Impact of Course Learning Factors on Student Interest in Business Analytics Careers

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ABSTRACT

Advancements in internet technology have fundamentally changed how companies conduct their business activities, leading us into a business analytics (BA) era. In this article, the authors aim to investigate factors that could shape students’ career choice considerations toward BA jobs after they have been exposed to BA course content in an undergraduate BA course. They investigated various theoretical perspectives, including experiential and active learning theories and social cognitive career theory, and developed a research model. The model testing results show that the organization and logical flow in how the course was designed and delivered, the help offered to manage difficulty of content, and students’ individual learning effort could influence perceived learning outcomes, which in turn, had a significant influence on their learning interest. In addition, increases in both learning interest and subjective norm had positive impacts on career choice considerations, with learning interest having a much stronger influence over subjective norm.

KEYWORDS
Business Analytics (BA), Career Choice Considerations, Experiential and Active Learning, Learning Factors, Social Cognitive Career Theory

INTRODUCTION

Web 2.0, with user-generated and shared content as well as enhanced collaboration, has not only enabled two-way communication between individual Internet users and the cloud, but has also brought tremendous advantages to various aspects of people’s lives and to society as a whole (Chen, 2009). This great revolution has changed how the Internet is used for all kinds of online activities and services, and has led to new ways of thinking such that Internet-based services are now driving comprehensive processes in many different spheres (e.g., Business 2.0, Politics 2.0, Health 2.0, etc.) (Chen, 2009).

Derived from the concept of business intelligence, the term business analytics (BA) was introduced by Davenport (2006), which refers to the use of advanced analytical algorithms, tools, and software to collect, analyze, and act on business data in order to gain insights and drive decision making and problem-solving activities.
Over time, society has experienced three generations of BA, with each generation having its own focus and computing power. The first generation, dubbed Analytics 1.0 (or BA 1.0), is the era of business intelligence in which leading companies started to leverage data management tools and techniques to make sense of structured online business data (Chen & Storey, 2012; Davenport, 2009). The second generation, Analytics 2.0 (or BA 2.0), is the era of “big data” (Davenport, 2009), in which Internet-based social networking companies began leveraging the large amount of unstructured, user-generated data to advance their business activities and facilitate better decision making (Chen & Storey, 2012; Davenport, 2009). Now in the third generation of BA, or Analytics 3.0; this is an era where data-enriched offerings drive business strategy. Here, analytic tools and algorithms are used to make sense of business data and focused upon generating competitive advantages (Davenport, 2009; Goebel et al., 2015). Many firms consider the investment in BA as the top priority in their business strategy development (Turel & Kapoor, 2016).

The great impact and popularity of BA has also significantly influenced the job market (Davenport & Patil, 2012; Turel & Kapoor, 2016) and various industries (Silva et al., 2021). BA has become one of the fastest growing job markets for business school students (Turel & Kapoor, 2016), as organizations need individuals who have a mix of technical background, analytic skill, and comfort with decision making. Unfortunately, a significant gap has been identified between job market demands for BA and the supply of college graduates with the requisite BA training (Jalil & Leen, 2021; Turel & Kapoor, 2016). To address this gap in job market needs, many universities and colleges have started to promote the BA career path by offering BA classes, BA certificates, and even BA-specific majors for those who seek to specialize in this multidisciplinary field.

Unfortunately, little academic effort has been dedicated toward empirically investigating factors that could potentially influence students’ career choice toward BA. Therefore, the authors developed a research model, tested with students who were completing a senior-level, undergraduate, business analytics class that addresses several influencing factors. To develop their research model, they leveraged constructs and theories from several theoretical perspectives, including IS education and career development.

The remainder of this paper is organized as follows: First, the related literature is outlined and a set of hypotheses was developed. Second, details on the research method are provided. Third, data analyses and results are reported. The paper concludes with a discussion of the research contributions, implications, limitations, and future research directions.

RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

Experiential Learning Theory and Active Learning Theory

Experiential learning theory (ELT), developed by Kolb (1984), states that learning is “the process whereby knowledge is created through the transformation of experience” (Kolb, 1984, p. 41). ELT emphasizes the central role of experience in learning and suggests a learning by doing mentality. This theory treats learning as a four-stage process (i.e., concrete experience—CE, reflective observation—RO, abstract conceptualization—AC, and active experimentation—AE), and emphasizes that the learner needs to go through all four stages to internalize knowledge effectively. Here, CE emphasizes the activity of building experiences and suggests that to ensure the learning process is successful, the learner needs to be willing to be actively involved in the experience itself. Such an experience can help the learner to retain facts and new information (McCarthy, 2010). RO emphasizes the activity of reflection and suggests that the learner needs to reflect on the experience itself to facilitate meaningful learning (McCarthy, 2010). AC focuses on the activity of thinking, and emphasizes the importance of conceptualizing the experience in the learner’s mind when applying learned techniques (Itin, 1999; McCarthy, 2010). AE focuses on action and stresses the learner needs to make decisions where and how they apply what has been learned from experiential exercises to specific problem-solving activities (Itin, 1999).
ELT is especially helpful in learner-centered education, and can be used as a guideline to develop effective teaching methods and curriculum (Beard & Wilson, 2002; Cheng et al., 2019). ELT has also been applied in various domains, including nursing education (de Oliveira et al., 2015), computer science education (Konak et al., 2014), environmental science education (Cheng et al., 2019), information systems education (Riordan et al., 2017), and online marketing education (Croes & Visser, 2015).

Another germane learning theory is active learning theory (ALT), which defines active learning as “a method of learning in which students are actively or experientially involved in the learning process” (Bonwell & Eison, 1991). Active learning activities are those that are “course-related, [and something] that all students in a class session are called upon to do other than simply watching, listening, and taking notes [which would be considered passive learning]” (Felder & Brent, 2009, p. 2). Active learning could be considered the opposite of the traditional way of instruction, where students are passive recipients of knowledge delivered by an instructor using mostly one-way communication (Romanow et al., 2020). ALT is very different from traditional instruction and emphasizes the importance of student-centered learning and promotes stronger student engagement (Riordan et al., 2017). Extant literature mentions problem-based learning as an effective method to implement active learning (Prince, 2004; Romanow et al., 2020). When utilizing this method, the problem set serves as the mechanism students will use to actively generate experiences and further their own learning (Romanow et al., 2020).

Previous literature has leveraged ALT for course design and development. For example, Riordan et al. (2017) designed three types of active learning class activities for a junior-level, introductory information systems course, including interactive lectures, problem-solving activities, and projects. In a more recent study on teaching a business intelligence (BI) class, Romanow et al. (2020) examined the impact of active learning on students’ BI skills. Their BI class was designed with the combination of both interactive lectures/discussions and hands-on lab assignments using certain software tools (i.e., Microsoft Power BI, and Smart PLS 2). They developed a research model that was empirically tested, with results showing both active learning assignments and class discussions could significantly influence students’ BI skills (Romanow et al., 2020).

Following this extant work, the authors designed an undergraduate BA class with both interactive lectures/discussions and hands-on lab projects. Here, there was a heavy focus on lab work for students to gain experience and “learn by doing.” This approach directly follows the overall class design presented by Romanow et al. (2020) for their BI course. Specifically, in the course described here, lectures/discussions were used as a foundation to emphasize what is important to consider when designing BA initiatives, while the hands-on lab projects were used as the mechanism for students to learn how to effectively use and apply specific BA techniques and algorithms to address real-world problems.

### Social Cognitive Career Theory

A major goal of this research is to examine factors that could influence students’ choice of a future career in business analytics. One of the most well-known theories of career development is the social cognitive career theory (SCCT) (Lent et al., 1994). SCCT focuses on the interactions among a variety of personal, environmental, and behavioral variables that can influence the process of one’s academic and career pursuits (Lent et al., 1994). This theory has been used in various settings to understand career planning, transition, decision, and development (Wendling & Sagas, 2020). SCCT consists of four distinct but overlapping models, namely the interests model, the choice model, the performance model, and the satisfaction model (Lent, 2013). The first three models were developed first (Lent et al., 1994), with the fourth model added later (Lent & Brown, 2006). Around all these models, three basic building blocks are emphasized, and how they could influence individuals’ career-related interest, choice, performance, and satisfaction are explained, respectively. These building blocks include self-efficacy, outcome expectations, and goals (Lent, 2013; Lent & Brown, 2006; Lent et al., 1994).
Previous research has leveraged SCCT as the framework to explain students’ academic goals and career intentions. For example, Chan (2020) applied SCCT to investigate factors that could influence the career goals of Taiwanese college athletes. The results showed that outcome expectations and self-efficacy could significantly influence students’ vocational interests, which, in turn, influenced their career goals. Interestingly, social support was not a significant factor for consideration. However, in another study by Chan using college athletes but with a much larger sample size, Chan (2018) developed and reported a research model where the impacts of social support, self-efficacy, and career exploration were all found to be significant factors on career choice.

Additionally, Lent et al. (2008) applied SCCT in the computing domain to better understand students’ major choice goals. They examined a group of factors including outcome expectations, self-efficacy, interests, social support, and social barriers. All these factors were found to be significant determinants of major choice goals. In addition, outcome expectations and self-efficacy could significantly influence interests.

In a study on how to inspire students to pursue computing degrees, by leveraging SCCT, Akbulut and Looney (2007) developed and tested a major choice goals model—including outcome expectations, self-efficacy, interest, and choice goals—that was specifically tailored to the computing domain. Model test results showed that both outcome expectations and self-efficacy could influence interest, which in turn, impacted choice goals. No significant direct influence was found from outcome expectations and self-efficacy on choice goals. In another computer field study, Alexander et al. (2011) leveraged SCCT to examine differences in factors affecting career choice between students in computing as compared to other disciplines. They investigated outcome expectations, self-efficacy, interest, and intentions/goals for career choice, and found interest to be the most important factor across both groups. For both groups, interest and outcome expectations were found to be significant factors in influencing intentions/goals for career choice. Yet, the group of computing majors treated self-efficacy as more important than majors in other disciplines.

In a more recent study, Amalia (2023) used SCCT to examine career choice perceptions of younger generation workers who had experienced significant workplace disruption during a major developmental period in their careers (i.e., the COVID-19 healthcare pandemic). Using a narrative review methodology based upon literature reviews of extant work, the author found both cognitive-person and environmental variables had significant influences on career expectations. Following the height of the pandemic, both Generation Y workers (born 1980–1995) and Generation Z workers (born 1995–2010) preferred jobs offering opportunities for well-being and happiness, work-life balance, salary, and financial security, as well as flexible work schedules that match their personal lives, and remote employment opportunity with clear goals and objectives. Interestingly, Generation Y workers expressed low preference for jobs in the public sector, while Generation Z was more comfortable with public sector careers as long as the public sector offers stronger job security than the higher-paid private sector.

Learning Related Factors

The authors included several theoretical constructs from the existing information systems (IS) education literature and the social cognitive career choice theory when developing hypotheses for their conceptual model.

The way a class is structured and organized is of significant importance for enhanced student learning (Alshare et al., 2015; Riordan et al., 2017). Course structure has been studied in the extant IS literature, and specifically refers to the degree of clarity about learning objectives and the organization of course materials (Alshare et al., 2015). Other related constructs have also been examined in IS education literature, including instructor organization (i.e., how good the instructor is at arranging course related materials) (Wall & Knapp, 2014); overall course design (i.e., how well a class has been designed) (Liu et al., 2010); instructor characteristics (Bhuasiri et al., 2012) or called instructor attitude (Cheng, 2012) (i.e., instructor’s own attitude toward the learning platform).
In this study, the authors specifically focus on the organization of course materials and whether course topics are presented to students in a logical manner. BA courses are typically extremely technical, and the related data analytics techniques/algorithms often rely upon sophisticated mathematical and statistical analysis. Consequently, this material could be considered difficult for students to learn. It seems imperative that a well-organized course (including a reasonable and logical flow of course topics over the semester) is instrumental to ensuring successful student learning outcomes. Therefore, the authors hypothesize that:

**H1:** Course organization and logical flow of course topics has a positive impact on student perceived learning outcomes.

It is the authors’ experience that many students may have difficulty and experience frustration as they seek mastery of BA course topics. Perceived difficulty drives the need for additional effort and study to grasp each of the techniques and algorithms covered in the class. Difficulty management refers to how well students proactively manage the perceived difficulty associated with the subject of learning (Wall & Knapp, 2014). Wall and Knapp (2014), in their study of managing difficulty in IS courses, found that effective difficulty management could positively influence students’ perceived learning outcomes.

In this study, instead of addressing difficulty management directly, the authors assess the level of helpfulness provided in the business analytics course toward managing perceptions of difficulty. As difficulty management and helpfulness toward managing difficulty are certainly related, they also expect a positive relationship between helpfulness with managing difficulty and student learning outcomes. Specifically, if a student perceives stronger help with difficulty management, he/she would be more likely to realize enhanced learning outcomes. Thus, the authors hypothesize that:

**H2:** Help managing course difficulty has a positive impact on student perceived learning outcomes.

In addition to efforts made by the instructor and course designer(s) to assist managing course difficulty, students’ own effort in conducting the learning activities could also be an important factor in influencing their leaning outcomes (Al-Azawi & Lundqvist, 2015; Alshare et al., 2015; Fisher & Ford, 1998; Shea & Bidjerano, 2010). Previous research found enhanced learning effort could significantly influence student perceptions of their own cognitive presence in online and blended learning environments (Shea & Bidjerano, 2010). In addition, Al-Azawi and Lundqvist (2015) examined the impact of learning effort on student learning performance in a programming class, and found the impact to be significantly positive. Furthermore, effort was also found to be a significant antecedent in determining behavioral intention in e-learning (Decman, 2015). In this study, the authors would expect students’ own leaning effort to be a significant factor in influencing their perceptions of learning outcomes. Therefore, the authors hypothesize that:

**H3:** Students’ own learning effort has a positive impact on their perceived learning outcomes.

**Career Choice-Related Factors**

As mentioned before, a key theoretical perspective utilized in this study is the social cognitive career choice theory (SCCT) (Lent et al., 1994), as this theory has been widely used to help explain students’ vocational interest and degree selection (Chan, 2018, 2020; Wendling & Sagas, 2020).

When studying students’ choice of computing-related majors and careers, extant literature tailored SCCT to focus on several key variables, including outcome expectations, self-efficacy, topical interest, and choice goals (Akbulut & Looney, 2007; Alexander et al., 2011; Chan, 2018; Lent et al., 2008; Shea & Bidjerano, 2010), as well as social support/influence (Chan, 2018; Lent et
al., 2008; Shea & Bidjerano, 2010). In general, outcome expectations and self-efficacy were found to significantly influence topical interest (Akbulut & Looney, 2007; Alexander et al., 2011; Shea & Bidjerano, 2010). In addition, interest (Alexander et al., 2011; Shea & Bidjerano, 2010) and social support (Shea & Bidjerano, 2010) significantly influence choice goals. As to the direct impacts of outcome expectations and self-efficacy on choice goals, the literature is mixed with certain studies finding a significant positive relationship (Shea & Bidjerano, 2010), while other studies did not (Akbulut & Looney, 2007).

To better fit the research context and purpose of this study, the authors use the terminology “career choice considerations” instead of choice goals. They define career choice considerations here as the willingness of students to consider business analytics as an option for future careers.

SCCT defines outcome expectations as “the imagined consequences of performing particular behaviors” (Lent et al., 1994, p. 83). In lieu of outcome expectations, the authors use a related-term—learning outcomes, which for this study, is defined as students’ expectations on how well they have learned the material and grasped the skills presented in their business analytics course.

Further following SCCT theory, learning interest is defined as an emotion that arouses attention to, curiosity about, and concern with a certain major or career (Akbulut & Looney, 2007; Alexander et al., 2011). In this study, the authors assess the degree to which course exposure and success affects interest in learning more about business analytics, which, in turn, affects career choice considerations. Consequently, the authors posit the following:

**H4:** Students’ perceived learning outcomes have a positive impact on their learning interest.

**H5:** Improvement in students’ learning interest has a positive impact on their considerations of business analytics as a future career.

Social influence is not specifically mentioned in the original four SCCT models (Lent, 2013; Lent & Brown, 2006; Lent et al., 1994). However, extant literature suggests this may be an important environmental variable to consider (Lent et al., 2008). Beyond social support, other research has used a more general view of support, which could include both social and financial support (Shea & Bidjerano, 2010). In an effort to better reflect the goals of this study, the authors use the construct subjective norm which has been well examined in IS education literature (Alshare et al., 2015). Subjective norm is defined as “the perceived social pressure to perform or not to perform a particular behavior…from classmates and other close members to the students” (Alshare et al., 2015, p. 121). Prior work found social norm could significantly influence students’ performance expectancy (Alshare et al., 2015), students’ intention to use e-learning systems (Cheng, 2011), and students’ attitude toward mobile learning (Kumar et al., 2020). Subjective norm was also found to be an important factor in influencing students’ career choice toward engineering jobs (Mishkin et al., 2016).

Following this logic, the authors further apply SCCT theory to the current study, despite the use of more specific and adapted constructs, and hypothesize the following:

**H6:** Students’ perceived learning outcomes have a positive impact on their career choice considerations of business analytics.

**H7:** Students’ subjective norm has a positive impact on their career choice considerations of business analytics.

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

Research Process and Data Collection

A quantitative survey of students completing a senior-level, undergraduate, business analytics course was conducted. The BA course is a newer offering that covers various topics, techniques, and algorithms on business analytics from a data mining perspective. Additionally, the course includes an overview of potential career options in the BA field. The major topics covered in this course include data exploration and visualization, linear regression, logistic regression, association analysis, k-nearest neighbors (k-NN), decision trees, artificial neural networks, and clustering. Each topic area is presented via a thorough lecture and discussion on the mathematical and statistical function of the related algorithms, followed by hands-on lab projects for students to practice applying algorithms/techniques to contemporary business problems using datasets from various domains. Since the course is quite technical and could be deemed difficult for students in general, a significant amount of effort was made to ensure a course design that was heavily organized and methodical, with a strong use of experiential exercises and hands-on labs, so students are supported as they learn.

It should be noted that the course is required for both Information Systems (IS) and Marketing majors, with other business majors having the option to use the course as an elective offering. In addition to analytics, IS students are required to complete other courses, such as e-commerce, enterprise resource planning, and software development, while Marketing majors have different mandatory requirements, including sales management, digital marketing, and social marketing.

This curriculum structure is important as it allows students to explore different perspectives within their majors of study. So, while the population of students here must complete this BA course, these students are also exposed to content in different courses that they may find more appropriate than BA for their future careers. It should also be mentioned that undergraduate business students, no matter their major, share a core business curriculum giving them general exposure to the different business domains.
For this study, the authors focus only upon students who have taken the BA course as analytics, which is not a general business requirement, and students will likely need general exposure to domain content before being comfortable enough to express interest in a career trajectory.

Student participation in the survey was voluntary and extra credit incentives (which comprised a very small portion of the total class points possible) were offered to those who completed the survey. After IRB approval, the survey invitation was sent to all students who were completing the BA class, regardless of course performance, major, or history. The authors intentionally administered the survey two weeks before the end of the semester, as students should have already learned the key topics, techniques, and algorithms related to BA, and should have a clearer understanding of the business analytics field and its related career options. In total, 121 of 167 students completed the survey (for a participation rate of 72.46%). On average, respondents were 21.49 years old and had been college students for 3.67 years, which is representative of senior-level business students at the target university.

Measures of Constructs in the Research Model

The Appendix offers specific details around each of the measurement items included in the conceptual model. All constructs were measured using the 7-point Likert scale, with 1 being “strongly disagree” and 7 being “strongly agree.”

- **Course Organization/Logical Flow:** This measure is focused on the general organization and flow of course topics over the semester. To measure course organization and logic flow, the authors built on the work of Alshare et al. (2015) on course structure, which is defined as “the clarity and organization of the course objectives and materials” (Alshare et al., 2015, p. 121). A 3-item measure was used, including the sample item “How the topics are organized in this class is reasonable.” Chronbach’s alpha is α = 0.865.

- **Help Managing Course Difficulty:** To the best of the authors’ knowledge, no prior studies have specifically empirically measured helpfulness toward difficulty management. Consequently, the authors incorporated a measure developed for this study. For the BA course used in this study, two major and related efforts were made in the course design to help improve student learning outcomes, including highly organized course topics with a smooth transition between topics over the semester, and the inclusion of various types of hands-on lab projects designed to help students learn how to apply the techniques and algorithms to real-world problem solving. Here, the authors developed a 2-item measure so that each major effort is included. A sample item includes, “The hands-on lab component of the class has helped me manage the difficulty in learning business analytics.” Chronbach’s alpha is α = 0.831.

- **Student Learning Effort:** To measure student learning effort, the authors adapted and refined the measurement items from (Alshare et al., 2015) to better fit the purpose of this study. A 3-item measure was used with the following sample item, “I have put my best effort in learning business analytics.” Chronbach’s alpha is α = 0.908.

- **Perceived Learning Outcomes:** To measure student perceived learning outcomes, the authors adapted and refined the measurement items from (Wall & Knapp, 2014). A 3-item measure was used with the following sample item, “I have developed skills in this class that I didn’t have previously.” Chronbach’s alpha is α = 0.907.

- **Improvements in Learning Interest:** Inspired by the idea of assessing the improvement in learning interest from (Jewer & Evermann, 2015), the authors developed their own 3-item measure for this construct. Sample item: “This class has increased my interest in doing more exploration on business analytics-related topics and issues.” Chronbach’s alpha is α = 0.940.

- **Subjective Norm:** A 3-item measure of subject norm was adopted from (Alshare et al., 2015), with minor wording changes to fit the context of this study. A sample item includes “People who are important to me think that I should learn business analytics.” Chronbach’s alpha is α = 0.919.
• Career Choice Considerations: As to career choice considerations, the authors developed their own 2-item measure, which was deemed a stronger fit to the goals of this study. A sample item includes, “After taking this class, I will seriously consider business analytics as one potential direction for my future career.” Chronbach’s alpha is $\alpha = 0.968$.

Table 1 summarizes the descriptive statistics. Overall, descriptive statistics show that students had positive opinions of the BA course and gave particularly high ratings on the organization and flow of the class, as well as on the help offered toward difficulty management.

**DATA ANALYSIS AND RESULTS**

To test the hypothesized research model, the authors used partial least squares structural equation modeling (PLS-SEM), which is a widely used and robust method for causal model assessment (Chin, 1998). Particularly, SmartPLS 3.0 (Ringle et al., 2015) was used to conduct both the measurement model and structural model assessment.

**Measurement Model Assessment**

To assess the measurement model, both reliability and validity tests were performed. Table 2 displays the reliability test results, with Cronbach’s alpha values and item loadings for all indicators of the latent variables in the research model. The Cronbach’s alpha values of all constructs are higher than 0.7. Item loadings are all above the general guideline of 0.7 and are all statistically significant at the p<0.0001 level. These results indicate that all measurement items are reliable indicators of the corresponding latent variables (Au et al., 2008; Chin, 1998; Hair et al., 1998).

Table 3 displays the validity test results, with composite reliability, average variance extracted (AVE), and correlation values across latent variables. The composite reliability values are all above 0.7, suggesting internal consistency (Au et al., 2008). All AVE values are higher than 0.5 (which equals to the square root of AVE being higher than 0.707), which exhibits convergent validity (Chin, 1998). In addition, the square root of AVE for each construct is greater than its correlations with other latent variables, suggesting high discriminant validity (Chin, 1998; Gefen & Straub, 2005).

**Structural Model Assessment**

The research model test results are displayed in Figure 2. As shown, course organization/logical flow could significantly influence perceived learning outcomes, with the path coefficient of 0.299 (p=0.017), lending support to H1. Additionally, both help managing course difficulty and student learning effort had significantly positive impacts on perceived learning outcomes, with path coefficients of 0.392 (p=0.003) and 0.287 (p=0.006), respectively. Thus, H2 and H3 were also supported.

Table 1. Descriptive statistics

<table>
<thead>
<tr>
<th>Construct</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Course Organization/Logical Flow</td>
<td>6.008</td>
<td>1.092</td>
</tr>
<tr>
<td>Help Managing Course Difficulty</td>
<td>5.909</td>
<td>1.134</td>
</tr>
<tr>
<td>Student Learning Effort</td>
<td>5.518</td>
<td>1.304</td>
</tr>
<tr>
<td>Perceived Learning Outcomes</td>
<td>5.518</td>
<td>1.304</td>
</tr>
<tr>
<td>Improvement in Learning Interest</td>
<td>4.879</td>
<td>1.724</td>
</tr>
<tr>
<td>Subjective Norm</td>
<td>4.871</td>
<td>1.591</td>
</tr>
<tr>
<td>Career Choice Considerations</td>
<td>4.397</td>
<td>1.929</td>
</tr>
</tbody>
</table>
Perceived learning outcomes showed a significant impact on improved learning interest, with a path coefficient of 0.713 (p<0.0001), indicating support for H4. The impact of improvement in learning interest was also found to be significant on career choice considerations, with a path coefficient of 0.582 (p<0.0001), and lending support for H5. On the other hand, no significant direct influence was
found from perceived learning outcomes to career choice considerations, so H6 was not supported. It should be noted that this does not mean that learning outcomes would have no or little influence on career choice considerations. The significance of H4 and H5, together with the insignificance of H6, suggests a full mediation effect of improvement in learning interest on the impact from learning outcomes to career choice considerations.

As to the impact of subjective norm on career choice considerations, the result showed a path coefficient of 0.188, with p-value of 0.056, which is on the borderline of being statistically significant. This may suggest that subjective norm could be included as a factor to consider when examining students’ career considerations on business analytics; however, its impact may not be overly strong, especially when compared to improvement in learning interest.

The R-squared value of 0.689 on learning outcomes indicates that course organization/logical flow, help with difficulty management, and student learning effort explained 68.9% of the variance of perceived learning outcomes combined, which then in turn explained 50.8% of the variance of improvement in learning interest. In addition, improvement in learning interest and subjective norm combined explained 60.0% of the variance of career choice considerations.

**DISCUSSION**

**Research Contributions**

This study has made several contributions to the research field. The first contribution is the combination of multiple theoretical perspectives, which were used to build the conceptual model. Using both constructs and theories in computing education and career development, the authors leveraged the experiential learning theory (Kolb, 1984) and active learning theory (Bonwell & Eison, 1991), which...
were applied to BA course design and career choice interest. To identify specific factors that could influence students’ career choice considerations on business analytics, the authors leveraged the social cognitive career theory (Lent et al., 1994) and related theoretical constructs from the IS education literature. Specifically, three learning-related independent variables—course organization/logical flow, help managing course difficulty, and student learning effort, were examined and found to be significant determinants of students’ perceived learning outcomes. Based on the social cognitive career theory, two factors—improvement in learning interest, and subjective norm—were found to be able to influence student considerations of business analytics as a potential career path. A third factor—perceived learning outcomes—while not statistically significant as a direct factor still seems like it could potentially be a determinant of career choice decisions (via the mediation of improvement in learning interest).

The second contribution is the development of the proposed research model, which incorporates the identified constructs from different theoretical perspectives into a nomological network. The model was then empirically tested with students who were about to complete a senior-level business analytics course. The results suggest that the degree to which business analytics class and its topics were organized and communicated over the semester could have a significantly positive impact on students’ perceived learning outcomes. As expected, the level of helpfulness that the course provided to students to help them manage difficulty also suggested a significant influence on students’ learning. In addition, students’ own learning effort also appeared to positively shape their perceived learning outcomes. These results are generally consistent with findings in existing IS education literature (Alshare et al., 2015; Shea & Bidjerano, 2010; Wall & Knapp, 2014), although it should be mentioned again that the authors measured help with difficulty management instead of difficulty management itself and they measured course organization/logical flow of concepts instead of the more generally used construct of course structure.

Additionally, the second half of the conceptual model was based on the social cognitive career theory (Lent et al., 1994). Although the authors measured the improvement of learning interest instead of learning interest itself, and model test results generally indicated that social cognitive career theory was also highly applicable to the field of business analytics. Specifically, learning outcomes had a significant impact on improvement in business analytics learning interest, and improvement in learning interest and subjective norm were two significant influential factors on student considerations of BA as a career option. These results are generally consistent with existing studies, which have applied and validated social cognitive career theory (Lent, 2013; Lent & Brown, 2006; Lent et al., 1994). Mixed results were found in previous literature about the impact of social, environmental factors on choice goals and intentions (Chan, 2018, 2020). Thus, the relatively weak and borderline influential power of subjective norm is somewhat expected. In addition, the non-significant direct impact from learning outcomes to career choice considerations suggested a full mediation effect of improvement in learning interest.

A final contribution is that the authors developed, operationalized, and examined several important constructs in the proposed research model. Specifically, considering the technical and difficult-to-learn nature of business analytics classes, they used the construct of course organization/logical flow of topics instead of a more general measure—course structure (Alshare et al., 2015), and, consequently, developed items for measurement. Similarly, the authors developed measure items for the construct of help managing difficulty instead of using a general difficulty management measure (Wall & Knapp, 2014). Additionally, instead of using the general construct of interest (Akbulut & Looney, 2007; Alexander et al., 2011), the authors focused on improvement of learning interest and developed measurement items accordingly. For the dependent variable, they used career choice considerations and developed measurement items in lieu of the general choice goals (Lent, 2013; Shea & Bidjerano, 2010). The authors believe these constructs are better representative of this study and allowed them to link course design and student efforts to inevitable career choice interests. The
authors hope these construct modifications and their consequent item measures can be helpful for future research studying determinants of students’ career choices.

Practical Implications

The current study offers several practical implications as well. In academia, inevitable student career interests are not always considered germane to how courses are conceptualized, designed, and delivered. In fact, course objectives are frequently theory-based, and linking course content to specific career paths can be criticized as a “trade school” mentality. Perhaps this mindset should be reconsidered, especially in today’s environment where the value of a university education is sometimes questioned as too expensive, too lofty, and not directly tied to a specific career path. BA offers a particularly interesting opportunity to link course design and delivery to career interests as analytics, which is a “hot” field where specific skills and knowledge are highly valued by potential employers. While the right course content is certainly critical to inevitable success in the BA field, the current study investigates other factors that likely lead to ongoing career interests and inevitable career selection. As expected, learning effort was positively associated with course learning, yet learning itself was, in a surprising manner, not strongly related to career choice consideration. Perhaps, this is because students, in general, have trouble translating what they have learned into specific career paths. This could also be a result of business students seeing a wide variety of career options available to them.

Regardless, for students to perceive BA learning outcomes as having value, they need a strong personal work ethic with enhanced learning efforts, partnered with well-designed and logical classes that have built-in help mechanisms. Satisfaction with learning outcomes likely leads to better confidence and higher levels of self-efficacy, which seem necessary to trigger ongoing interest in a particular field—especially with a multi-disciplinary area like BA. Inspiring ongoing interest is critical, especially if the end game is to inspire students to consider specific career trajectories. Here, students need to explicitly understand the value of what they are learning and how specific skill acquisition aligns with their desired career path.

Additionally, one cannot underestimate the power of certain social and environmental factors in establishing future career interests. With a career orientation, it is critical that students see the social and environmental value of their career choices, as interest in a subject alone may not be enough to inspire them toward certain careers. In many ways, the course instructor can serve as social and mental support for their students as well. Professor opinions on BA were included when considering how subjective norms were measured. By offering enhanced support systems and opportunities to help students manage difficulty, BA course instructors can inspire students toward stronger interest, which was, by far, the biggest component of career choice variance in the conceptual model.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The current study has several limitations. It is certainly possible that completing a course in BA could amplify career considerations toward an analytics career. Consequently, it would be particularly interesting to examine career choice-related behaviors when comparing students with BA course experience with general business students who have less exposure to analytics content. Additionally, the level of study may have an impact as well, with graduate students likely conceptualizing career choice differently than undergraduate students who have fewer work and life experiences. Future research should investigate an expanded group of students, including graduate students and majors from different business domains. Specifically, the authors suggest a cross-pool comparison study examining differences in professional career-related options when comparing students who have studied analytics with those who have not.

Another potential limitation of this study is that the authors investigated “career interest” by using a course learning/student experience perspective. While the authors find this perspective to be
particularly valuable and practical, as course instructors have control over how content is delivered and can help shape student experience via course design, future work should expand beyond an experience-based perspective to include market-based factors affecting career choice. Luckily, a clear career trajectory is currently aligned with the analytics domain, so this work could be significantly strengthened by including factors beyond student experience and preferences, such as salary structure, job security, location, and upward mobility. Additionally, many careers are being disrupted by advanced technology (e.g., automation, robotics, and artificial intelligence-based systems), so it seems probable that future career interest and inevitable career choices will be impacted by perceptions of career longevity and the robustness of career paths to withstand uncertain market needs.

Beyond current limitations, the authors see several potential ways to expand upon the current study. For example, future research could extend the conceptual model to other technical courses and other academic domains. This work would be valuable as it would allow deeper understanding of student career choices and would expand the generalizability of insights beyond analytics.

Additional factors could also be investigated as extensions of this research model. For example, future research could investigate the impact of self-efficacy as a potentially rich source of variance for how students make career choices. The authors excluded self-efficacy in their model because BA is a relatively new subject, and it is rare for undergraduate students to have prior experience in the field. In addition, they perceived that self-efficacy would be low as BA is considered challenging by students. That said, certainly student assessments of their own self-efficacy are at play when they make critical decisions about their future careers. If a student perceives they are not competent completing certain types of work, they will likely shy away from that work and focus on areas where they perceive higher competence instead.

Future research should also incorporate longitudinal and/or cross-cultural studies to examine changes in students’ career choice considerations over time and to investigate any possible cultural differences. The addition of a longitudinal design may be helpful in identifying other exogenous factors that drive career choice considerations. In addition, applying and testing the proposed research model using learners from different cultural backgrounds, nationalities, and geographic locations would add to the richness and generalizability of the career choice literature.

Lastly, the authors must also mention that any future work in this domain must consider the interaction of analytics and artificial intelligence-based systems. With the recent arrival of ChatGPT, and comparable systems, the business world is realizing the tremendous power and likely disruption coming from expanded use of AI. It is widely believed that AI will have a significant impact on both daily life and the way modern business is conducted. Future research should examine not only career-related choices and opportunities in the field of BA, but also those related to general AI.

CONFLICT OF INTEREST

We have no known conflict of interest to disclose.

AUTHOR NOTE

We have no known conflict of interest to disclose.

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REFERENCES


APPENDIX: MEASUREMENT ITEMS

Course Organization/Logical Flow (of Topics)

ORGLOG 1: How the topics are organized in this class is reasonable.
ORGLOG 2: The course organization is good.
ORGLOG 3: The logic flow of topics covered in this class has helped my learning process (from relatively easy topics to more difficult topics) to be smooth.

Help Managing Course Difficulty

DIFHELP1: The way the course is organized has helped me manage the difficulty in learning the class material.
DIFHELP2: The hands-on lab component of the class has helped me manage the difficulty in learning business analytics related technical skills.

Student 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.

Learning Outcomes

LOUT1: I have learned a lot in this class.
LOUT2: I have developed skills in this class that I didn’t have previously.
LOUT3: I am happy with my learning in this class.

Improvement in Learning Interest

INT1: This class has increased my interest in learning business analytics.
INT2: This class has increased my interest in doing additional reading on business analytics related topics.
INT3: This class has increased my interest in doing more exploration on business analytics related topics and issues.

Subjective Norm

NORM1: People whose opinions I value (such as your parents, professors, friends, classmates, and managers and co-workers—if any) would like me to learn business analytics.
NORM2: People who are important to me think that I should learn business analytics.
NORM3: People who influence my behavior think I should learn business analytics.
Career Choice Considerations

CHOICE1: After taking this class, I will seriously consider business analytics as one potential direction for my future career.

CHOICE2: After taking this class, I am more willing to consider and potentially take the business analytics area for my future career.

CHOICE3: After taking this class, I am more interested in choosing the business analytics area for my future career.