Examining Essential Factors on Student Performance and Satisfaction in Learning Business Analytics

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Abstract

With businesses increasingly prioritizing data-driven decision making, the demand for business analysts is high and expected to grow. In response, many universities and institutions have developed courses and programs related to business analytics to prepare more graduates for careers in this field. Business analytics programs and educators consistently strive to achieve a high level of student learning success, ensuring competence in working in the business analytics field after graduation. In this study, we aim to examine key factors influencing student learning in business analytics, focusing on performance expectancy and satisfaction. We examined specific factors, including personal interest, career relevance expectancy, learning effort, and perceived course structure effectiveness, from perspectives related to both students and instructors. A research model was developed and empirically tested. The results showed that all factors significantly influenced both perceived academic performance and learning satisfaction. Additionally, personal interest and career relevance expectancy could significantly impact learning effort.

Keywords: Business analytics, student learning, personal interest, career relevance, course structure, learning effort

Recommended Citation: Dang, M.Y., Zhang, Y.G., Williams, S., Anderson, J., (2024). Examining Essential Factors on Student Performance and Satisfaction in Learning Business Analytics *Information Systems Education Journal* v22(n4) pp 48-61. https://doi.org/10.62273/JBVL2064

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1. INTRODUCTION

The data world continues to evolve beyond big data with the addition of the internet of things and industrial internet of things (Amarnath, 2023). In addition, the internet now reaches 63% of world population (Domo, 2022). Organizations are facing increasing amounts of data from vendors, customers, and their internal operations.

This data is viewed by organizations as an asset, even labeled "the new oil" – a term coined by Clive Humby in 2006 (Amarnath, 2023). Extracting value from this data to support and inform decision-making is the role of business analytics. To extract useful information, this data must be analyzed to find patterns, make predictions, and garner insights. Organizations must have managers who can utilize the results to inform decisions.

Both the U.S. Bureau of Labor Statistics and some academic literature use the term *data science* as an umbrella term for fields and professional positions that "use analytics tools and techniques to extract meaningful insights from data" (U.S. Bureau of Labor Statistics, 2023) which includes business analytics, data analytics, and data science. Here, we use data science as an umbrella term and business analytics as the field where data is transformed using analytics tools and techniques to gain insight for business decision-making. Gartner Group is predicting a shortfall in data skills and literacy making it difficult for organizations to achieve their data-driven goals (Sallam & Goasduff, 2022). The job outlook for data scientists for 2021-2031 is a 36% increase which is expected due to increased demand for data-driven decisions (U.S. Bureau of Labor Statistics, 2023). Analytics is permeating other business majors, as evidenced by the inclusion of 'Human Resource Analytics Manager' in LinkedIn's list of the 25 fastest-growing job titles over the past 5 years (LinkedIn, 2023).

Academia has responded to this gap in data science talent by creating courses, certificates, and programs designed to train students of all levels and disciplines to use data to inform decisions. It has been suggested that all business students need to have some level of knowledge about business analytics and think as a data strategist (BizEd, 2019).

In addition to the challenge of insufficient talent supply, roles and skills needed to conduct data science are poorly understood and defined (Davenport, 2020; Fayyad & Hamutcu, 2021). Organizations have assumed that each hired data scientist would have all skills needed. However, this set of skills is broad and encompasses multiple fields – statistics, data engineering, analytics, and now artificial intelligence. Such a data scientist has been labeled a unicorn (Davenport, 2020; Fayyad & Hamutcu, 2021). What is needed instead is a team from a variety of specialties with complementary skills. Such a team, however, is also not well defined. Davenport (2020) described a large bank that studied the roles and skills of its data scientists, finding 100 teams of 2,000 employees. They identified seven job families with 65 roles in analytics and data science. Clearly, data science is an "umbrella term" (Fayyad & Hamutcu, 2021).

The novelty and breadth of the term "data science" and its associated job market demands make teaching business analytics classes quite challenging. With the ultimate goal of ensuring student learning success, a significant amount of research effort has been dedicated to the design and development of business analytics classes and programs (Anderson & Williams, 2019; Eckroth, 2018; Olson, 2018; Paul & MacDonald, 2020; Yap, 2020; Zadeh et al., 2021; Zhang et al., 2020). This includes a variety of courses ranging from less technical ones to programming-heavy ones, encompassing general education as well as domain-specific areas such as marketing business analytics and healthcare analytics. Overall, these research works have provided valuable insights into curriculum development, course content, and pedagogical approaches in business analytics education.

However, another possible way to contribute to the research field of business analytics education is to investigate factors that may influence student learning in this context. Unfortunately, in comparison to the aforementioned group of studies, significantly less effort has been devoted to empirically examining influencing factors on student learning, particularly through the lens of nomological networks, which serve as theoretical frameworks for analyzing research constructs.

Recognizing this gap, the current study aims to make a meaningful contribution to the existing literature on business analytics education. The primary objective is to develop and evaluate a research model that focuses on investigating the impacts of influential factors on student learning in the field of business analytics. By doing this, the study seeks to provide a more balanced understanding of the interconnections among different variables and their collective influence on student learning success.

The remainder of this paper is organized as follows: Section 2 presents the related literature and develops a set of hypotheses. Following that, Sections 3 and 4 provide details on the research method and the results of the data analysis, respectively. Finally, the paper concludes with a discussion of the research contributions, implications, and future research directions in Section 5.

2. RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

In the field of business analytics education, a substantial body of literature exists on the creation of business analytics classes, including details on class designs and utilization of learning platforms (Eckroth, 2018; Olson, 2018; Yap, 2020; Zadeh et al., 2021; Zhang et al., 2020). Furthermore, significant effort has been dedicated to the development of business analytics-related programs (Clayton & Clopton, 2019; Molluzzo & Lawler, 2015), both at the undergraduate and graduate levels (Choi et al., 2017; Klašnja-Milićević et al., 2019; Paul & MacDonald, 2020). Some of these studies also incorporate an evaluation component with quantitative analysis based on students' ratings (Eckroth, 2018; Zadeh et al., 2021), while others focus solely on providing details regarding class and/or program design (Anderson & Williams, 2019; Clayton & Clopton, 2019; Jaggia et al., 2020; Liu & Levin, 2018).

For example, in a relatively recent study, Zhang et al. (2020) presented detailed information on the design of a business analytics course at two universities. The study included information on class topics, assignments, labs, and teaching tools. While the learning objectives, outcomes, and modules were consistent, there were slight variations in the labs and tools used at different universities. Furthermore, the researchers utilized the university's official teaching evaluation survey results to assess the course design.

In another study, Eckroth (2018) presented the design of a highly technical data analytics class that involved utilization of multiple programming languages and tools. The study included a thorough discussion of the course's learning objectives, topics, and schedules. Additionally, a set of six questions was employed to assess the effectiveness of the course design.

Regarding the literature on designing business analytics programs, Clayton and Clopton (2019) provided a comprehensive discussion of the redesign of the business curriculum, including the incorporation of the BA certificate program. In another study, Tremblay et al. (2017) presented the development of a program aimed at integrating business analytics across clinical and administrative disciplines. This program was a collaborative effort across colleges at Florida International University. In the study conducted by Liu and Levin (2018), the authors discussed a progressive approach to transforming the existing marketing program into one with a focus on analytics. Furthermore, Paul and MacDonald (2020) identified skill-based gaps between industry and academia. They proposed specific courses based on clustering by similarity those skills, industry requirements, and intangible student traits.

Compared to the aforementioned literature focused on course/program design, there has been relatively less effort dedicated to developing research models for examining and assessing student learning in the context of business analytics classes. Therefore, this study aims to contribute to this body of literature. We include three factors that are primarily controlled by either students themselves or instructors: students' personal interest in the business analytics subject, their expectations regarding the relevance of the topics covered in the class to their future career needs, and the course structure that is designed and provided to them by their instructors.

In the context of this study, personal interest is defined as students' intrinsic passion for acquiring knowledge in the field of business analytics. Previous research has emphasized the importance of personal interest in learning information systems (Li et al., 2014). Based on survey results from Li et al. (2014), IS majors tended to have a higher level of personal interest in this subject compared to general business students. It is reasonable to believe that students with a higher level of personal interest in the subject of learning would generally be more dedicated to their learning.

Moreover, when investigating the impact of personal interest on learning effort in the domain of enterprise resource planning (ERP), Alshare et al. (2015) found that students' own attitudes toward ERP systems significantly influenced their level of effort in learning this subject. This suggests that students' level of interest in a particular subject directly affects their motivation and dedication to learning. Similarly, a recent study by Herpratiwi and Tohir (2022) examined the relationship between learning interest and learning motivation. The findings revealed that a high level of interest in learning positively influenced students' motivation to learn. Drawing from these findings, it can be inferred that if students have a higher level of interest in business analytics, they could be more likely to hold a positive attitude towards learning and be more motivated to learn the subject matter. Consequently, it is reasonable to assume that they would be more willing to put effort into learning business analytics. Therefore, we propose H1 as follows:

> H1: Students' personal interest has a positive impact on their effort in learning business analytics.

Based on the concept of career relevance stated by Alshare et al. (2015), we define students' expectancy on career relevance as their perception of the relevance of learning and understanding business analytics to their future careers. In the study conducted by Alshare et al. (2015) in the context of ERP system learning, it was found that career relevance significantly influenced students' performance expectations, such as an increase in productivity and effectiveness in completing learning tasks. These positive outcomes may be attributed to the fact that students who perceived the career relevance of the subject were more motivated to learn and invested greater effort in their studies.

Furthermore, a recent study by Soeprijanto et al. (2022) found that students who had a clear view of their future careers were more likely to achieve better learning outcomes. This may also be because those students were more motivated to learn and were willing to put more effort into learning.

Other research has found that possessing a positive attitude toward learning could lead to an increased performance expectancy (Islam, 2013). In another study, Nguyen et al. (2016) examined and identified that attitude played an important role in perceived learning performance. In line with these findings, we anticipate a positive relationship between general learning attitude and expected learning performance. Such a positive attitude may serve as a driver for students to learn the subject matter, thus naturally leading to a higher level of willingness for students to put effort into their learning. Therefore, a positive relationship between learning effort and perceived performance could be expected.

Applying these insights to our context, if students believe that learning business analytics is relevant to their future careers, it is reasonable to expect they could be more dedicated to learning and, as a result, put forth greater effort in studying the subject. Consequently, this may lead to higher expectations regarding their academic performance. Hence, we propose H2 and H3 as follows:

> H2: Students' expectancy regarding the relevance of the business analytics class to their future career has a positive impact on their effort in learning business analytics.

> H3: Students' learning effort has a positive impact on their perceived academic performance in business analytics.

When examining the impact of students' learning effort on their learning satisfaction, Bećirović et al. (2022) conducted a study and found that students who invested additional effort into learning not only achieved better class performance but also experienced significantly higher levels of satisfaction with their learning. This suggests that the more effort students put into their studies, the more satisfied they can be with their learning outcomes.

In a recent study by Shi et al. (2023), which involved a large-scale survey of 385 students, the authors examined the relationship between learning effort, learning intention, and learning satisfaction. They found that learning effort had a significant impact on learning intention, which, in turn, significantly influenced learning satisfaction. This study highlights the important role of learning effort in shaping students' intention to learn and their subsequent satisfaction with the learning process.

Based on these previous findings and considering our context, we hypothesize that learning effort

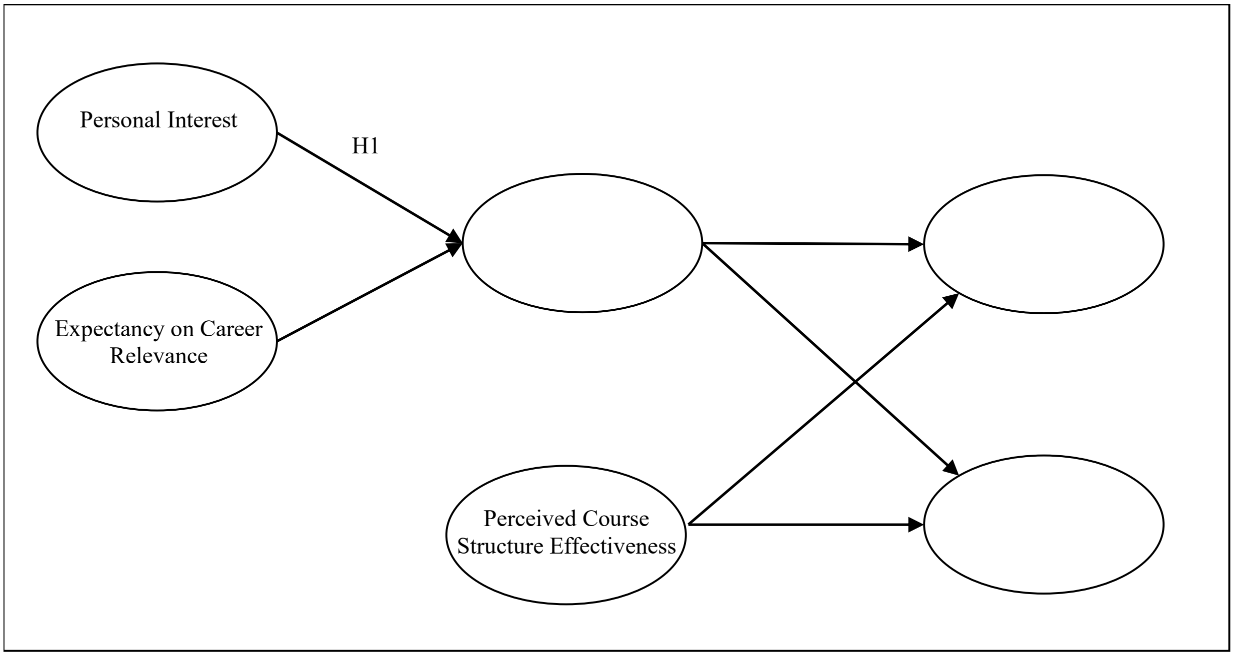

Figure 1 Research Model and Hypotheses

positively influences students' learning satisfaction in the field of business analytics education. Students who invest more effort into their studies are likely to experience higher levels of satisfaction with their learning outcomes. Therefore, we propose H4 as follows:

> H4: Students' learning effort has a positive impact on their satisfaction with learning business analytics.

Course structure is defined as the clarity and organization of the course topics and related materials (Alshare et al., 2015). Although Alshare et al. (2015) defined course structure in objective language, they assessed it based on students' perceptions on this construct. Thus, to make it clearer, we refer to it as "perceived course structure effectiveness" in this paper. Previous research has demonstrated the significant influence of course structure on students' performance. For instance, Alshare et al. (2015) conducted a study in the context of ERP system learning and found that the way the course was structured had a substantial impact on students' effort expectancy, which, in turn, significantly influenced their expectations regarding their performance outcomes, such as increased productivity and effectiveness in completing learning tasks. These findings suggest that a well-structured course can help positively shape students' performance expectations and motivate them to excel in their studies.

In a study by Wall and Knapp (2014) that explored the specific learning environment created by instructors, it was found that the organization of courses and adoption of effective teaching styles had a significant impact on students' learning outcomes. The way instructors structure their courses can influence students' engagement, comprehension, and retention of course material, ultimately affecting their overall learning experience.

More recently, Baber (2020) conducted a cross-country study with undergraduate students from both South Korea and India universities. The findings revealed that course structure had significant effects on both student learning outcomes and satisfaction. A well-designed and organized course structure was found to enhance students' understanding of the subject matter and foster a positive learning experience and outcome expectations, leading to higher levels of satisfaction.

In our context of business analytics education, we propose that course structure plays a crucial role in shaping students' perceptions of their academic performance and learning satisfaction. A clear and well-organized course structure is expected to provide students with a solid foundation for understanding and applying business analytics concepts, leading to higher perceived academic performance. Furthermore, an effectively structured course is likely to promote a positive learning environment, engage students, and increase their satisfaction with the learning experience. Hence, we propose H5 and H6 as follows:

> H5: The perceived course structure effectiveness of the business analytics class has a positive impact on students' perceived academic performance.

> H6: The perceived course structure effectiveness of the business analytics class has a positive impact on students' learning satisfaction.

The proposed research model is summarized in Figure 1.

3. RESEARCH METHOD

To assess the proposed research model, a survey was conducted with students enrolled in a senior-level undergraduate business analytics course. All business majors can enroll in this course. Students who take the course are typically in their junior and senior years of study. This course focused on various techniques and algorithms related to data mining, with an emphasis on teaching students how to effectively utilize and apply them to analyze and interpret business data. The course covered major topics and algorithms such as linear regression, logistic regression, association analysis, k-nearest neighbors (k-NN), decision trees, artificial neural networks, and clustering. While this course is highly technical, it has been designed to be accessible to all business majors, accommodating students with diverse backgrounds. The class does not necessitate the use of programming languages; instead, it leverages RapidMiner (https://rapidminer.com/), a well-known and powerful tool that enables the execution of various data analyses without the need of programming.

Each week, the course is dedicated to a specific algorithm, and accompanied by comprehensive learning materials. To enhance students' understanding, lecture videos and hands-on demonstration videos were provided, allowing them to review and reinforce their knowledge throughout the semester. In addition, students were required to complete one or two hands-on lab projects each week, providing them with practical experience and an opportunity to apply what they learned.

To gauge their comprehension, students also had weekly quizzes based on the respective topics covered. All learning materials were organized and accessible through an online learning management system. Furthermore, weekly reminder emails were sent to all students at the beginning of each week, outlining the main topic to be covered and providing deadlines for all course activities. Table 1 summarizes the course design and structure.

Component	Design
Major topics/algorithms	• Linear regression • Logistic regression • Association analysis • K-nearest neighbors (k-NN) • Decision trees • Artificial neural networks • Clustering
Assignments	Weekly hands-on lab projects
Assessments	Weekly concept quizzes and two hands-on exams
Learning materials	Lecture slides, lecture videos and demonstration videos, and other reading materials

Table 1: Course Design and Structure

After obtaining IRB approval, a survey invitation was sent to all 167 students who were enrolled in the course during the study period, and 121 students completed the survey. The survey was conducted two weeks before the end of the semester, after covering all major topics, which we believed to be a good timing. We offered extra credit worth about 1.5% of the total class grade to those who completed the survey. The respondents consisted of 61 males and 60 females. The average age of the participants was approximately 21.5 years old.

To assess personal interest, we utilized the concepts of "match with interest" and "personal interest" as described in Li et al. (2014), based on which we developed a set of three specific measurement items for this construct.

For measuring expectancy on career relevance, we employed the measures of career relevance from Alshare et al. (2015), which were originally developed to assess student effort in learning ERP systems. We modified these items to align with the context of our study. Additionally, we introduced one additional item (CAREER4) to capture this construct.

The measures for perceived course structure effectiveness were adapted from Alshare et al. (2015). Items related to learning effort were developed based on the description of this construct in Alshare et al. (2015). To assess perceived academic performance, we adapted items from Islam (2013). Similarly, items for measuring 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." For a comprehensive list of the measurement items, please refer to Appendix A.

Construct	Mean	Standard Deviation
Personal Interest	4.548	1.785
Expectancy on Career Relevance	5.858	1.123
Perceived Course Structure Effectiveness	6.140	1.013
Learning Effort	5.518	1.304
Perceived Academic Performance	5.932	1.106
Learning Satisfaction	5.813	1.266

Table 2: Descriptive Statistics

Table 2 provides a summary of the descriptive statistics for all constructs. In general, students expressed positive opinions about the course, with the perceived course structure effectiveness receiving particularly high ratings (mean rating of 6.140 out of 7). This was followed by perceived academic performance and expectancy on career relevance (mean ratings of 5.932 and 5.858).

4. DATA ANALYSIS RESULTS

To test the research model, we utilized SmartPLS 4.0 (Ringle et al., 2022), a widely used software package that is based on the least squares structural equation modeling (PLS-SEM) technique. The reliability and validity test results are presented in Tables 3 and 4, respectively.

As presented in Table 3, 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 (except for AP3, which is borderline), and they are all statistically significant. These results indicate reliability of the measurement items for their respective constructs.

Construct	Cronbach's Alpha	Item	Loading	T-Statistics	P-Value
Personal Interest	0.979	PERINT1	0.971	34.245	<0.0001
		PERINT2	0.964	33.645	<0.0001
		PERINT3	0.973	36.924	<0.0001
Expectancy on Career Relevance	0.944	CAREER1	0.944	12.661	<0.0001
		CAREER2	0.882	13.865	<0.0001
		CAREER3	0.866	12.129	<0.0001
		CAREER4	0.902	15.844	<0.0001
Perceived Course Structure Effectiveness	0.831	STRUCT1	0.760	10.804	<0.0001
		STRUCT2	0.839	12.756	<0.0001
		STRUCT3	0.765	10.327	<0.0001
Learning Effort	0.908	EFFORT1	0.896	22.679	<0.0001
		EFFORT2	0.800	15.105	<0.0001
		EFFORT3	0.929	25.211	<0.0001
Perceived Academic Performance	0.843	AP1	0.885	18.671	<0.0001
		AP2	0.723	9.799	<0.0001
		AP3	0.699	9.696	<0.0001
		AP4	0.729	10.986	<0.0001
Learning Satisfaction	0.921	SAT1	0.988	30.162	<0.0001
		SAT2	0.898	17.79	<0.0001
		SAT3	0.791	8.969	<0.0001

Table 3: Reliability Test Results

Furthermore, 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).

Model testing results are presented in Figure 2. The analysis reveals a significant and positive impact of personal interest on students' effort in

Construct	Composite Reliability	AVE	CAREER	STRUCT	EFFORT	SAT	AP	PERINT
CAREER	0.945	0.808	**0.899**					
STRUCT	0.834	0.623	0.484	**0.789**				
EFFORT	0.913	0.768	0.514	0.359	**0.876**			
SAT	0.934	0.803	0.475	0.549	0.598	**0.896**		
AP	0.854	0.578	0.575	0.714	0.720	0.782	**0.760**	
PERINT	0.979	0.940	0.607	0.183	0.551	0.430	0.544	**0.970**

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

learning business analytics. The path coefficient of 0.374 ($t=3.525$, $p<0.0001$) indicates that students who possess a higher level of personal interest in the subject are more likely to invest greater effort in their learning endeavors. This finding aligns with H1, which suggests that students' personal interest influences their commitment to learning business analytics.

Furthermore, it demonstrates that students' expectancy on the relevance of the business analytics class to their future career also plays a significant role in shaping their learning effort. The path coefficient of 0.289 ($t=2.455$, $p=0.015$) provides empirical support for H2, indicating that students who perceive the course's relevance to their future career are more inclined to exert effort in mastering the subject matter.

Additionally, the analysis reveals that students' learning effort plays a crucial role in determining their perceived academic performance. The path coefficient of 0.542 ($t=6.408$, $p<0.0001$) provides robust evidence for H3, indicating that students who invest greater effort in learning business analytics tend to achieve higher levels of perceived academic performance. This finding suggests that the more effort students put into their studies, the more likely they are to perceive themselves as performing well academically in the context of business analytics.

Also, it demonstrates that students' learning effort significantly influences their learning satisfaction. The path coefficient of 0.463 ($t=4.917$, $p<0.0001$) supports H4, indicating that students who exert more effort in their learning experiences tend to experience higher levels of satisfaction. This finding suggests that students who dedicate themselves to mastering the concepts and techniques of business analytics are more likely to derive a sense of fulfillment and contentment.

Moreover, the findings demonstrate that perceived course structure effectiveness plays a crucial role in shaping students' perceived academic performance and learning satisfaction. The analysis reveals a significant and positive impact of perceived course structure effectiveness on both outcomes, providing substantial support for H5 and H6.

The path coefficient of 0.510 ($t=6.133$, $p<0.0001$) for H5 indicates that perceived course structure effectiveness has a strong influence on perceived academic performance in the context of business analytics. A well-structured course, characterized by clear and organized topics and materials, fosters an environment for effective learning. When students encounter a well-designed course structure, they are more likely to comprehend and engage with the content, leading to a higher perception of their academic performance.

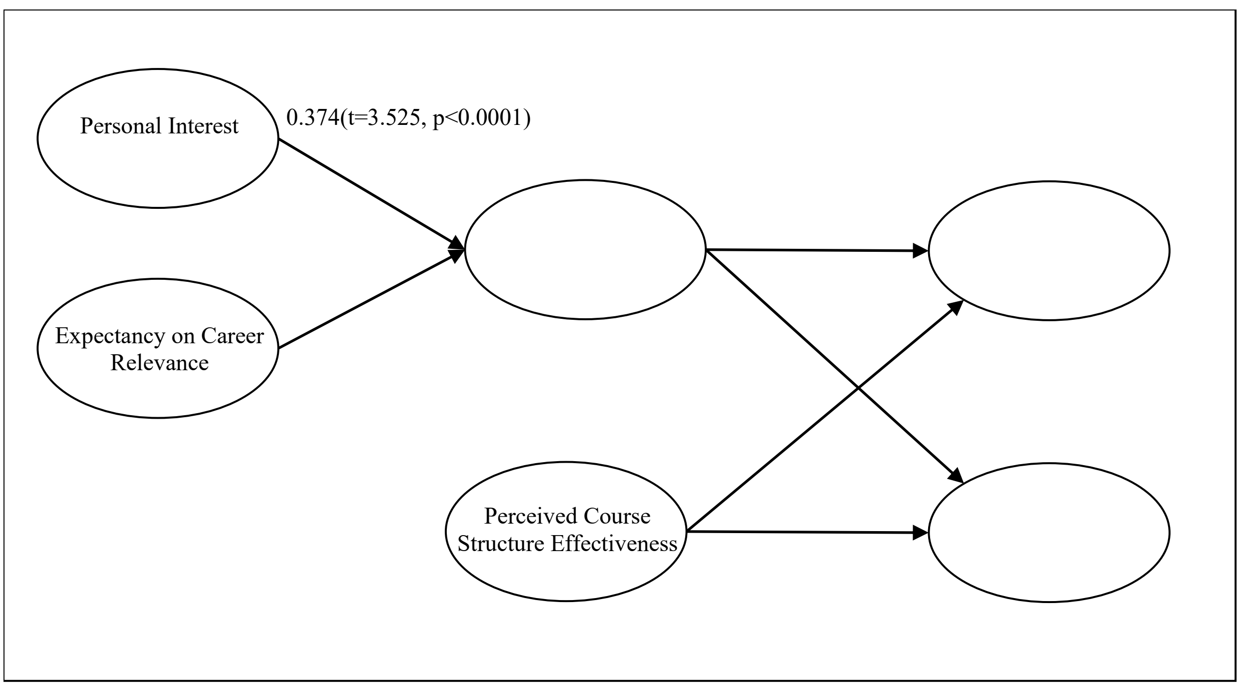

Figure 2 Research Model Test Results

The path coefficient of 0.380 ($t=3.603$, $p<0.0001$) for H6 highlights the positive impact of perceived course structure effectiveness on students' learning satisfaction. When students perceive that the course is well-constructed and supports their learning needs, they are more likely to experience higher levels of satisfaction. Clear instructions, well-structured learning materials, and effective organization of course components contribute to a positive learning experience, ultimately leading to increased satisfaction among students.

The R-squared value of 0.354 for learning effort suggests that the combination of personal interest and expectancy on career relevance accounted for 35.4% of the variance in students' learning effort. This indicates that these factors play a significant role in explaining students' motivation and dedication to learning business analytics.

Furthermore, the combined effects of learning effort and perceived course structure effectiveness accounted for 75.5% of the variance in perceived academic performance and 48.6% of the variance in learning satisfaction. These findings highlight the substantial impact that students' engagement and the organization of the course have on their perceived academic performance and overall satisfaction with the learning experience.

These results emphasize the importance of both individual factors (personal interest, expectancy on career relevance) and contextual factors (learning effort, perceived course structure effectiveness) in shaping students' academic outcomes and satisfaction in the context of business analytics education.

5. CONCLUSIONS

Research Contributions

In this study, our aim was to investigate factors that could influence student learning in the field of business analytics. The major contribution of this study lies in development of the research model that focuses on potential influential factors, namely personal interest, expectancy on career relevance, and perceived course structure effectiveness. Personal interest takes into consideration students' internal passion and intrinsic motivation for the subject of learning. It recognizes that students who have a genuine interest in business analytics are more likely to be motivated and engaged in their learning process. Expectancy on career relevance assesses the extent to which students perceive the alignment between business analytics and their future career needs. It highlights the importance of students recognizing the practical relevance and applicability of the subject matter to their desired career paths. Perceived course structure effectiveness measures the effectiveness of the instructor in organizing and presenting the learning content and materials to students. It acknowledges the role of well-structured and coherent instructional designs.

These factors, derived from different perspectives, cannot be solely determined by either students or instructors. By incorporating them into the proposed research model, we aim to provide a more balanced view of understanding student learning success in the field of business analytics. Furthermore, the research model includes two dependent variables: one focusing on measuring students' learning satisfaction, and the other assessing their performance expectations. By considering both, we can possibly gain a more comprehensive understanding of the impact of the identified factors on student learning experiences.

In addition to the model itself, the empirical testing results can also help solidify our understanding of student learning in business analytics by further validating the proposed relationships within the model. Specifically, the results indicate that all three factors, personal interest, expectancy on career relevance, and perceived course structure effectiveness, have significant and positive impacts on student learning in business analytics. Students who exhibit a higher level of personal interest in the subject are more likely to invest effort into learning it. Similarly, students who perceive a higher level of match between business analytics and their future career aspirations are more motivated to put in the necessary effort. Furthermore, students who exert more effort in their learning endeavors tend to experience higher levels of satisfaction and expect better performance outcomes. Additionally, the study highlights the importance of a well-designed course structure, as it positively influences both student satisfaction and performance expectations.

Furthermore, we adapted and developed measurement items for the constructs used in the business analytics context. Special attention was given to developing measures for personal interest, expectancy on career relevance, and learning effort. We hope that future research will find these measurement items helpful and utilize them in their studies.

Practical Implications

In summary, the study results provide valuable insights for educators in the field of business analytics. To ensure student learning success, educators must focus on specific key factors. Of utmost importance is the role of career relevance, serving as a lever for educators to enhance learning effort, ultimately leading to increased satisfaction and perceived academic achievement.

Compared with other well-established business majors and focuses, business analytics is still relatively new. In recent years, some universities in the US have developed specific programs and majors for it, while others may only now be starting to offer individual courses or certificates related to it. Additionally, there are universities where the discussion about implementing such programs has just begun. Due to this unique characteristic, aligning business analytics education with the job market and students' personal career development may be more challenging compared to traditional business majors. Therefore, clear communication and study plans that help students understand how various business analytics techniques and skills could benefit them in their future careers are of great importance. When teaching specific business analytics classes, educators must make it clear how class materials are relevant to different types of careers because, as found in this study, when students perceive the career relevance of course topics, it increases their learning effort, leading to greater learning satisfaction and perceived academic performance.

Along with the above discussions, faculty teaching business analytics should be intentional about including career relevance early and throughout their courses. It is also important to acknowledge that all students in business analytics classes are not necessarily headed for a business analytics career. That doesn't mean that business analytics will not be part of their career as a marketer or human resource manager. Providing information about how business analytics is involved in all parts of business is suggested and can be achieved via various ways such as inviting guest speakers (Alshare et al., 2015), using data sets on industry applications, and providing related readings such as Google's people analytics (Garvin, 2013).

Additionally, assisting students in formulating a clear career path plan is crucial. Educators can play a pivotal role in guiding students towards business analytics career paths. This can be achieved by providing comprehensive information about various job choices and opportunities related to business analytics. By offering up-to-date insights and industry trends, educators can equip students with necessary knowledge to make informed decisions about their future career endeavors.

Furthermore, educators should prioritize attracting students who possess a genuine interest in business analytics. To foster student interest, educators can highlight the significance of the subject matter and underscore its high demand in the current job market. By emphasizing practical relevance and potential career opportunities associated with business analytics, educators can help motivate students to potentially develop a true passion for the subject.

Finally, a well-designed course structure is critical for maximizing student learning outcomes. Educators should invest time and effort in developing instructional strategies and materials that are engaging, relevant, and aligned with the specific needs of business analytics education. By incorporating real-world examples, practical exercises, and hands-on projects, educators can enhance students' learning experiences and facilitate their mastery of business analytics concepts and skills.

Limitations and Future Research Directions

This study has several limitations that future research could further address, such as the limited set of factors, the use of one class for testing, and the lack of comparisons across students with different backgrounds.

First, future research could expand the current research model by incorporating additional factors from various perspectives. This will help enrich our understanding of student learning in business analytics. For instance, future studies could explore the influence of additional individual characteristics, such as cognitive abilities, motivation, or prior experience, on student learning outcomes.

Furthermore, while this study focused on a specific business analytics class, future research could extend the investigation to different types of business analytics courses. By examining a diverse range of courses, such as introductory-level or specialized courses, researchers can evaluate the generalizability of the proposed model across different educational contexts. Comparing the effects of the model in various course settings would provide insights into factors that influence student learning across different levels and scopes of business analytics education.

Moreover, considering the potential differences between student backgrounds is another important avenue for future research. Investigating the variations in learning outcomes between business students and non-business majors would shed light on the unique challenges and opportunities faced by different student populations. Additionally, comparing undergraduate and graduate students would enable researchers to assess the impact of educational level on the relationship between influential factors and student learning in business analytics.

Another limitation of this study is that we didn't include open-ended questions in our survey to gather more specific information about student learning in the business analytics course. To address this, future research may consider using the interview method for more in-depth qualitative analysis, which could provide us with further insights into the factors influencing student learning in business analytics and the magnitude of their influential power.

In conclusion, this study contributes to the existing literature on business analytics education by developing a research model that encompasses influential factors such as personal interest, expectancy on career relevance, and perceived course structure effectiveness. The empirical results support the significant and positive impacts of these factors on student learning outcomes. While the study has certain limitations, it sets the stage for future research endeavors to further explore and enhance our understanding in business analytics education.

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Appendix A: Measurement Items

Personal Interest

PERINT1: I am genuinely interested in the subject of business analytics.
PERINT2: I have true interest the subject of business analytics.
PERINT3: I have personal interest in the subject of business analytics.

Expectancy on Career Relevance

CAREER1: Understanding business analytics (both concepts and techniques) will advance my future career.
CAREER2: Understanding business analytics (both concepts and techniques) could be important to my future career.
CAREER3: Understanding business analytics (both concepts and techniques) could be relevant to my future career.
CAREER4: Learning business analytics could better prepare me for my future career.

Perceived Course Structure Effectiveness

STRUCT1: The objectives and procedures of this class are clearly communicated.
STRUCT2: The class materials are organized into logical and understandable components.
STRUCT3: The expectations from this class are clearly stated.

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.

Perceived Academic Performance

AP1: I can accomplish my learning tasks effectively in the business analytics class.
AP2: I can accomplish my learning tasks efficiently in the business analytics class.
AP3: I anticipate good grades in the business analytics class.
AP4: Overall, I am satisfied with my performance in the business analytics class.

Learning Satisfaction

SAT1: I am pleased with the business analytics class.
SAT2: I am satisfied with the business analytics class.
SAT3: The business analytics class satisfies my learning needs.