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Drivers of Student Learning Success in Business Analytics: A Model Investigating Learning Outcomes and Intentions

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ABSTRACT

In response to the heavy demand for business analysts in various industries, many universities have developed business analytics-related courses and programs, which aim to develop a competent labor force that can help companies make sense of business data and generate sustainable competitive advantages. Ensuring high levels of student success in these courses and programs is essential to achieving this goal. This study developed and tested a research model investigating important psychological factors, including learning motivation, teaching presence and cognitive gains, that can influence student learning outcomes in business analytics. The results indicate that both motivation and teaching presence could significantly influence learning effort. Additionally, cognitive gains had a significant impact on the perceived usefulness of the subject. Subsequently, the combined influence of learning effort and subject usefulness significantly affected student learning outcomes, which in turn impact future learning intentions.

Keywords: Business analytics, Student learning success, Learning intention, Learning factors

1. INTRODUCTION

Data analytics has become increasingly popular in business practice, leading to strong demand in the job market for data analysts and a boon for data analytics education in colleges and universities (Mills et al., 2022). Many universities are actively offering data analytics courses and programs for both undergraduate and graduate students, with some establishing Ph.D. programs as well (Hu & Cleland, 2019). While many of these course offerings and programs are offered as standalone disciplines in engineering, informatics, and/or business, efforts toward interdisciplinary collaboration across disciplines have also been observed (Hu & Cleland, 2019). According to an online survey platform (https://ryanswanstrom.com/colleges/), as of January of 2024, there are over 630 registered programs in data science and data analytics worldwide.

Significant research efforts have been made to better support student learning and success in business analytics courses and programs. These efforts have largely been centered around two main research tracks.

The most dominant area of research focuses on effective design and development of business analytics courses and programs (Burns & Sherman, 2019; Hu & Cleland, 2019; Olson, 2018; Sharef & Akbar, 2021). Depending on the background of the student body targeted, courses may be offered at an introductory and generalized level (Burns & Sherman, 2019; Hu & Cleland, 2019; Pomykalski, 2021), or at a more advanced and technical level (Klašnja-Milićević et al., 2019; Sharef & Akbar, 2021). Furthermore, some course offerings are designed around a heavy use of various programming languages (Eckroth, 2018; Sharef & Akbar, 2021), while others are less programming-centric and utilize integrated tools for student learning instead (Burns & Sherman, 2019; Hu & Cleland, 2019). A common thread across these different course and program offerings is teaching students how to utilize various techniques to conduct in-depth analyses on business data, followed by effective data visualization and presentation, and communication to key decision makers (Hu & Cleland, 2019).

The second area of extant research focuses on identifying and analyzing situational factors, collaborative experiences, and peer-supportive behaviors that impact student learning in business analytics (Mills et al., 2024; Shamroukh & Johnson, 2023). To date, little empirical research has been done to develop research models which investigate specific factors that can influence students' learning and interest in business analytics classes. The extant research on business analytics model development has mainly involved examining users' adoption behavior of business analytics systems in organizations (Al-Okaily et al., 2021; Jalil & Hwang, 2019; Ramakrishnan et al., 2020). Moving forward, empirical research needs to expand beyond work on adoption behaviors to better understand how diverse students from a variety of backgrounds can become more effective data-driven professionals. Shamroukh and Johnson (2023) emphasize that there is a strong need to make business analytics offerings relevant for different student audiences via flexible pedagogical approaches and more inclusive and accessible educational environments where interdisciplinary skills are considered invaluable. Under future research directions, they highlight the need for building hands-on learning environments with more collaboration, adaptability, and peer support.

Educators need a better understanding of what factors drive learning intention and inevitable student success in business analytics course offerings. Consequently, we developed and empirically tested a research model specifically focused on examining the impact of learning-related factors on students' learning intention in business analytics. We focused particularly on two groups of potential factors affecting students' learning: factors generally controllable by the students themselves and factors more under the control of their instructors. We aimed to address and explore how these factors could generally influence students' learning effort, outcomes, and intentions for continued learning on business analytics.

While this first section of this paper offered a general introduction to business analytics education, the remainder is organized as follows. Section 2 presents the extant academic literature and develops a conceptual research model with a set of hypotheses. Sections 3 and 4 are focused on model testing and provide details on the research methodology, the data analyses, and empirical results. Finally, the paper concludes with Section 5, a discussion of the main research contributions, implications for practice, and suggestions for future research.

2. RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

In this study, our aim is to investigate factors that influence students' learning in business analytics. Specifically, we examine the impacts of both student-based factors (i.e., learning motivation, cognitive gains) and instructor/class structure-based factors (i.e., teaching presence, teaching quality) on students' learning effort and perceptions of usefulness of business analytics. Additionally, we aim to assess the further impact of learning effort and perceptions of usefulness on students' perceived learning outcomes and future learning intentions.

To improve the logical flow of our presentation of related literature and its supportive role in our hypothesis development, we have organized this section into subsections, each based on a specific effect variable. In each subsection, we discuss and present the causes related to that particular effect, which inform the formation of our hypotheses.

2.1 Hypothesis Development on Learning Effort

In this subsection, we focus on discussing factors related to students' learning effort. Specifically, we have incorporated two factors into our research model: future-oriented learning motivation and teaching presence, each based on different perspectives. Students themselves have more control over the former, while instructors have more control over the latter.

2.1.1 Future-Oriented Learning Motivation. Motivation is a broad term and has been found to impact people's behavior and decision-making in various scenarios, such as education, business, and personal life (Kenyon & Benson, 2022; Simon et al., 2015). When studying how to motivate students in learning, a widely adopted motivational design model is the Attention, Relevance, Confidence, and Satisfaction (ARCS) model (Keller, 1987; 2012). This model emphasizes that to better motivate students, instructors need to focus on capturing students' attention, clearly communicating the reasons for learning the subject matter, helping to build students' confidence in mastering the subject, and assisting students in fostering a sense of achievement and accomplishment (Keller 1987; Li & Keller, 2018). The model has been utilized to investigate student learning motivation across various countries, in different courses, and with different student bodies and course delivery modalities (Li & Keller, 2018). Overall, a significant body of literature has highlighted the importance of adopting ARCS-enhanced learning materials (Li & Keller, 2018).

Motivation can be both intrinsic and extrinsic, with both playing important roles in shaping human behavior (Simon et al., 2015; Wu & Hwang, 2010). In the context of education, motivation is defined as the incentives that propel students to work hard and actively engage in their learning process (Wu & Hwang, 2010). Unlike business settings where both intrinsic motivations (e.g., gaining reputation, personal feelings of success) and extrinsic motivations (e.g., bonuses, promotions) are crucial, in educational settings, research has consistently shown and emphasized the importance of learners' intrinsic motivation in determining their learning behavior (Kenyon & Benson, 2022; Simon et al., 2015). One crucial type of intrinsic motivation for students to possess is related to how well they perceive the learning process as aligned with and beneficial to their future lives and careers, also known as "future-oriented motivation" (Kenyon & Benson, 2022).

A recent study examined students' learning anxiety regarding difficult-to-learn subjects and their perceptions of future-oriented motivation in learning (Kenyon & Benson, 2022). This study comprehensively assessed future-oriented motivation, revealing that students with clear plans for their futures and a strong connection between their learning efforts and future goals tend to display a more positive approach to their studies.

In another study investigating the impact of intrinsic motivation on students' choice of STEM (i.e., science, technology, engineering, mathematics) degree programs, Simon et al. (2015) examined factors influencing intrinsic motivation and its impact on students' persistence in choosing STEM programs. Their analysis indicates that students' self-efficacy and achievement goals can significantly influence their intrinsic motivation, which, in turn, impacts their persistence to continue learning.

Other studies have also examined the impacts of students' learning motivation on various learning-related constructs. For example, Law et al. (2019) studied the impact of learning motivation in a blended learning environment and found that it enhances students' intentions to enroll in classes and positively influences perceptions of social presence (i.e., students' perceptions of their ability to relate to and communicate with classmates; students' perceptions of belonging and their ability to form personal and productive classroom relationships). Kong et al. (2012) examined the impact of student motivation in an online, game-based collaborative learning environment and found that motivation positively influences students' intention to learn.

2.1.2 Teaching Presence. Teaching presence is driven by the course instructor and overall structure and facilitation of the course in the context of a learning community. Here, teaching presence is defined as the degree to which the class can provide students with clear design, sufficient facilitation in learning, and directions in performing their learning tasks in ways that help them achieve desired learning outcomes (Law et al., 2019). Teaching presence is sometimes referred to as teaching quality (Giannakos et al., 2017).

When examining the impact of teaching presence on student learning in the context of blended learning, Law et al. (2019) found that teaching presence significantly influences students' perceptions of cognitive presence (i.e., perceived ability to establish thoughtful meaning through exploration, critical discourse, and sustained reflection) and social presence (i.e., perceptions of relatability, belonging, and freedom of expression) in the learning environment. Moreover, the impact of teaching presence, cognitive presence, and social presence culminates in an educational experience, which significantly impacts students' performance.

In another study focusing on investigating student retention in computer science education, the same construct (i.e., teaching quality in their study) was leveraged to assess students' behavior at the program level (Giannakos et al., 2017). Specifically, they found that students' perceptions of the usefulness of the computer science degree, teaching quality, personal values, and satisfaction with learning effectiveness significantly influence their retention in the program.

Additional literature on course structure has also examined how clarity, organization, and course design can influence student learning (Alshare et al., 2015). For instance, Alshare et al. (2015) found that course structure impacts students' effort expectancy, which, in turn, significantly influences their expectations regarding learning outcomes, including increased productivity and effectiveness. In a relatively recent cross-cultural analysis of South Korean and Indian students during the COVID-19 pandemic, Baber (2020) found that course structure significantly affects both student learning outcomes and satisfaction.

2.1.3 Learning Effort. Learning effort is defined as the exertion that students put into learning a subject (Alshare et al., 2015). Previous studies have explored factors influencing students' learning efforts. In a study on ERP systems, Alshare et al. (2015) found that students' attitudes significantly impact their learning effort. Specifically, students with positive attitudes toward ERP software tend to invest a higher level of effort toward learning it. In a more recent study, Soeprijanto et al. (2022) discovered that students with a clear vision of their future careers are more dedicated to putting effort into learning and saw improved performance.

In the context of business analytics education, we posit that students' intrinsic motivation, particularly motivational factors associated with future lives and careers, can significantly shape their learning efforts. Given the growing popularity of business analytics and the promising job market in the foreseeable future, it is reasonable to expect students in this field to embrace positive attitudes toward their future careers in the industry in both cognitive and affective ways, thereby fostering greater motivation to learn the subject. The optimistic outlook for employment in this field post-graduation serves as a compelling driving force for their motivation to learn, leading them to willingly invest more effort in their studies. Consequently, we hypothesize that:

H1: Future-oriented learning motivation positively impacts student effort in learning business analytics.

On top of students' intrinsic motivational influence, we also posit that the course instructor and overall course design also play a pivotal role in shaping students' willingness to invest effort in their learning. Specifically, instructors who design quality courses, offer ample assistance to aid students in understanding the subject, and deliver clear instructions and guidance throughout the learning process, should expect students to be more likely to work diligently and to actively engage in their studies. Consequently, we hypothesize that:

H2: Teaching presence positively impacts student effort in learning business analytics.

2.2 Hypothesis Development on Subject Usefulness

When pursuing a subject of study, its usefulness can play an important role. Therefore, in this subsection, we focus on discussing the usefulness of the subject and explore the impact of cognitive gains on it.

2.2.1 Cognitive Gains. Cognitive gains refer to the intellectual or cognitive benefits individuals acquire through learning and education (Anderson, 1995; Giannakos et al., 2017). Prior research suggests that cognitive gains play a crucial role in shaping human beliefs, as a more salient acquisition of cognitive gains tends to lead to more positive beliefs and attitudes (Lent & Brown, 2006). Moreover, cognitive gains have been identified as an influential factor in shaping behavior, including learning intentions and performance (Chow et al., 2012; Kori et al., 2015).

Lamb et al. (2018) conducted a comprehensive meta-analysis investigating the influence of student cognition, affect, and learning outcomes using educational games and simulation platforms. A total of 2,151 original articles were initially identified and, following four rounds of study coding and consistency checks across coders were subsequently refined to 49 highly relevant empirical studies for in-depth analysis. Their conclusive findings indicate that the integration of educational games and simulations in learning correlates with heightened cognitive gains as well as increases in positive affect toward learning (i.e., students developed more positive attitudes).

In a recent study, Klimova and Pikhart (2023) examined the adoption of a digital learning environment for foreign language learning from the perspective of students' cognitive gains. The study specifically compares and analyzes students' cognitive gains when using digital textbooks versus traditional paper-based texts. The findings indicate that printed texts tend to be more effective for cognitive gains in students' language learning compared to electronic ones. However, exposing students to a variety of techniques that engage multiple senses may help mitigate this gap and promote more positive perceptions of cognitive gains.

2.2.2 Subject Usefulness. Subject usefulness is students' perception of the value of an academic discipline which can be considered the basis of preparation for a given profession (Cheng et al., 2020; Mahdi, 2006). In their study of student motivation in massive open online courses (MOOCs), Zhou et al. (2015) found subject usefulness was positively correlated with enthusiasm for learning a subject. Sahin and Shelley (2008), in their study of student satisfaction with distance education, found that students who believe a course subject is useful will enjoy their learning experience more.

When examining the impact of cognitive gains on perceived usefulness at the subject or program level, a previous study found that cognitive gains significantly influence students' perception of the usefulness of a computer science program (Giannakos et al., 2017). In our model, we anticipate a similar impact at the subject level, particularly when students are learning business analytics. Thus, students who perceive that taking a business analytics class will provide them with higher intellectual and cognitive benefits may develop a positive attitude toward business analytics, thereby regarding the subject as more useful overall. Subsequently, along this line of thinking, we hypothesize that:

H3: Cognitive gains positively impact the perceived usefulness of learning business analytics.

2.3 Hypothesis Development on Learning Outcomes

2.3.1 Learning Outcomes. Learning outcomes refer to the specific knowledge, skills, and attitudes that students are expected to acquire after completing their learning experience (Wall & Knapp, 2014). One of the ultimate goals of education is for students to achieve a high degree of mastery of all learning outcomes. Over the years, educators and researchers have been striving to design and develop new learning tools and methods that will help improve student learning outcomes (Law et al., 2010; Wall & Knapp, 2014).

Prior research has explored factors influencing students' learning outcomes (Wall & Knapp, 2014). Wall and Knapp (2014) examined the impact of students' perceptions of technical computing course topic complexity and their difficulty realizing learning outcomes. The authors argue that the perceived difficulty of these topics can be a barrier to learning and that instructors should take steps to manage this difficulty, including providing clear explanations of technical concepts, using real-world examples to illustrate technical concepts, providing opportunities for hands-on practice, and providing feedback on student performance.

When examining students' learning outcomes, similar constructs have been explored in the extant literature, such as perceived learning performance (Dang et al., 2023; Law et al., 2019) and achievement (Nguyen et al., 2016; Simon et al., 2015; Sun et al., 2018). For example, Sun et al. (2018) studied students' learning experiences in a math class that employed a flipped classroom learning methodology. Their findings indicated that students' math self-efficacy and help-seeking strategies significantly impact their learning achievement. When examining students' learning in business statistics, Nguyen et al. (2016) discovered that attitude plays a significant role in perceived learning achievement. Similarly, when studying science and technology-related subjects, Simon et al. (2015) found that both self-efficacy and performance goals play crucial roles in students' learning achievement.

In line with previous literature, we anticipate the existence of a positive relationship between business analytics students' general attitude toward the learning subject and their anticipated learning outcomes. A positive attitude toward studying business analytics, in itself, may serve as a driving force for student learning, leading students to be more willing to invest additional effort into subject mastery and the stronger realization of learning outcomes. Therefore, we hypothesize that:

H4: Learning effort positively impacts the perceived learning outcomes in business analytics.

In addition, prior research has also explored the relationship between perceived subject usefulness and perceived learning performance (Islam, 2013). Islam (2013) found that perceptions of usefulness significantly shape the building of the learning community and expectations of learning assistance, which, in turn, ultimately influences performance outcomes. We anticipate a similar situation. Business analytics students who believe the subject is highly useful may be more inclined to actively engage in their learning tasks and learning communities, leading to higher expectations, stronger positive attitudes toward learning, and better learning outcomes. Thus, we hypothesize that:

H5: Subject usefulness positively impacts the perceived learning outcomes in business analytics.

2.4 Hypothesis Development on Future Learning Intention

2.4.1 Future Learning Intention. Learning intention involves students' willingness to take specific actions using training and education to help resolve a discrepancy between one's current knowledge and the desired level of knowledge (Lai et al., 2022). Students' learning intention has been extensively examined in existing literature and is commonly employed as a dependent variable in research models related to student learning. Various factors have been investigated and identified as influential in shaping student learning, including learning satisfaction (Chiu & Tsai, 2014), perceived interactions (Liu et al., 2010), perceived usefulness and ease of use (Cheng, 2012; Decman, 2015; Liu et al., 2010), perceived enjoyment (Cheng, 2012), perceived fit (Lin, 2012), and social norm (Tarhini et al., 2013).

Maurer et al. (2003), testing their model of work-related learning and development activities, found that learning intention is a strong predictor of actual learning participation. When investigating the influence of learning outcomes on learning intention, Simon et al. (2015) conducted a study at the program level and discovered that students' perceptions of their achievement in a science and technology-related program significantly influenced their expected persistence in the program. Consistent with their findings, we anticipate a similar impact at the course level when studying business analytics. Therefore, we hypothesize that:

H6: Subjects' perceived learning outcomes positively impact their future intention in learning business analytics.

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

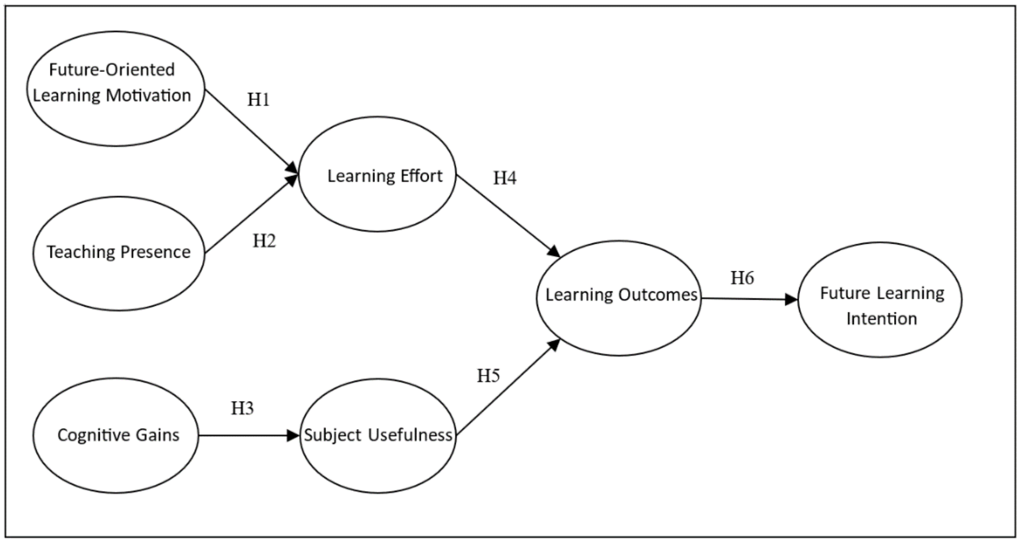

Figure 1. Research Model and Hypotheses

3. RESEARCH METHOD

3.1 Research Process and Data Collection

To test the proposed research model and hypotheses, a survey was conducted using students enrolled in a business analytics course offered by a business school at a southwestern university. This business analytics class is open to both business majors and students from across the university who are interested in learning about business analytics. The class is technical in nature, with a focus on teaching various types of data mining algorithms and techniques. Major course topics covered include linear regression, logistic regression, association analysis, k-nearest neighbors (k-NN), decision trees, artificial neural networks, and clustering. To effectively support students with various backgrounds, specific programming languages are not emphasized in the course. Instead, a well-known and powerful tool for conducting data mining and business analytics tasks, RapidMiner (https://rapidminer.com/), is used so that programmers and non-programmers can work and learn together.

Over the semester, the course is organized around major topics and algorithms, with a different major topic highlighted each week. Lecture slides, lecture videos, and additional reading materials are used as learning materials to further assist students. In addition, lab projects and weekly quizzes, as well as hands-on exams, are employed as means to assess student learning.

After obtaining IRB approval, an online survey invitation was sent to students enrolled in all sections of the class. All sections adopted the same learning materials and assessment tools. The study took place approximately 2 weeks before the end of the semester, after covering all major topics and algorithms. Student participation was completely voluntary, with extra credit worth about 1.5% of the total class points used as an incentive.

In total, the survey invitation was sent to 211 students, and 192 students participated and completed the study, generating a 91.0% response rate. The survey respondents accurately represented the course population, comprising 119 males (62%) and 73 females (38%), with an average age of 22.9 years.

3.2 Measures of Constructs

Appendix A offers specific measurement items for all measures included in the conceptual model. All constructs were measured using a 7-point Likert scale, ranging from 1 for “strongly disagree” to 7 for “strongly agree.”

3.2.1 Future-Oriented Learning Motivation. To assess future-oriented learning motivation, we adapted the measures from Kenyon and Benson (2022) and modified the wording to align with our study’s context. A sample item includes, “Taking this business analytics class could benefit me in general for my future, either on continued education or job seeking.” Chronbach’s alpha is $\alpha = .923$.

3.2.2 Teaching Presence. Teaching presence was measured using the instruments developed by Law et al. (2019) for the construct of teaching presence and Giannakos et al. (2017) for teaching quality with self-development. A sample item includes, “The class design is organized and clear for me to follow.” Chronbach’s alpha is $\alpha = .95$.

3.2.3 Learning Effort. Learning effort was measured using the scales introduced by Alshare et al. (2015) for the same construct. A sample item includes, “I have put my best effort in learning business analytics.” Chronbach’s alpha is $\alpha = .911$.

3.2.4 Cognitive Gains. Our measures of cognitive gains were developed based on the construct’s definition from Giannakos et al. (2017). A sample item includes, “The class helps improve my ability in solving real-world business problems.” Chronbach’s alpha is $\alpha = .956$.

3.2.5 Subject Usefulness. For assessing subject usefulness, we consulted measures from Giannakos et al. (2017) for degree’s usefulness and Nguyen et al. (2016) for perceived usefulness, adapting them to create our measures. A sample item includes, “Business analytics is an important factor in the success of modern businesses.” Chronbach’s alpha is $\alpha = .939$.

3.2.6 Learning Outcomes. Learning outcomes measures were adopted from Wall and Knapp (2014). A sample item includes, "I have developed skills in this class that I didn't have previously." Chronbach's alpha is α = .941.

3.2.7 Future Learning Intention. Future learning intention measures were adapted from the original measures of behavioral intention in the UTAUT model (Venkatesh et al., 2003) to suit the specific context of our study. A sample item includes, "After taking this class, I intend to learn more about business analytics." Chronbach's alpha is α = .972.

Table 1 summarizes the descriptive statistics for all study constructs. Overall, students provided high ratings on all dimensions, indicating generally positive attitudes toward their learning experience. Subject usefulness received the highest average rating of 6.428 out of 7, followed by perceived learning outcome (6.299) and future-oriented learning motivation (6.280).

Construct	Mean	Std. Dev.
Future-Oriented Learning Motivation (MOV)	6.280	1.183
Teaching Presence (TP)	6.035	1.532
Cognitive Gains (GAIN)	6.191	1.254
Learning Effort (EFFORT)	6.160	1.364
Subject Usefulness (USE)	6.428	1.044
Learning Outcomes (LRNOUT)	6.299	1.200
Future Learning Intention (INT)	5.971	1.481

Table 1. Descriptive Statistics of the Constructs

4. DATA ANALYSIS AND RESULTS

To measure the proposed research model and evaluate the hypotheses, we utilized the partial least squares structural equation modeling (PLS-SEM) technique (Chin, 1998). Specifically, SmartPLS 4.0 (Ringle et al., 2022), which is a widely used and robust tool for casual relationship analysis, was employed to perform the detailed statistical analysis.

To assess the measurement model, reliability and validity tests were performed (with Tables 2 and 3 displaying the reliability and validity test results). Specifically, we utilized Cronbach's Alpha values and item loadings to assess reliability, and the square root of AVE, composite reliability, and correlation measures to assess validity.

As shown in Table 2, Cronbach's alpha values for all constructs well exceed the suggested threshold value of 0.70 (Au et al., 2008; Chin, 1998; Hair et al., 1998). Overall, the results indicate a high level of reliability for all constructs, with all item loadings statistically significant at the $p<0.0001$ level.

As shown in Table 3, the composite reliability values for all constructs are above the recommended threshold of 0.70, indicating strong internal consistency (Au et al., 2008). In addition, the average variance extracted (AVE) values are all higher than the suggested threshold of 0.50, which is consistent with the guideline of the square root of AVE threshold of 0.707 (Au et al., 2008; Chin, 1998). These findings suggest robust convergent validity for the model. Furthermore, the square root of AVE for each construct exceeds its correlation values with other constructs, affirming good discriminant validity (Chin, 1998; Gefen & Straub, 2005).

The inner model testing results are illustrated in Figure 2. The analysis reveals a significant impact of future-oriented learning motivation on learning effort, with a path coefficient of 0.335 ($t=2.647$, $p=0.008$). This suggests that students with a higher level of intrinsic motivation, who believe that learning business analytics could be beneficial to their future career or education, are more inclined to invest effort in studying this subject. Therefore, H1 is supported. Additionally, the analysis shows that teaching presence can also significantly influence learning effort, with a path coefficient of 0.377 ($t=2.644$, $p=0.008$), supporting H2. This indicates that students who perceive a higher level of class presence provided by the instructor are more willing to invest effort in their learning.

Furthermore, the analysis results demonstrate that cognitive gains play a crucial role in determining students' perceptions of the usefulness of business analytics. The path coefficient of 0.663 ($t=8.451$, $p<0.0001$) supports H3. This implies that students who anticipate higher gains from the class tend to perceive business analytics as more useful.

In addition, the model reveals that both learning effort and subject usefulness significantly impact students' perceptions of their learning outcomes, with path coefficients of 0.566 ($t=5.140$, $p<0.0001$) and 0.278 ($t=2.522$, $p=0.012$), supporting H4 and H5, respectively. These findings indicate that students who invest more effort in their learning tend to expect better outcomes, and those who believe business analytics is useful are more inclined to anticipate better performance in the class.

Furthermore, the research findings demonstrate that students' perceived learning outcomes significantly impact their future learning intentions, with a path coefficient of 0.698 ($t=9.386$, $p<0.0001$), supporting H6. This indicates that students with a positive attitude toward their current class learning outcomes are more inclined to pursue further studies and delve into the field of business analytics.

The R-squared value of 0.430 for learning effort suggests that the combination of future-oriented learning motivation and teaching presence accounted for 43% of the variance in students' learning effort. This indicates that these two factors play a significant role in explaining students' motivation and dedication to learn business analytics.

Furthermore, the R-squared value of 0.440 for subject usefulness indicates that cognitive gains accounts for 44% of the variance, emphasizing the importance of having a positive attitude toward personal cognitive gains from the class in influencing students' overall perception of the subject's usefulness.

Additionally, the combination of learning effort and subject usefulness explained 57.1% of the variance in learning outcomes. These findings highlight the substantial impact of both students' individual effort in learning and their positive attitude towards the subject's usefulness on their expectations of learning outcomes.

Finally, perceived learning outcomes accounted for 48.7% of the variance in students' future learning intention, underscoring the importance of positive expectations for learning outcomes in shaping students' willingness to engage in further business analytics study.

Construct	Cronbach's Alpha	Item	Loading	T-Statistics	P-Value
Learning Effort	0.911	EFFORT1	0.946	78.885	<0.0001
		EFFORT2	0.945	72.968	<0.0001
		EFFORT3	0.873	17.992	<0.0001
Cognitive Gains	0.956	GAIN1	0.927	46.985	<0.0001
		GAIN2	0.944	81.645	<0.0001
		GAIN3	0.944	68.590	<0.0001
		GAIN4	0.943	54.722	<0.0001
Future Learning Intention	0.972	INT1	0.960	107.362	<0.0001
		INT2	0.973	138.997	<0.0001
		INT3	0.964	132.097	<0.0001
		INT4	0.946	67.944	<0.0001
Learning Outcomes	0.941	LRNOUT1	0.954	69.170	<0.0001
		LRNOUT2	0.929	42.424	<0.0001
		LRNOUT3	0.955	91.523	<0.0001
Future-Oriented Learning Motivation	0.923	MOV1	0.870	23.204	<0.0001
		MOV2	0.906	37.866	<0.0001
		MOV3	0.923	48.501	<0.0001
		MOV4	0.907	38.427	<0.0001
Teaching Presence	0.950	TP1	0.934	51.788	<0.0001
		TP2	0.953	69.539	<0.0001
		TP3	0.912	31.172	<0.0001
		TP4	0.931	42.738	<0.0001
Subject Usefulness	0.939	USE1	0.922	40.610	<0.0001
		USE2	0.903	26.011	<0.0001
		USE3	0.916	30.271	<0.0001
		USE4	0.938	61.077	<0.0001

Table 2. Reliability Test Results

Construct	Composite Reliability	AVE	GAIN	INT	MOV	EFFORT	LRNOUT	USE	TP
GAIN	0.956	0.882	**0.939**						
INT	0.974	0.923	0.790	**0.961**					
MOV	0.925	0.813	0.795	0.609	**0.902**				
EFFORT	0.918	0.850	0.767	0.618	0.649	**0.922**			
LRNOUT	0.944	0.895	0.814	0.727	0.716	0.775	**0.946**		
USE	0.940	0.846	0.699	0.529	0.849	0.597	0.628	**0.920**	
TP	0.951	0.870	0.809	0.646	0.742	0.653	0.808	0.666	**0.933**

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

Table 3. Internal Consistency and Validity Test Results

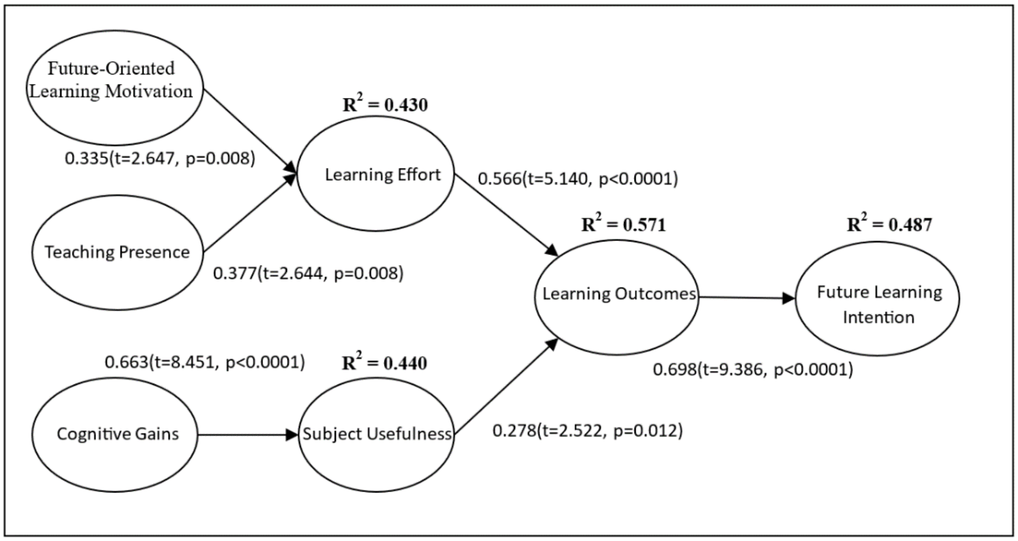

Figure 2. Research Model Test Results

5. CONCLUSIONS

5.1 Research Contributions

This study contributes to the existing business analytics education literature in several ways. While most extant efforts in data analytics education research have primarily centered on the design, development, and/or delivery of various data analytics courses and programs, our study follows a psychological approach, which is very complementary to previous discovery efforts.

First, our study focuses on students' perceived learning outcomes (which hints at learning satisfaction) and future learning intentions (which denotes planned learning behavior), concepts that are both widely recognized as crucial indicators of student learning success in the computing-related education domain. Drawing insights from existing literature on technology-supported education and information systems education, we identify and investigate a group of potential factors, including students' future-oriented learning motivation, perceptions of teaching presence or quality, student cognitive gains, student learning effort, as well as student perceptions and attitudes toward the usefulness of business analytics. Through our comprehensive analysis, we demonstrate that each of these identified factors plays a pivotal role in shaping student learning in data analytics. By addressing these aspects of the educational landscape, our study enriches the existing literature and provides valuable insights for both educators and researchers involved in data analytics education.

A second contribution lies in the integration of factors from different perspectives—including students and the learning environment instructors provide—creating a cohesive and integrated nomological network. Our research addresses a notable gap in the literature by making a concerted effort to investigate potential student-related and course-related factors influencing business analytics learning. On the student-related aspect, we explore intrinsic motivation tied to their future professional careers and the intellectual and cognitive benefits they anticipate gaining throughout the learning process. Simultaneously, we include a learning environment-related factor, namely teaching presence, which encompasses the organization, clarity, and facilitation the instructor provides in delivering teaching quality.

Our results underscore the importance of all three exogenous factors, with particular emphasis on the significant impact of future-oriented learning motivation and cognitive gains on learning effort. Additionally, cognitive gains serve as a key influencer in shaping student perceptions of subject usefulness, which further emphasizes the interconnected nature of how these factors influence the learning process.

Furthermore, our study reveals particularly influential impacts of both learning effort and subject usefulness on students' perceived learning outcomes and general satisfaction with their learning. These perceived learning outcomes, in turn, play a pivotal role in shaping students' planned behaviors toward learning business analytics moving forward. The insights derived from our research model can be expected to serve as theoretical guidance for educators and researchers who are interested in business analytics education, prompting a more in-depth understanding of the driving forces behind student learning success in this domain. Ultimately, we hope that our findings will provide valuable insights for future business analytics education and will help educators better understand student attitudes and performance behavior.

Lastly, another important contribution of this research lies in our further development of reliable measurement items for the constructs included in our research model. We utilized existing items from original research as our foundation, which we refined and developed to enhance clarity and alignment with the specific context of our study. To facilitate transparency and encourage future research endeavors, we have included all the measures in the Appendix of this paper. It is our hope that these updated measures will prove useful for researchers in this field as a reference point for future investigations.

5.2 Practical Implications

Higher education is often criticized as overly expensive, too broadly focused, and not career-centric enough. With business analytics, educators have a tremendous opportunity to share a clear value proposition with learners, who must build self-efficacy over time via ongoing skill development and the mastery of different analytic techniques. An educator's guiding hand can certainly help to shape positive attitudes toward learning and future career development.

The current study offers many practical implications for educators beyond improvements to teaching pedagogy and course quality, which have been the focus of much of the existing research in analytics education thus far. In particular, the inclusion of certain student-centered constructs included in our model are especially powerful areas for educators to focus attention upon, including student perceptions of subject usefulness, students' perceptions of learning outcomes, and student future learning intentions.

The perception of subject usefulness construct used in our study can be considered a proxy, of sorts, for student attitudes toward the value of business analytics. Here, educators can help shape positive learning attitudes by stressing the practical real-world benefits of business analytics as useful for problem-solving, appropriate for modern business careers, and valuable for building sustainable competitive advantages and effective business strategies.

Additionally, educators can help shape more positive perceptions of learning outcomes via continuous reflection and reinforcement of what students are learning. Once students have completed a given learning module, educators should remind students what, specifically, they have learned and help them to realize other real-world problems and situations where they could apply their newly acquired skills and knowledge. Students often do not fully comprehend the context of their learning, so educators should emphasize learning reflection to help students better understand what they have learned and the value of their knowledge gains beyond the classroom.

While future learning intentions are an outcome variable in our conceptual model, educators can also seek to shape future planned behaviors as a strategy to drive additional learning and to generate excitement about a highly valuable career trajectory. Students often lack confidence and have a difficult time translating what they have previously learned into specific future career paths. Consequently, business analytics educators can emphasize the valence of business analytics as a logical path to a solid career and to generate potential excitement about a promising future. Business analytics is a broad interdisciplinary field with many potential career options available. Unfortunately, the luxury of having many career paths could be daunting to students who do not know how to focus their interests on a specific career path that is appropriate for them to pursue. Analytics educators are in a good position to help learners navigate this new and exciting world.

5.3 Limitations and Future Research Directions

This research has several limitations that future research should address. The empirical testing of the research model was conducted using only one business analytics course offering. Future research could enhance the robustness and generalizability of the model by expanding the study to validate the proposed research model across a variety of different classes (i.e., program-level assessments), covering different periods (i.e., longitudinal assessments), and catering to students with different backgrounds and interests (i.e., assessments using samples across different disciplines).

Another limitation of this study is that the research model incorporates a limited set of student learning factors which could certainly be expanded moving forward. Future investigations could be conducted by exploring additional factors and integrating them into an expanded research model. This could help provide a more comprehensive understanding of the intricate influences on student learning in business analytics. While the current study focused on student learning motivation and student cognitive gains as important factors for shaping learning attitudes, outcomes, and future planned behaviors, it omits student affective response (i.e., emotional response) and past experiences as shaping mechanisms. For example, student feelings and affective-based gains could impact student attitudes toward learning as well. It would be interesting to see how positive emotions toward business analytics offerings, as well as past behaviors and learning experiences, could shape student perceptions of subject usefulness and/or student learning effort. The subject usefulness construct included in the current study focuses heavily on cognitive-based perceptions of the value of business analytics, an expanded measure of student attitudes toward business analytics including student affective response could be especially powerful. Other student-level constructs for possible future consideration include self-efficacy, student learning independence, student concentration/focus, and past learning experiences. Past learning experience seems like a particularly interesting shaping mechanism for perceptions of subject usefulness, learning outcomes, and future learning intentions.

Another limitation of this study is that the research model incorporates a limited set of outcome variables which could also be expanded moving forward. For example, while the learning outcomes construct included in the current study hints at learning satisfaction, student learning outcomes could be expanded to include a more focused measure of learning satisfaction. Other potential outcome variables for future consideration could include student engagement, student grades/performance, and professional commitment.

It is also worthwhile to mention that the survey methodology used in this paper to assess drivers and factors of student success in business analytics represents just one way to study them. The survey method, which heavily relies on subjective responses, generally has its own constraints, errors, and biases. While the use of SEM and survey data worked well for this initial investigation, further research that empirically tests parts of the model – instead of relying solely on student perceptions – can help further validate the findings of this study and provide a more in-depth understanding.

Furthermore, a key area of future research derived from our study is the exploration of how future-oriented learning motivation, an intrinsic motivator, interacts with teaching presence, an extrinsic factor, in shaping students' learning experiences. This becomes particularly relevant when considering the unique aspects of business analytics as distinct from computer/data science. Future studies could greatly benefit from a more nuanced analysis of teaching presence. For instance, it would be valuable for future research to measure teaching presence based on two fine-grained types: one focusing on technology (e.g., programming, methodology-oriented) and the other on business applications (e.g., storytelling, problem-solving-based). Exploring how these distinct types of teaching presence interact with future-oriented learning motivation can provide deeper insights into their combined effects on student learning outcomes. Such insights could inform and enhance curriculum design and teaching strategies in business analytics courses.

Ultimately, we hope the current study offers valuable insights to researchers in this field, which will catalyze further development of this research area. Through increased efforts and potential joint contributions among researchers, our overarching goal is to contribute to the ongoing improvement of student learning experiences in business analytics, aiming to provide the best possible methods, environments, and support to students in driving their learning experience.'

6. REFERENCES

Al-Okaily, A., Ping, T. A., & Al-Okaily, M. (2021). Towards Business Intelligence Success Measurement in an Organization: A Conceptual Study. *Journal of System and Management Sciences*, 11(2), 155-170. https://doi.org/10.33168/JSMS.2021.0210

Alshare, K. A., El-Masri, M., & Lane, P. L. (2015). The Determinants of Student Effort at Learning ERP: A Cultural Perspective. *Journal of Information Systems Education*, 26(2), 117-133.

Anderson, J. R. (1995). *Cognitive Psychology and Its Implications*. New York: Freeman.

Au, N., Ngai, E., & Cheng, T. (2008). Extending the Understanding of End User Information Systems Satisfaction Formation: An Equitable Needs Fulfillment Model Approach. *MIS Quarterly*, 32(1), 43-66. https://doi.org/10.2307/25148828

Baber, H. (2020). Determinants of Students' Perceived Learning Outcome and Satisfaction in Online Learning During the Pandemic of COVID-19. *Journal of Education and e-Learning Research,* 7(3), 285-292. https://doi.org/10.20448/journal.509.2020.73.285.292

Burns, T., & Sherman, C. (2019). A Cross Collegiate Analysis of the Curricula of Business Analytics Minor Programs. *Information Systems Education Journal*, 17(4), 82-90. http://isedj.org/2019-17/

Cheng, C., Yuen, S., & Liu, V. (2020). The Impact of the Adoption of Classroom Response Systems on University Students' Subject Learning Experience. *International Journal of Innovation, Management and Technology*, 11(2), 51-56. https://doi.org/10.18178/ijimt.2020.11.2.875

Cheng, Y.-M. (2012). Effects of Quality Antecedents on E-Learning Acceptance. *Internet Research*, 22(3), 361-390. https://doi.org/10.1108/10662241211235699

Chin, W. W. (1998). Issues and Opinion on Structural Equation Modeling. *MIS Quarterly*, 22(1), vii-xvi.

Chiu, Y.-L., & Tsai, C.-C. (2014). The Roles of Social Factor and Internet Self-Efficacy in Nurses' Web-Based Continuing Learning. *Nurse Education Today*, 34(3), 446-450. https://doi.org/10.1016/j.nedt.2013.04.013

Chow, A., Eccles, J. S., & Salmela-Aro, K. (2012). Task Value Profiles Across Subjects and Aspirations to Physical and IT-Related Sciences in The United States and Finland. *Developmental Psychology*, 48(6), 1612-1628. https://doi.org/10.1037/a0030194

Dang, M. Y., Zhang, Y. G., & Albritton, M. D. (2023). Impact of Course Learning Factors on Student Interest in Business Analytics Careers. *International Journal of Information and Communication Technology Education*, 19(1), Article 60 (pp. 1-19). https://doi.org/10.4018/IJICTE.324160

Decman, M. (2015). Modeling the Acceptance of E-Learning in Mandatory Environments of Higher Education: The Influence of Previous Education and Gender. *Computers in Human Behavior*, 49, 272-281. https://doi.org/10.1016/j.chb.2015.03.022

Eckroth, J. (2018). A Course on Big Data Analytics. *Journal of Parallel and Distributed Computing*, 118 (Part 1), 166-176. https://doi.org/10.1016/j.jpdc.2018.02.019

Gefen, D., & Straub, D. (2005). A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotated Example. *Communications of the Association for Information Systems*, 16(1), 91-109. https://doi.org/10.17705/1CAIS.01605

Giannakos, M. N., Pappas, I. O., Jaccheri, L., & Sampson, D. G. (2017). Understanding Student Retention in Computer Science Education: The Role of Environment, Gains, Barriers and Usefulness. *Education and Information Technologies*, 22, 2365-2382. https://doi.org/10.1007/s10639-016-9538-1

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate Data Analysis*. Prentice Hall.

Hu, M., & Cleland, S. (2019). A Pilot Study of Developing Introductory Course in Data Analytics and Business Intelligence. *Proceedings of the 2019 IEEE Frontiers in Education Conference*, Covington, KY, USA. http://doi.org/10.1109/FIE43999.2019.9028649

Islam, A. K. M. N. (2013). Investigating E-Learning System Usage Outcomes in the University Context. *Computers & Education*, 69, 387-399. https://doi.org/10.1016/j.compedu.2013.07.037

Jalil, N. A., & Hwang, H. J. (2019). Technological-Centric Business Intelligence: Critical Success Factors. *International Journal of Innovation, Creativity and Change*, 5(2), 1499-1516.

Keller, J. M. (1987). Development and Use of the ARCS Model of Instructional Design. *Journal Of Instructional Development*, 10(3), 2-10. https://doi.org/10.1007/BF02905780

Keller, J. M. (2012). ARCS Model of Motivation. In: Seel, N.M. (eds) *Encyclopedia of the Sciences of Learning*. Springer, Boston, MA. https://doi.org/10.1007/978-1-4419-1428-6_217

Kenyon, C. M., & Benson, L. (2022). First-Year Engineering Student Perceptions of Calculus Exams and Future-Oriented Motivation. *Proceedings of the 2022 ASEE Annual Conference & Exposition* (pp. 1-15), Minneapolis, MN. https://doi.org/10.18260/1-2--41021

Klašnja-Milićević, A., Ranković, N., & Ivanović, M. (2019). Integration of Business Intelligence Course to Master Academic Studies in Informatics. *The 20th CompSysTech Conference*, Bulgaria. https://doi.org/10.1145/3345252.3345287

Klimova, B., & Pikhart, M. (2023). Cognitive Gain in Digital Foreign Language Learning. *Brain Sciences*, 13, 1074. http://doi.org/10.3390/brainsci13071074

Kong, J. S.-L., Kwok, R. C.-W., & Fang, Y. (2012). The Effects of Peer Intrinsic and Extrinsic Motivation on MMOG Game-Based Collaborative Learning. *Information & Management*, 49(1), 1-9. https://doi.org/10.1016/j.im.2011.10.004

Kori, K., Pedaste, M., Tõnisson, E., Palts, T., Altin, H., Rantsus, R., Sell, R., Murtazin, K., & Rüütmann, T. (2015). First-Year Dropout in ICT Studies. *Proceedings of the 2015 I.E. Global Engineering Education Conference* (pp. 437-445), Tallinn, Estonia. http://doi.org/10.1109/EDUCON.2015.7096008

Lai, N. Y. G., Foo, W. C., Tan, C. S., Kang, M. S., Kang, H. S., Wong, K. H., Yu, L. J., Sun, X., & Tan, N. M. L. (2022). Understanding Learning Intention Complexities in Lean Manufacturing Training for Innovation on the Production Floor. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(3), 110. https://doi.org/10.3390/joitmc8030110

Lamb, R. L., Annetta, L., Firestone, J., & Etopio, E. (2018). A Meta-Analysis With Examination of Moderators of Student Cognition, Affect, and Learning Outcomes While Using Serious Educational Games, Serious Games, and Simulations. *Computers in Human Behavior*, 80, 158-167. https://doi.org/10.1016/j.chb.2017.10.040

Law, K. M. Y., Geng, S., & Li, T. (2019). Student Enrollment, Motivation and Learning Performance in a Blended Learning Environment: The Mediating Effects of Social, Teaching, and Cognitive Presence. *Computers & Education*, 136, 1-12. https://doi.org/10.1016/j.compedu.2019.02.021

Law, K. M. Y., Lee, V. C. S., & Yu, Y. T. (2010). Learning Motivation in E-Learning Facilitated Computer Programming Courses. *Computers & Education*, 55(1), 218-228. https://doi.org/10.1016/j.compedu.2010.01.007

Lent, R. W., & Brown, S. D. (2006). On Conceptualizing and Assessing Social Cognitive Constructs in Career Research: A Measurement Guide. *Journal of Career Assessment*, 14(1), 12-35. https://doi.org/10.1177/1069072705281364

Li, K., & Keller, J. M. (2018). Use of the ARCS Model in Education: A Literature Review. *Computers & Education*, 122, 54-62. https://doi.org/10.1016/j.compedu.2018.03.019

Lin, W.-S. (2012). Perceived Fit and Satisfaction on Web Learning Performance: IS Continuance Intention and Task-Technology Fit Perspectives. *International Journal of Human-Computer Studies*, 70(7), 498-507. https://doi.org/10.1016/j.ijhcs.2012.01.006

Liu, I.-F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C.-H. (2010). Extending the TAM Model to Explore the Factors that Affect Intention to Use an Online Learning Community. *Computers & Education*, 54, 600-610. https://doi.org/10.1016/j.compedu.2009.09.009

Mahdi, A. E. (2006). Introducing Peer-Supported Learning Approach to Tutoring in Engineering and Technology Courses. *International Journal of Electrical Engineering Education*, 43(4), 277-287. https://doi.org/10.7227/IJEEE.43.4.1

Maurer, T. J., Weiss, E. M., & Barbeite, F. G. (2003). A Model of Involvement in Work-Related Learning and Development Activity: The Effects of Individual, Situational, Motivational, and Age Variables. *Journal of Applied Psychology*, 88(4), 707-724. https://doi.org/10.1037/0021-9010.88.4.707

Mills, R. J., Fadel, K. J., Olsen, T., Chudoba, K. M., & Dupin-Bryant, P. A. (2022). Examining Trends in Business Analytics Education From 2011 to 2020 in AACSB-Accredited Information Systems Programs. *Journal of Information Systems Education*, 33(3), 232-244. https://aisel.aisnet.org/jise/vol33/iss3/4

Mills, R. J., Fyfe, E. R., Beaulieu, T., & Mills, M. (2024). Are You Inspired or Overwhelmed? The Benefits of Teachers Setting Challenging Expectations. *Instructional Science*, 52, 693-709. https://doi.org/10.1007/s11251-023-09658-0

Nguyen, T. H., Charity, I., & Robson, A. (2016). Students' Perceptions of Computer-Based Learning Environments, Their Attitude Towards Business Statistics, and Their Academic Achievement: Implications From a UK University. *Studies in Higher Education*, 41(4), 734-755. https://doi.org/10.1080/03075079.2014.950562

Olson, D. L. (2018). Business Analytics Course Development at UNL. *The 27th International Conference on Information Systems Development*, Lund, Sweden.

Pomykalski, J. J. (2021). Moving to Business Analytics: Re-Designing a Traditional Systems Analysis and Design Course. *Information Systems Education Journal*, 19(6), 55-63.

Ramakrishnan, T., Khuntia, J., Kathuria, A., & Saldanha, T. J. V. (2020). An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance. *Communications of the Association for Information Systems*, 46, Article 31 (pp. 723-750). https://doi.org/10.17705/1CAIS.04631

Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS 4. Oststeinbek: SmartPLS*. https://www.smartpls.com

Sahin, I., & Shelley, M. (2008). Considering Students' Perceptions: The Distance Education Student Satisfaction Model. *Journal of Educational Technology & Society*, 11(3), 216-223.

Shamroukh, S., & Johnson, T. (2023). Using Factor Analysis to Determine the Factors Impacting Learning Python for Non-Technical Business Analytics Graduate Students. *Journal of Data Analysis and Information Processing*, 11(4), 512-535. https://doi.org/10.4236/jdaip.2023.114026

Sharef, N. M., & Akbar, M. D. (2021). Learning Analytics of Online Instructional Design during COVID-19: Experience from Teaching Data Analytics Course. *2021 International Conference Advancement in Data Science, E-learning and Information Systems* (pp. 1-6), Bali, Indonesia. https://doi.org/10.1109/ICADEIS52521.2021.9702058

Simon, R. A., Aulls, M. W., Dedic, H., Hubbard, K., & Hall, N. C. (2015). Exploring Student Persistence in STEM Programs: A Motivational Model. *Canadian Journal of Education*, 38(1), 1-27.

Soeprijanto, S., Diamah, A., & Rusmono, R. (2022). The Effect of Digital Literacy, Self-Awareness, and Career Planning on Engineering and Vocational Teacher Education Students' Learning Achievement. *Journal of Technology and Science Education*, 12(1), 172-190. https://doi.org/10.3926/jotse.1434

Sun, Z., Xie, K., & Anderman, L. H. (2018). The Role of Self-Regulated Learning in Students' Success in Flipped Undergraduate Math Courses. *The Internet and Higher Education*, 36, 41-53. https://doi.org/10.1016/j.iheduc.2017.09.003

Tarhini, A., Hone, K., & Liu, X. (2013). User Acceptance Towards Web-Based Learning Systems: Investigating the Role of Social, Organizational and Individual Factors in European Higher Education. *Procedia Computer Science*, 17(1), 189-197. https://doi.org/10.1016/j.procs.2013.05.026

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Towards a Unified View. *MIS Quarterly*, 27(3), 425-478. https://doi.org/10.2307/30036540

Wall, J. D., & Knapp, J. (2014). Learning Computing Topics in Undergraduate Information Systems Courses: Managing Perceived Difficulty. *Journal of Information Systems Education*, 25(3), 245-259. https://aisel.aisnet.org/jise/vol25/iss3/8

Wu, W., & Hwang, L.-Y. (2010). The Effectiveness of E-Learning for Blended Courses in Colleges: A Multi-Level Empirical Study. *International Journal of Electronic Business Management*, 8(4), 312-322.

Zhou, M., Cliff, A., Krishnan, S., Nonnecke, B., Crittenden, C., Uchino, K., & Goldberg, K. (2015). M-CAFE 1.0: Motivating and Prioritizing Ongoing Student Feedback During Moocs and Large On-Campus Courses Using Collaborative Filtering. *Proceedings of the 16th Annual Conference on Information Technology Education* (pp. 153-158), New York, NY, United States. https://doi.org/10.1145/2808006.2808020

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APPENDIX

Measurement Items

Future-Oriented Learning Motivation

MOV1: Taking this business analytics class could better prepare me for my future education if I have interest in learning more on this topic.
MOV2: Taking this business analytics class could better prepare me for my future career if I decide to choose business analytics as my career path.
MOV3: Taking this business analytics class could benefit me in general for my future, either on continued education or job seeking.
MOV4: Taking this business analytics class could better prepare me with skills to solve problems in real-world businesses.

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 tool/system used in the class can facilitate my learning well.

Cognitive Gains

GAIN1: Taking this class is beneficial for me in terms of broadening my general education.
GAIN2: Taking this class is beneficial for me since the knowledge I have learned in this class could be potentially useful for my future job/work.
GAIN3: This class helps improve my critical thinking and analytical thinking abilities.
GAIN4: This class helps improve my ability in solving real-world business problems.

Learning Effort

EFFORT1: I have put my best effort in learning business analytics.
EFFORT2: I have put the maximum effort possible in learning business analytics.
EFFORT3: I have put a significant amount of effort in learning business analytics.

Subject Usefulness

USE1: Business analytics is very useful.
USE2: Business analytics is an important factor in the success of modern businesses.
USE3: Studying business analytics could provide me with skills I may potentially use in future employment.
USE4: Studying business analytics could help develop my skills in solving problems for businesses.

Learning Outcomes

LRNOUT1: I have learned a lot in this class.
LRNOUT2: I have developed skills in this class that I didn’t have previously.
LRNOUT3: I am happy with my learning in this class.

Future Learning Intention

INT1: After taking this class, I would like to do more exploration and further learning on business analytics.
INT2: After taking this class, I intend to learn more about business analytics.
INT3: After taking this class, I am willing to learn more about business analytics.
INT4: After taking this class, when there is an opportunity, I would like to continue my learning on business analytics.

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