful, are inherently subjective and may be influenced by numerous factors including cultural norms, individual perception, and reporting biases. The study assumes a certain level of digital literacy among the participants. Students with a higher degree of familiarity with technology might perform differently compared to those who are not as adept, which might have influenced the results. The study was conducted over a single term or semester. Longer-term studies could provide more reliable insights into the sustained impacts of the multiple intelligences teaching strategy with technology-enriched environments on students' self-efficacy, confidence, and learning outcomes. Future studies could address these limitations by adopting a more diverse sample, utilizing more objective measures, where possible, considering the influence of digital literacy, controlling for more external variables, extending the duration of the study, and carefully considering the choice of digital tools and platforms.

The limitations of this study warrant careful consideration. Primarily, the research was circumscribed to a singular business administration department at one university with a sample of 276 students. This specificity potentially restricts the applicability of findings across diverse international business student populations, especially those hailing from different institutions or cultural backgrounds. Furthermore, the reliance on self-reported measures, particularly for constructs like self-concept, ability, and motivation, introduces an element of subjectivity. The influence of external factors, such as cultural norms or individual biases, could sway these self-reported results. Another pivotal assumption was that participants possessed a baseline digital literacy. This could mean that those more familiar with technology might have inherently responded differently to the interventions, thus skewing the results. The study's duration, spanning just a single term, raises questions about the long-term impacts and sustainability of the integrated teaching strategy. Additionally, without a deeper exploration into the specific digital tools and platforms used, it's challenging to ascertain if the observed effects were more a product of tool efficacy rather than the teaching methodology. These constraints suggest a need for more expansive and detailed future research to better validate and build upon the presented findings.

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

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