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Exploring Factors Affecting Learning Effectiveness and Satisfaction in Business Analytics: A Gender and Academic Level Perspective

Mandy Dang
Mandy.Dang@nau.edu

Yulei Gavin Zhang
Gavin.Zhang@nau.edu

Bo Wen
Bo.Wen@nau.edu

Steven Liu
Steven.Liu@nau.edu

Department of Information Systems, Management, and Marketing
The W. A. Franke College of Business
Northern Arizona University
Flagstaff, Aziaona 86011, USA

Abstract

In this study, our aim is to investigate the factors influencing students' learning in business analytics. Specifically, we developed a research model to examine the effects of cognitive presence, teaching presence, quantitative analytics self-efficacy, and prior experience on students' perceived learning effectiveness and satisfaction. Additionally, we tested the model across different student demographics, including undergraduate and graduate levels, as well as gender. The model generally held true based on the overall analysis results. However, variations in impacts were observed among different groups. Notably, prior experience did not show significant effects on undergraduate students, but it significantly influenced the learning effectiveness of male graduate students. Conversely, cognitive presence significantly impacted undergraduates' learning effectiveness, but not graduate students. Moreover, our model appeared less effective in understanding the female graduate group.

Keywords: Business analytics, learning effectiveness, learning satisfaction, gender differences, undergraduate and graduate students

1. INTRODUCTION

Over recent years, business analytics has emerged as a critical tool in today's data-driven business world, playing an increasingly pivotal role in decision-making processes across industries (Mills et al., 2022). With the exponential growth of digital data, businesses are recognizing the necessity of harnessing this information to gain valuable insights and competitive advantages. Business analytics enables organizations to extract meaningful patterns, trends, and correlations from vast amounts of data to help develop strategic decisions, optimize operations, and identify new opportunities (Power et al., 2018). As the volume

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v10 n6123

and complexity of data continue to expand, the importance of business analytics will only continue to grow, shaping the future of business strategies and innovation.

With the increasing demand for data-driven decision-making, higher education institutions have recognized the importance of offering business analytics education to train experts in this field (Burns & Sherman, 2019; Mills et al., 2022). Many universities have developed related courses and programs to produce competent professionals capable of supporting companies and organizations in performing business analytics activities in today's rapidly evolving business landscape. By equipping students with the necessary skills and knowledge to analyze and interpret complex data sets, these courses and programs empower students to succeed in their careers while also driving productivity and fostering further development in the global business landscape.

Thus, ensuring students' learning outcomes and success is critically important in business analytics education. There are two major categories of existing research on business analytics education and systems adoption, mainly focusing on course design and development (Burns & Sherman, 2019; Hu & Cleland, 2019; Mills et al., 2022; Olson, 2018) and model development and assessment for business analytics adoption in organizations (Fink et al., 2017; Jalil et al., 2019; Ramakrishnan et al., 2020; Rouhani et al., 2018). However, relatively less effort has been dedicated to empirically investigating student learning in business analytics through the development of nomological networks and models. Therefore, in this study, we aim to enrich the business analytics education literature by developing a research model to systematically investigate factors that influence students' learning effectiveness and satisfaction in this field.

The paper is organized as follows: In Section 2, we discuss the related literature and hypothesis development. Then, in Section 3, we provide detailed information on the research method. Subsequently, in Section 4, we present our data analysis results, followed by discussions on research contributions, implications, as well as limitations and future research directions in Section 5.

2. RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

Drawing from related literature, we first identified the factors influencing students' learning in business analytics, with a particular focus on their perceptions of learning effectiveness and satisfaction. We then reviewed relevant studies that motivate our investigation into how these factors differ based on gender and academic level.

Factors Affecting Student's Learning in Business Analytics

The first group of factors we examine includes cognitive presence and teaching presence, both of which are believed to influence learners' knowledge formation and empirical inquiry (Garrison et al., 2000). Cognitive presence refers to the extent to which students can construct meaning through communication and reflection within their learning community (Garrison et al., 2000; Law et al., 2019). This aspect typically represents the connections learners make through their ideas, thoughts, and beliefs, which play a crucial role in fostering in-depth learning and knowledge construction (Law et al., 2019). Therefore, a learning environment with a high level of cognitive presence can facilitate students in exploring, engaging, integrating, and reflecting during their learning process, ultimately aiding in problem-solving and achieving solutions.

Teaching presence, on the other hand, refers to the design, facilitation, and direction of a learning environment aimed at creating meaningful student learning outcomes (Law et al., 2019). This concept bears some similarity to teaching quality, which concerns the overall level of support for students' learning needs provided by the instructor and the learning environment (Giannakos et al., 2017).

When examining student learning in blended environments, prior research has found that both cognitive and teaching presence can significantly influence students' perceived learning performance (Law et al., 2019). In another study on Massive Open Online Courses (MOOCs), B. Liu et al. (2022) analyzed over 400,000 posts across 13 MOOCs and found a strong influence of cognitive presence on students' learning performance. Furthermore, Caskurlu et al. (2020) conducted a systematic meta-analysis on teaching presence, revealing strong correlations with both perceived learning performance and learning satisfaction.

In our study context, we similarly anticipate significant influences of both cognitive and teaching presence on student learning, particularly in terms of their perceived learning effectiveness and satisfaction. Therefore, we

ISSN: 2473-4901
v10 n6123

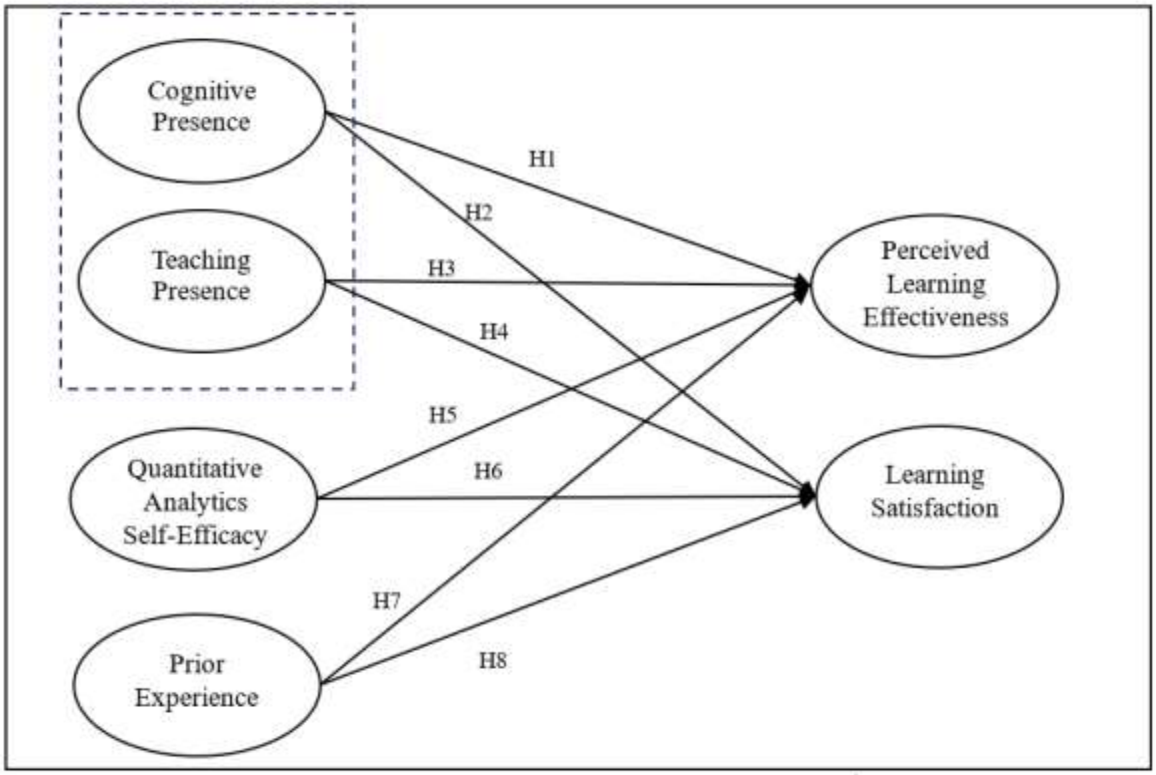

Figure 1 Research Model and Hypotheses

posit that:

H1: Cognitive presence positively impacts students' perceived learning effectiveness.

H2: Cognitive presence positively impacts students' learning satisfaction.

H3: Teaching presence positively impacts students' perceived learning effectiveness.

H4: Teaching presence positively impacts students' learning satisfaction.

Self-efficacy is defined as one's perception of their ability to accomplish a given task (Akbulut & Looney, 2007; Rosson et al., 2011). In studying specific scenarios or course topics, some existing literature adopts more specific concepts than the general term "self-efficacy." For instance, when examining student learning in computer and information systems courses, previous studies have employed the concept of "computer self-efficacy (CSE)", which assesses one's self-efficacy specifically toward the use of computer and information technology (Hasan, 2003; Selim, 2007). Prior research has indicated that CSE can significantly influence students' perceptions of the ease of use and satisfaction with online learning support systems (Roca et al., 2006).

Furthermore, when investigating student learning in web development courses, the concept of "web development efficacy" was introduced. It was discovered that this factor significantly influenced students' perceived accomplishments and enjoyment, subsequently affecting their future learning intentions (Zhang & Dang, 2015).

When examining student learning in flipped math courses, Sun et al. (2018) utilized the concept of "math self-efficacy," which denotes students' perceived confidence in their ability to learn math and complete math tasks. Their research revealed that math self-efficacy significantly impacted students' academic achievement in both pre- and in-class learning environments.

In our context, we have opted for a domain-specific concept of self-efficacy. Given that business analytics fundamentally revolves around the application of quantitative methods and techniques to derive insights from business data, we have chosen to employ the term "quantitative analytics self-efficacy" in our study. This concept assesses students' overall ability and confidence in analyzing numerical data, as well as understanding and interpreting the results. When investigating business analytics, we anticipate a positive impact of self-efficacy on learning

ISSN: 2473-4901
v10 n6123

outcomes. Thus, we hypothesize that:

H5: Quantitative analytics self-efficacy positively impacts students' perceived learning effectiveness.

H6: Quantitative analytics self-efficacy positively impacts students' learning satisfaction.

Prior literature has also emphasized the potential impact of prior experience on student learning. In education, prior experience encompasses the knowledge, skills, or abilities that students already possess and can bring to the learning process (Sun et al., 2018).

For example, Wall and Knapp (2014) investigated and discovered that students' prior experience with technical topics could significantly impact their assessment of the difficulty level of information systems courses, as well as their ability to manage and navigate this difficulty during the learning process. Similarly, when examining student learning in math courses, Sun et al. (2018) found that students' prior knowledge of math could influence their selection and development of learning strategies.

In our study, we anticipate that students' prior experience with business analytics concepts and techniques will positively influence their learning outcomes. Thus, we posit that:

H7: Prior experience positively impacts students' perceived learning effectiveness.

H8: Prior experience positively impacts students' learning satisfaction.

The proposed research model and hypothesized relationships are summarized in Figure 1.

Gender and Academic Level Differences

Gender differences in the technology fields have garnered significant attention from researchers. Over the years, with the development and advancement of computer and information technology (IT), various types of gender differences have been identified and studied. These include differences in attitudes toward IT, self-efficacy in using IT, and IT usage and adoption in general (Siddiq & Scherer, 2019). When it comes to gender differences in IT-related education, Cai et al. (2017) conducted a meta-analysis and found that male students tended to exhibit higher levels of IT literacy and more positive attitudes toward IT compared to female students. However, when investigating students' learning outcomes in IT courses, mixed results have been reported, with some studies indicating that female students outperformed male students, and vice versa (Siddiq & Scherer, 2019).

When investigating college students' technostress, which refers to the maladaptation resulting from students' challenges in interacting with various technologies and systems during their learning process, Wang et al. (2020) found that overall, female students were more susceptible to burnout when using technology. In another study examining students' readiness for online learning during COVID-19, Tang et al. (2021) discovered that factors such as learning motivation, technology readiness, online communication, self-directed learning, and learner control tended to exert slightly greater influence on female students than on their male counterparts. In a study focusing on small and medium-sized enterprises, Al-edenat and Hawamdeh (2022) found that gender significantly moderated the impact of employees' business analytics competency on process effectiveness.

In addition to gender differences, prior research has also investigated differences in student learning across academic levels, particularly between undergraduate and graduate students. For instance, Y. Liu et al. (2022) examined students' mental health conditions in the US. Through the analysis of two large-scale online surveys – one with 2,067 participants in 2022 and another with 3,627 participants in 2018 – they found that undergraduates tended to report poorer mental health than graduate students. In another study examining differences in learning styles, Shukr et al. (2013) compared preferences between undergraduate and graduate students across four types of learning: activist, reflector, theorist, and pragmatist. They found that undergraduates exhibited a much stronger preference for being activists, whereas graduates leaned more toward being reflectors or theorists.

Taken together, these studies underscore the importance of exploring gender and academic level differences, specifically focusing on understanding how student learning varies between genders and across undergraduate and graduate levels.

3. RESEARCH METHOD

Study Site: The Business Analytics Course

This study was conducted at a public university in the Southwestern United States. Specifically, the business analytics course we chose for this research is a technical course focusing on machine learning and data mining. This course is

ISSN: 2473-4901
v10 n6123

co-convened for both seniors in undergraduate programs (as a 400-level course) and students in graduate programs (as a 500-level course). For undergraduates, the course is open to all majors within the College of Business, as well as to seniors from other colleges. For graduate students, the course is also open to both business and non-business students. There were two instructors covering all sections of the course, one male and one female, who worked closely to ensure the consistency of course content and instructional methods.

The major concepts and techniques covered in the course include: linear regression, logistic regression, association analysis, k-nearest neighbors (k-NN), decision trees, artificial neural networks, and clustering. Textbooks, lecture slides, lecture videos, and weekly quizzes are utilized to help students grasp the key concepts, while weekly labs and exams are designed to help students gain practical skills in related machine learning and data mining techniques. Additionally, to ensure that students with various backgrounds, including those with and without programming experience, can take this course, the course adopts an advanced data analysis software tool, RapidMiner (https://academy.rapidminer.com/), instead of any specific programming language (such as R or Python). RapidMiner provides students with a GUI interface and a drag-and-drop mechanism for developing data analytics projects. However, although programming skills are not required for this course, a full understanding of the logic and technical details of each data mining algorithm is essential for students to use RapidMiner successfully in their lab projects and exams.

In this course, the learning materials for both undergraduate and graduate students are the same. They use the same textbooks and have access to the same lecture slides and videos. Both groups of students will complete the same weekly quizzes to assess their understanding of the concepts and techniques for a given topic. Additionally, they will undertake identical weekly lab projects and two lab-based exams throughout the semester to evaluate their practical skills in using algorithms to solve business analytics problems. However, for the graduate students, a semester-long lab project is an additional requirement for completing this course.

The Survey, Measurement, and Participants

An online survey was conducted to assess the research model and further explore the differences between undergraduate and graduate students across the two gender groups. After obtaining IRB approval, a survey invitation was emailed to all students taking different sections of this course about two weeks before the end of the semester. We believe this timing was appropriate, since by then students had learned all key concepts and techniques covered in the course, thus having a full learning experience related to the course topics. Student participation was voluntary. As an incentive, a small amount of extra credit (about 1% of their total possible course points) was offered to those who completed the online survey. In total, the survey invitation was sent to 374 students, and 309 of them participated and completed the study, generating a 82.6% response rate. They averaged 22.75 years old. Among them, 182 were male students and 127 were female students; 128 were undergraduate students and 181 were graduate students. There were no non-binary students or students who did not specify their gender. A breakdown is summarized in Table 1.

Group	Number of Participants	Average Age
Male Undergraduates	60	21.57
Female Undergraduates	68	21.40
Male Graduates	122	23.57
Female Graduates	59	23.81

Table 1: Participant Breakdown

To assess both cognitive and teaching presence, we adapted the measures from Law et al. (2019) to fit our context of study. For measuring quantitative analytics self-efficacy, we modified the measures of math self-efficacy from Sun et al. (2018) to align with our context. To measure prior experience, we employed the measures from Wall and Knapp (2014) and focused on students' prior experience toward the concepts and techniques covered in the business analytics course. In addition, our measures of perceived learning effectiveness were adapted from Law et al. (2019) and measures of learning satisfaction were adapted from Mohammadi (2015). All questionnaire items were rated on a 7-point Likert scale, ranging from 1 for "strongly disagree" to 7 for "strongly agree." Appendix A lists all the measurement items.

Table 2 summarizes the descriptive statistics for all constructs based on the participant groups, and Figure 2 plots the average ratings for a clear comparison. Overall, all groups of participants were positive toward the course (except for prior

 ISSN: 2473-4901
v10 n6123

Construct	(1) Male-Undergraduate	(2) Female-Undergraduate	(3) Male-Graduate	(4) Female-Graduate
	Mean/Std. Dev.	**Mean/Std. Dev.**	**Mean/Std. Dev.**	**Mean/Std. Dev.**
CP	5.45/1.17	5.57/1.10	6.57/0.78	6.54/0.97
TP	5.73/1.16	6.17/1.01	6.63/0.84	6.67/0.86
QASE	5.10/1.24	5.24/1.25	6.20/1.19	6.13/1.41
PEXP	3.63/1.65	3.79/1.85	4.83/2.13	4.31/2.21
PLE	5.33/1.21	5.71/1.22	6.56/0.86	6.61/0.89
LSAT	5.42/1.31	5.83/1.33	6.51/0.98	6.63/0.73

Note: CP-Cognitive Presence, TP-Teaching Presence, QASE-Quantitative Analytics Self-Efficacy, PEXP-Prior Experience, PLE-Perceived Learning Effectiveness, LSAT-Learning Satisfaction

Table 2: Descriptive Statistics

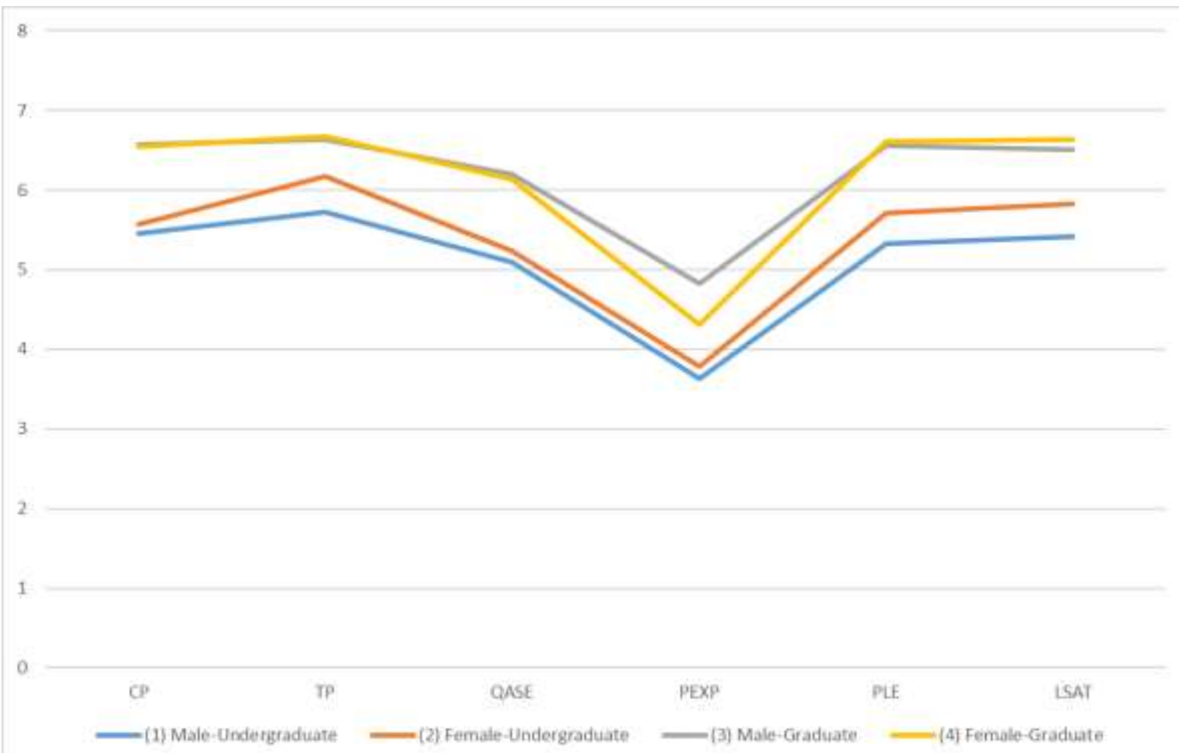

Figure 2 Average Ratings Across Groups

experience). Generally, graduate students viewed the course as more positive, with very similar average ratings between the two gender groups, except that the female group rated their prior experience much lower than the male group. As for undergraduate students, the female group rated all dimensions higher than their male counterparts. Overall, the patterns indicate that the male undergraduate students seem to be the least positive group regarding their learning.

4. DATA ANALYSIS RESULTS

To test the research model, we used SmartPLS 4.0 (Ringle et al., 2022), which is based on the partial least squares structural equation modeling (PLS-SEM) technique and has been widely adopted for causal relationship analysis. We first present the reliability and validity test results based on the whole data collection in Tables 3 and 4, respectively, followed by the overall model test results in Figure 3. After that, we display our detailed model test results for different participant groups in Figure 4 and summarize these findings in Table 5.

ISSN: 2473-4901
v10 n6123

Construct	Cronbach's Alpha	Item	Loading	T-Statistics	P-Value
Cognitive Presence	0.925	CP1	0.930	74.635	<0.001
		CP2	0.944	89.759	<0.001
		CP3	0.922	63.524	<0.001
Teaching Presence	0.940	TP1	0.911	34.295	<0.001
		TP2	0.938	72.404	<0.001
		TP3	0.911	42.606	<0.001
		TP4	0.921	61.468	<0.001
Quantitative Analytics Self-Efficacy	0.938	QASE1	0.937	76.341	<0.001
		QASE2	0.959	124.613	<0.001
		QASE3	0.935	45.280	<0.001
Prior Experience	0.956	PEXP1	0.946	99.439	<0.001
		PEXP2	0.970	177.507	<0.001
		PEXP3	0.960	135.502	<0.001
Perceived Learning Effectiveness	0.955	PLE1	0.947	97.204	<0.001
		PLE2	0.932	65.277	<0.001
		PLE3	0.947	77.638	<0.001
		PLE4	0.932	80.164	<0.001
Learning Satisfaction	0.951	LSAT1	0.957	89.646	<0.001
		LSAT2	0.960	85.965	<0.001
		LSAT3	0.945	84.229	<0.001

Table 3: Reliability Test Results

As presented in Table 4, the Cronbach's alpha values for all constructs exceed the generally accepted threshold of 0.7 (Au et al., 2008; Chin, 1998; Hair et al., 1998). The item loadings are all above the recommended guideline of 0.7 and statistically significant. These results indicate the

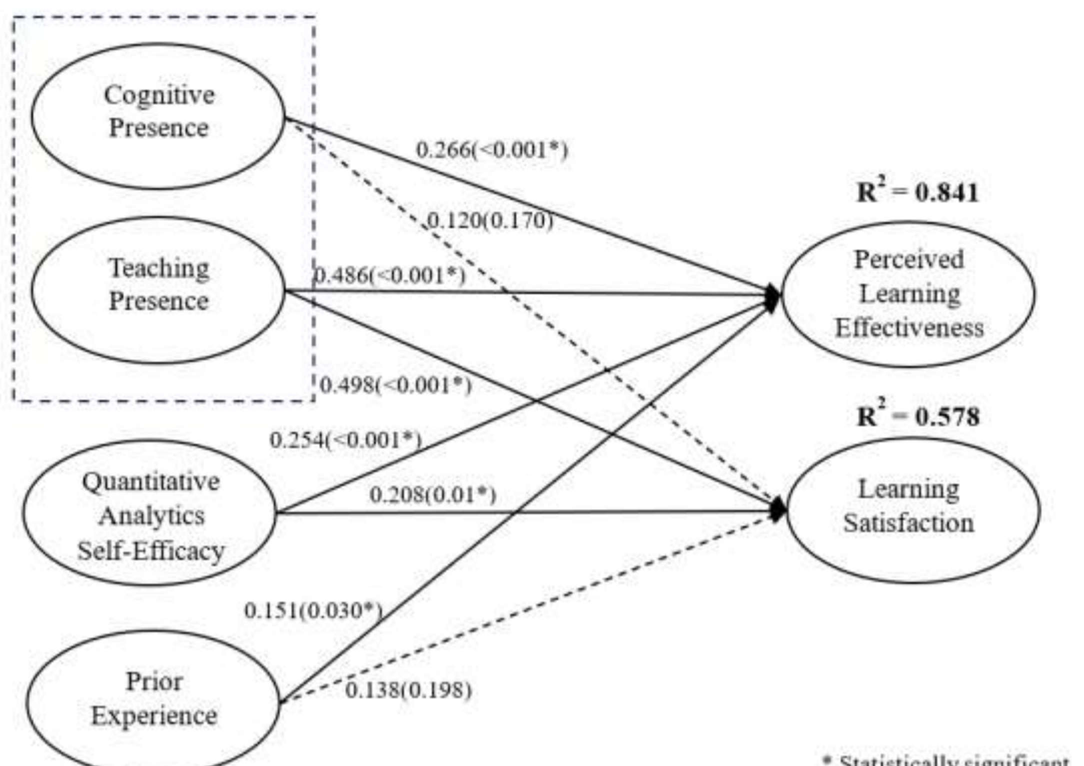

Figure 3 Overall Research Model Test Results Using All Data (n=309)

 ISSN: 2473-4901
v10 n6123

Construct	Composite Reliability	AVE	CP	LSAT	PLE	PEXP	QASE	TP
CP	0.926	0.869	**0.932**					
LSAT	0.951	0.910	0.664	**0.954**				
PLE	0.956	0.882	0.848	0.823	**0.939**			
PEXP	0.958	0.919	0.367	0.313	0.394	**0.959**		
QASE	0.942	0.890	0.723	0.658	0.808	0.386	**0.943**	
TP	0.942	0.847	0.753	0.768	0.898	0.304	0.684	**0.920**

Note: Diagonal elements in bold case are the square root of average variance extracted (AVE). Off-diagonal elements are correlations across constructs.

Table 4: Internal Consistency and Validity Test Results

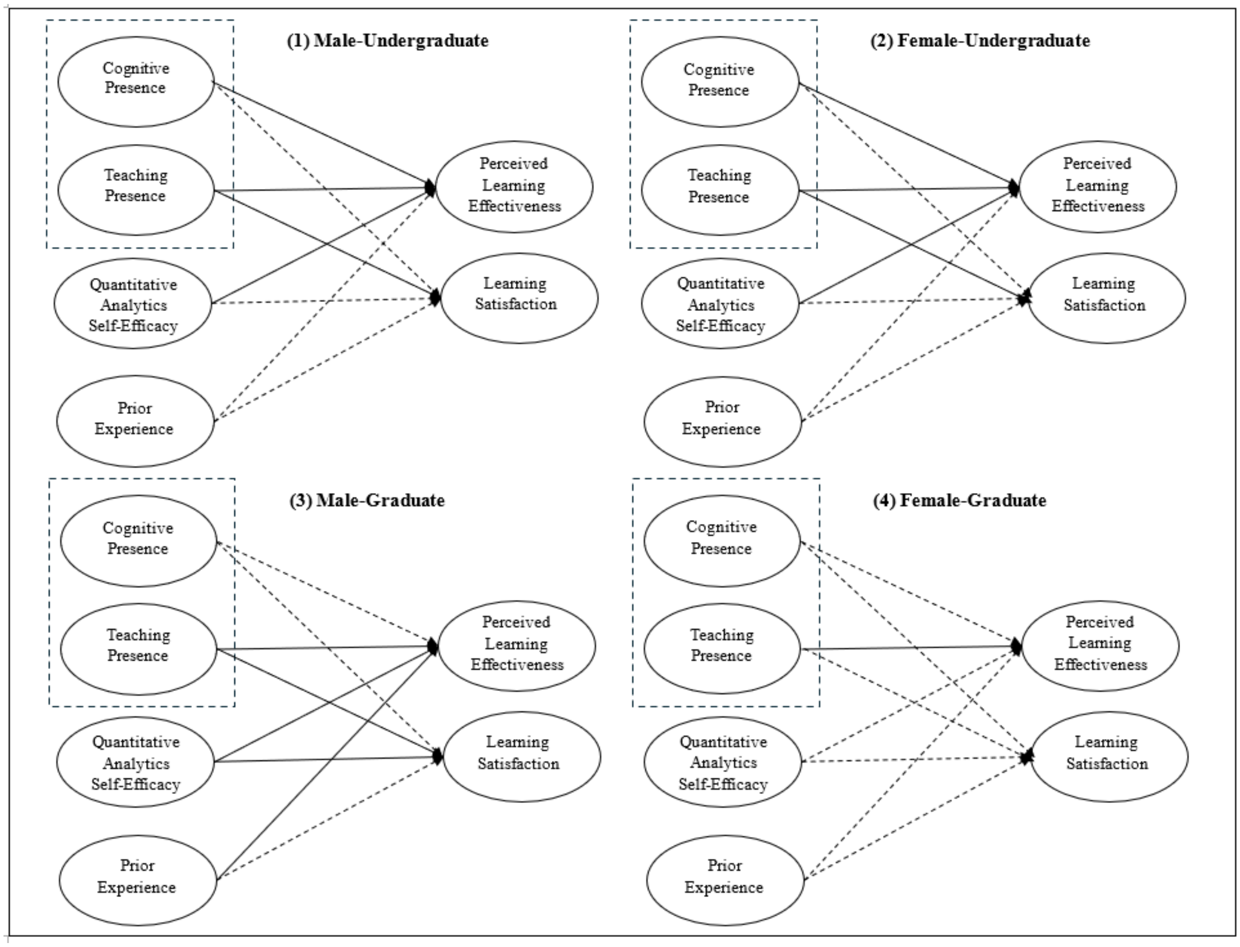

Figure 4 Research Model Test Results for All Groups

reliability of the measurement items for their respective constructs. Also, as shown in Table 4, the composite reliability values are all above 0.7, demonstrating good internal consistency (Au et al., 2008). The average variance extracted (AVE) values are all higher than the threshold of 0.5, which is equivalent to the guideline of the square root of AVE greater than 0.707, indicating convergent validity (Chin, 1998). Additionally, the square root of AVE for each construct is greater than its correlation values with other constructs, indicating high discriminant validity (Chin, 1998; Gefen & Straub, 2005).

As shown in Figure 3, cognitive presence has a significant impact on students' perceived learning effectiveness (a path coefficient of 0.266), but not on learning satisfaction, which supports H1 but not H2. This may indicate that if students find the setup and learning environment of the course to

 ISSN: 2473-4901
v10 n6123

Hypothesis	Path	(1) Male-Undergraduate	(2) Female-Undergraduate	(3) Male-Graduate	(4) Female-Graduate
		Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)
H1	CP → PLE	0.240(0.009*)	0.302(0.007*)	0.175(0.138)	0.087(0.502)
H2	CP → LSAT	0.078(0.572)	0.195(0.070)	0.232(0.296)	-0.041(0.443)
H3	TP → PLE	0.572(<0.0001*)	0.368(<0.001*)	0.563(<0.001*)	0.883(<0.001*)
H4	TP → LSAT	0.578(<0.0001*)	0.603(<0.001*)	0.404(0.019*)	0.280(0.057)
H5	QASE → PLE	0.195(0.0009*)	0.382(<0.001*)	0.256(<0.001*)	0.001(0.995)
H6	QASE → LSAT	0.120(0.060)	0.062(0.570)	0.310(0.010*)	0.160(0.059)
H7	PEXP → PLE	0.114(0.063)	-0.005(0.950)	0.183(0.050*)	-0.022(0.695)
H8	PEXP → LSAT	0.085(0.310)	0.051(0.567)	0.142(0.084)	-0.033(0.773)

Note: * Statistically significant

Table 5: Model Test Results Summary for All Groups

have a higher level of cognitive presence, which better helps them construct meaning, make sense of, and reflect on their learning process, they are more inclined to perceive a higher level of effectiveness in their learning of the course subjects. However, this increased sense of cognitive presence may not necessarily lead to increased satisfaction in their learning.

Teaching presence, however, shows a strong and positive impact on both perceived learning effectiveness and satisfaction, with path coefficients of 0.486 and 0.498 respectively. This finding aligns with H3 and H4 and suggests that when students perceive the overall course design and related learning support as helpful in achieving their learning goals, they tend to view the course as more effective and report greater satisfaction with their learning.

In addition, students' self-efficacy regarding their quantitative analytics skills plays a significant role in both perceived learning effectiveness and satisfaction (path coefficients of 0.254 and 0.208), providing substantial support for H5 and H6. This indicates that if students perceive themselves as having a higher level of overall quantitative analytics skills, they are more likely to have a positive attitude toward their learning effectiveness in the business analytics course and are more satisfied with their learning.

Furthermore, students' specific knowledge of business analytics concepts and techniques prior to attending the course significantly influences their perceived learning effectiveness (a path coefficient of 0.151), but not their satisfaction, supporting H7 but not H8. This suggests that having specific prior knowledge of the subjects covered in the course may help improve students' perceptions of their effectiveness in learning the business analytics course. However, such prior knowledge or experience may not necessarily increase their satisfaction with the course topics.

The R-squared value of 0.841 for perceived learning effectiveness suggests that the combination of all four independent variables accounted for 84.1% of the variance in it. In addition, the combined effects of teaching presence and quantitative analytics self-efficacy accounted for 57.8% of the variance in learning satisfaction.

To further explore whether there are any differences in the impact of the independent variables on the dependent variables across all participant groups, and to investigate the significance of the proposed hypotheses in each group, we further tested the model separately for each group. We summarize the results significant paths in Figure 4 and detail results in Table 5 across different groups.

Interestingly, when examining the specific participant groups, undergraduate students of both genders exhibit the same pattern – H1, H3, H4, and H5 are statistically significant, but not the others. These results suggest that for undergraduates, regardless of gender, cognitive presence, teaching presence, and quantitative analytics self-efficacy are essential factors influencing their perceived learning effectiveness. Among these, teaching presence also plays a key role in influencing their learning satisfaction; however, prior experience with the course topics does not seem to have a significant impact on either learning effectiveness or satisfaction.

As for the two graduate groups, very different results are observed. For male graduate students, H3 through H7 are significant. This shows that, unlike the undergraduate groups, prior experience – instead of cognitive presence as for

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v10 n6123

the undergraduate groups – is a key factor in influencing perceived learning effectiveness for male graduates. In terms of learning satisfaction, similar to the undergraduate groups, teaching presence also plays a significant role. However, the difference is that for male graduate students, quantitative analytics self-efficacy also impacts their learning satisfaction.

When it comes to female graduate students, surprisingly, only H3 is significant, indicating that teaching presence significantly influences perceived learning effectiveness for this group. However, overall, our proposed research model does not seem to be effective for this group of students. This suggests a need for further investigation into potential factors influencing their learning effectiveness and satisfaction.

5. CONCLUSIONS

Research Contributions

This study contributes to research in business analytics education in several ways. Firstly, unlike the majority of existing literature, which focuses on detailing the design and development of business analytics courses and programs or assessing the adoption of business analytics tools and systems in organizations, this study investigates factors influencing student learning in business analytics. Specifically, we explore various types of factors to understand their impacts on students' learning effectiveness and satisfaction. The first group of factors we examine includes cognitive presence and teaching presence. Both of these factors transcend individuals' personal characteristics and instead focus on their interactions within the learning environment and the resultant impacts on their learning process. Therefore, from the perspectives of cognitive and teaching presence, a positive learning experience requires effort from both learners themselves and others around them, such as their instructors, as well as the overall class setup.

In addition to examining cognitive and teaching presence, we also investigate the factor of self-efficacy. However, instead of employing a general term in this regard, we adopt a domain-specific one: quantitative analytics self-efficacy. We believe the use of this construct is more appropriate for two reasons. First, conducting business analytics fundamentally involves various forms of quantitative analysis on business data to derive useful patterns, trends, and correlations. Second, as business analytics is still a relatively young academic field compared to more traditional and established ones such as mathematics and statistics, few students may have been exposed to it before entering higher education. Therefore, directly inquiring about their self-efficacy in business analytics may not be suitable.

Furthermore, we also consider prior experience with related course topics and techniques as another potential influencing factor. Since students may come from diverse backgrounds and have different work and study experiences before enrolling in the business analytics course, any exposure they have had to related course topics and techniques beforehand may also impact their learning outcomes.

A second contribution of this study is the development and empirical testing of the proposed research model. With an overall sample size of 309 participants, the model was tested on students enrolled in the business analytics course with a focus on machine learning and data mining. On the overall level, the model held up well, indicating that both cognitive presence and teaching presence, quantitative analytics self-efficacy, as well as prior experience have strong impacts on students' learning effectiveness and satisfaction (with the exception of cognitive presence and prior experience on satisfaction).

In addition, we also examined gender and academic level differences across four student groups: male-undergraduate, female-undergraduate, male-graduate, and female-graduate. Through research model testing on these groups, interesting differences were observed. Overall, the two undergraduate groups exhibited similar patterns, showing significant impacts of cognitive presence, teaching presence, and quantitative analytics self-efficacy on learning effectiveness, as well as a significant influence of teaching presence on learning satisfaction. However, the results for the male-graduate group differed substantially, showing that both teaching presence and quantitative analytics self-efficacy had significant impacts on both learning effectiveness and satisfaction, along with a strong impact of prior experience on learning effectiveness. As for the female-graduate group, surprisingly, our model seemed to be less effective, with only one significant path from teaching presence to learning effectiveness. Overall, the results indicate the existence of gender and academic level differences.

Practical Implications

Our study also offers valuable insights for business analytics educators. As indicated in the model testing results, to motivate undergraduate

 ISSN: 2473-4901
v10 n6123

students to learn business analytics, educators need to focus on designing and providing a learning environment that fosters a higher level of both cognitive and teaching presence. To achieve this, educators may consider adopting strategies and teaching methods that create a supportive and engaging learning environment, promoting active participation, critical thinking, and meaningful interactions. Examples of specific activities include clearly defining course objectives and expectations; incorporating hands-on, problem-solving tasks and projects to encourage active learning; providing clear, timely, and constructive feedback on assignments; utilizing diverse instructional methods such as multimedia presentations, demonstrations, in-class case studies, and other activities in addition to traditional lecturing; encouraging students to ask questions or explore new ideas; and offering opportunities to solve real-world business problems using real-world datasets.

For graduate students, while cognitive presence does not appear to play a critical role in their learning, teaching presence, on the other hand, seems to be important. This finding suggests that when catering to the needs of graduate students, it is essential to provide a clear course design, offer sufficient facilitation during their learning process, and provide effective feedback and guidance to foster improved learning outcomes.

When teaching business analytics courses, educators should also consider the potential influence of students' self-efficacy on their quantitative analytics competencies and skills. This concept was found to be important for both undergraduates and graduates (male only). Therefore, when teaching technical courses in business analytics, educators may emphasize the importance of analytical skills in calculating and presenting numerical data. If necessary, additional learning materials and tools may be provided to students to help enhance their mathematical, statistical, or other quantitative analysis skills.

The specific prior study or work experience in business analytics does not seem to have a strong influence on undergraduate students. This might be because the majority of them may have had no or very limited exposure to business analytics in their education prior to college. However, for graduate students, the level of exposure could vary significantly before they enter the graduate program. Therefore, when teaching graduate students, educators may particularly want to assess students' prior knowledge and experience in the field and adjust their teaching methods, course designs, and topics coverage accordingly.

Limitations and Future Research Directions
This study also bears several limitations that can be explored and addressed by future research. Firstly, to our surprise, the research model is less effective on female graduate students, indicating the need to explore and examine other learning-related factors within this student group.

Additionally, our model was tested with students from one specific data analytics course focusing on machine learning and data mining. Future research may need to test and validate the model across other business analytics courses.

Furthermore, we encountered unbalanced numbers in our four student groups, with the number of male graduate students much larger than the other three groups. Future research may aim to obtain more balanced numbers within comparison groups.

Moreover, future research may consider further improving the proposed research model by incorporating and investigating additional learning-related factors and testing the model across students from different cultural backgrounds.

Also, future research may further explore the potential impact of students' socio-economic status and ages on their learning effectiveness, as well as instructor characteristics such as gender and age.

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APPENDIX A
Measurement Items

Cognitive Presence

CP1: This business analytics class provides me the chance to reflect what I have learned in the class.
CP2: This business analytics class allows me to explore ideas and integrate those ideas into solutions.
CP3: This business analytics class promotes and helps to improve my critical thinking abilities.

Teaching Presence

TP1: This class provides a clear guideline on learning.
TP2: This class distributes enough and useful tasks for learning (such as lecture materials, hands-on labs, and quizzes).
TP3: The class design is organized and clear for me to follow.
TP4: The tools and systems used in the class can facilitate my learning well.

Quantitative Analytics Self-Efficacy

QASE1: I am confident I can do well in quantitative analysis related tasks.
QASE2: I am confident in understanding concepts related to quantitative analysis.
QASE3: I typically expect to do well in quantitative analysis related tasks.

Prior Experience

PEXP1: Prior to this class, I knew a lot about the topics (both concepts and techniques) taught in this class about business analytics.
PEXP2: Prior to this class, I had acquired knowledge related to the topics (both concepts and techniques) taught in this class about business analytics.
PEXP3: Prior to this class, I had learned about the topics (both concepts and techniques) taught in this class about business analytics.

Perceived Learning Effectiveness

PLE1: My skills in solving business problems are improved by taking this class.
PLE2: My critical thinking skills are improved by taking this class.
PLE3: My confidence in conducting business analytics is improved by taking this class.
PLE4: I am able to apply the skills I have learned from this class to solve business analytics problems.

Learning Satisfaction

LSAT1: I am pleased with the business analytics class.
LSAT2: I am satisfied with the business analytics class.
LSAT3: The business analytics class satisfies my learning needs.