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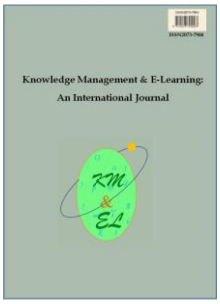

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Modeling students' intentions to learn data science: Using an extended theory of planned behavior

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Abstract: Academic and practitioner interest in data science has increased considerably. Yet scholarly understanding of what motivates students to learn data science is still limited. Drawing on the theory of planned behavior, we propose a research model to examine the determinants of behavioral intentions to learn data science. In the proposed research model, we also included constructs that are closely related to behavioral intentions. We used PLS-SEM to test the research hypotheses. The antecedents to behavioral intentions were found to explain 53% of variance in students' behavioral intentions to learn data science. Among the constructs in the research model, the findings indicate that only attitude toward learning data science and perceived usefulness are positively related to behavioral intentions. The results also indicate that the influence of core constructs of the theory of planned behavior (e.g., subjective norm and perceived behavioral control) on behavioral intentions may not be as strong under certain circumstances. The findings contribute to an initial understanding of the drivers of students' intentions to learn data science and open the door to new scholarship.

Keywords: Behavioral intentions; Data science; Theory of planned behavior; Motivations

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1. Introduction

User experiences are increasingly mediated through technology (Bazelais et al., 2022; Lemay et al., 2019a). At the same time, advances in computing power and computational methods have further expanded access to data in various forms (Abkenar et al., 2021; Zhang et al., 2021; Zhu et al., 2023). Indeed, data is suffusing everything (Kushwaha et al., 2021). Given the transformative potential in data, there is a need to put data to work in new ways to aid data-backed decision-making (Doleck et al., 2020; Khan et al., 2022). Data Science—“an [sic] multidisciplinary field that lies between computer science, mathematics and statistics, and comprises the use of scientific methods and techniques, to extract knowledge and value from large amounts of structured and/or unstructured data” (Martinez et al., 2021, p. 2)—plays a critical role in facilitating efforts to move forward with data (Saltz & Krasteva, 2022). In fact, a recent report by Anaconda (2021) notes that more companies and individuals are embracing data science. Accordingly, data science has received increasing academic and practical attention in recent years (Saura, 2021).

A major development in recent years has been an increased push to equip students with data science skills. Educational stakeholders increasingly recognize the important implications of data science for the benefit of learners and beyond; as such, recent academic research has proliferated around data science education (Donoghue, Voytek, & Ellis, 2021). To this point, Markow et al. (2017) note that “educators and training providers must proactively respond to the rising demand for analytics skills with programs that prepare students for the analytics-related roles of today and tomorrow, while existing workers must continuously monitor in-demand analytics technologies and update their skillsets according” (p. 4). In fact, in recent years, researchers have dedicated increasing attention to promoting data science education (Engel, 2017) to prepare students to work with data (Wise, 2020).

For students to develop important competencies, such as data science (Bonnell, Ogihara, & Yesha, 2022), it is imperative to understand the factors students consider important in gravitating to data science. We note a general lack of attention paid to understanding and uncovering the salient factors that shape students’ motivations to learn data science. To this end, the present study examined the factors that play an influential role in students’ behavioral intentions to learn data science. Such an exercise has important implications for both understanding student readiness for data science and for guiding students to learn data science. In the current study, we developed a research model, based on the theory of planned behavior, to explain how salient antecedents influence students’ intentions to learn data science. We extend the theory of planned behavior with additional salient variables.

2. Purpose of the study

Although it is clear that there are "large numbers of students who are interested in learning and practicing data science" (Donoghue, Voytek, & Ellis, 2021, p. S28), what motivates or inhibits students to learn data science has been largely neglected. Our research addresses this gap. In the present research we seek to understand the factors influencing students' behavioral intentions to learn data science through the theoretical lens of the theory of planned behavior, a widely used theoretical framework to examine behaviors in various contexts. Teasing out the drivers of students' intentions to learn data science brings clarity to our understanding of student readiness for learning data science.

In this article, we strive to expand our understanding of students' intentions to learn data science. We address the following research question: What are the determinants of students' intentions to learn data science?

3. Background

Educational research has long been interested in understanding students' motivations for learning (Dörnyei, 2003). One place to begin for insight into this is to scope the factors that have relevancy on behavior. We know from the literature that behavioral intentions—defined "as the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw & Davis, 1985, p. 214)—are regarded as key immediate predictors of behavior (Ajzen & Madden, 1986). As such, it is important to understand the factors driving behavioral intentions, with research in different fields and contexts highlighting this importance (Habibi et al., 2023; Petrick, 2004; Son et al., 2015; Vlachos & Vrechopoulos, 2008). Several frameworks for modeling antecedents to behavioral intentions have been put forward in the literature (Venkatesh et al., 2003) and a large body of literature has accumulated examining the utility of such frameworks (Doleck et al., 2018; Webb & Sheeran, 2006).

To model user behaviors, it is important to ground the research in well-established frameworks (Lemay et al., 2019b). Researchers across multiple disciplines have drawn upon the theory of planned behavior to model behaviors (Armitage & Conner, 2001). In this perspective, we examine how antecedent factors might affect behavioral intentions towards a specific behavior. Behavioral intentions hold a key position in the theory of planned behavior as it has been shown to be reliably related to subsequent behavior (Ajzen, 1985; Ajzen & Madden, 1986).

3.1. Theory of planned behavior

The use of the theory of planned behavior has been prevalent for a long time for understanding the drivers of behavioral intentions. The theory of planned behavior builds off foundational work by Azjen and Fishbein (1972)'s theory of reasoned action. Ajzen (1985) provided a way to illuminate the underlying psychological processes that explain behavioral decisions by linking beliefs to behavior. Succinctly, the theory of planned behavior "details the determinants of an individual's decision to enact a particular behavior" (Conner & Armitage, 1998, p. 1429). To this point, planned behaviors are intentional, which are predicted by behavioral intentions. Ajzen (1991) notes that "a central factor in the theory of planned behavior is the individual's intention to perform a given behavior" (p. 181). In other words, intention is considered the most proximal determinant of behavior. Understanding the drivers of intentions is key to understanding the intended behavior.

The theory of planned behavior (Ajzen, 1985; Ajzen, 1991) holds that behavioral intentions are influenced by attitude toward the behavior, subjective normative pressure, and perceived behavioral control (Ajzen & Madden, 1986). Attitude toward the behavior describes "the degree to which a person has a favorable or unfavorable evaluation of the behavior in question" (Ajzen & Madden, 1986, p. 454). Subjective norms relate to "the perceived social pressure to perform or not to perform the behavior" (Ajzen & Madden, 1986, p. 454). Perceived behavioral control refers to "the person's belief as to how easy or difficult performance of the behavior is likely to be" (Ajzen & Madden, 1986, p. 457). Much work educational research has placed intentions at the center of interest (Cheng et al., 2019). Support for use of the theory of planned behavior can be found in several different studies related to teaching and learning (Cheon, Lee, Crooks, & Song, 2012; Knauder & Koschmieder, 2019; Ly et al., 2023).

3.2. Integrating factors related to behavioral intentions

While prior researchers concur that the theory of planned behavior can be a useful vehicle for predicting a variety of behaviors, others have noted the need to go beyond the original formulation of the theory of planned behavior (Chen & Tung, 2014). Rather than engage in the direct application of the theory of planned behavior, some modifications are encouraged, especially, when integrating additional salient variables can increase the explanatory power of research models (Doleck et al., 2017 a and b). Indeed, scholars have suggested that there may be value in incorporating additional relevant determinants of behavioral intentions in the TPB framework (Conner & Armitage, 1998). As such, we incorporate additional salient constructs from other theoretical frameworks to develop an augmented research model. We draw upon two additional relevant theories: Technology Acceptance Model (Davis et al., 1989) and Social Cognitive Theory (Bandura, 1997). We focus on these theories because of the key positioning of behavioral intentions in these theories.

Our review of the literature points us to several examples of studies that rely on the two aforementioned frameworks (Boutaky & Sahib Eddine, 2023; Papakostas et al., 2023). From this literature, we identified two additional determinants of behavioral intentions: perceived usefulness from the technology acceptance model (Davis et al., 1989) and outcome expectancy from the social cognitive theory (Maddux et al., 1986). Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis et al., 1989, p. 320). There is a well-documented link between perceived usefulness and behavioral intentions (Venkatesh et al., 2003). Several studies from the education literature support this link (Doleck, Bazelais, & Lemay, 2016; Saadé & Bahli, 2005). Outcome expectations, on the other hand, "are the results or desired outcomes of intentional actions in which individuals choose to engage" (Fouad & Guillen, 2006, p. 131). Work in the education literature has also laid the foundation for linking outcome expectancy to behavioral intentions (Lin & Chiou, 2010; Stone & Bailey, 2007). These examples motivate the need to go beyond the original formulation of the theory of planned behavior. Taking all of this into account, we propose a research model in the following section.

4. Research model and hypotheses

The current work builds on and extends the theory of planned behavior (Ajzen, 1985; 1991) to develop and test a research model to unearth the drivers of students' behavioral intentions to learn data science. A research model illustrating the links between the variables is provided in Fig. 1. Based on prior research, the relationships in the research model are formulated as follows:

H1: Attitude toward the behavior is positively related to behavioral intentions

H2: Subjective norm is positively related to behavioral intentions

H3: Perceived behavioral control is positively related to behavioral intentions

H4: Outcome expectancy is positively related to behavioral intentions

H5: Perceived usefulness is positively related to behavioral intentions

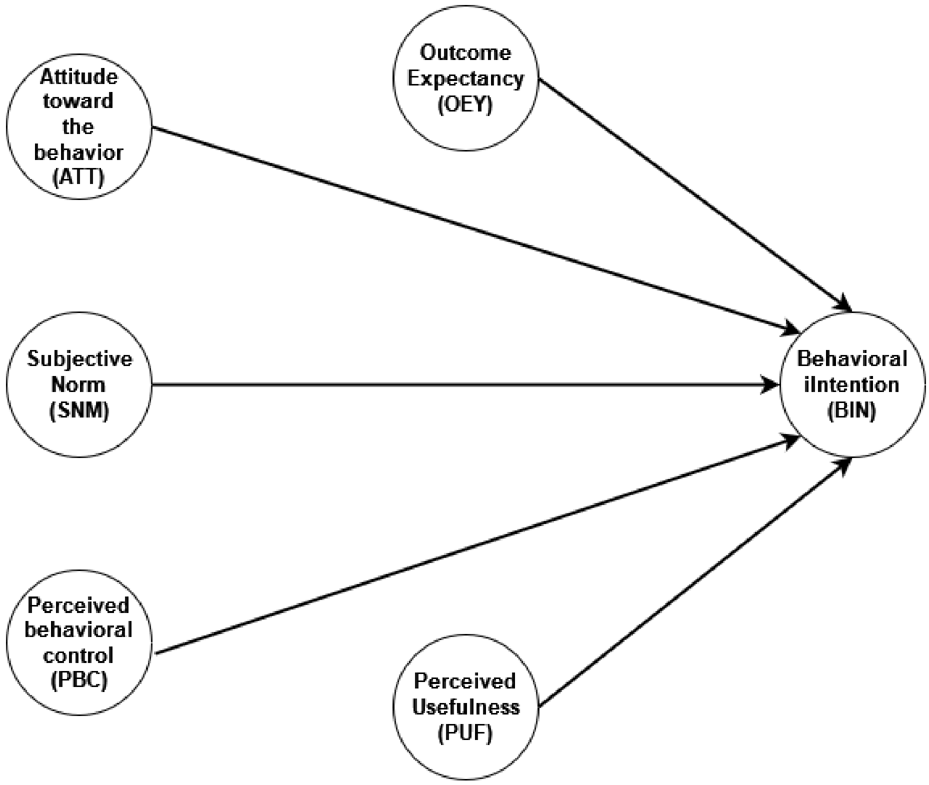

Fig. 1. Research model

5. Results

5.1. Participants and procedure

Participants were recruited through instructors' announcements in classes and email invitations. Participants (N = 71) in the present study were students from a southwestern university who volunteered to participate. The convenience sample included 12 females, 59 males; participants had a mean age of 22.93 years (SD = 5.48). In terms of level of study, 19.7% were Freshman, 12.7% were Sophomore, 19.7% were Junior, and 47.9% were Senior. Majority of the participants were STEM majors.

5.2. Measures

Participants completed a self-report questionnaire. All the variables in the present study were scored on a 7-point Likert-type rating scale (1 = strongly disagree to 7 = strongly agree), with participants being asked to rate a series of statements. We adapted the items developed by Venkatesh et al. (2003) to capture Subjective Norm, Perceived Behavioral Control, and Attitude toward the behavior. Items for Outcome Expectancy were adapted from Cheng and Chu (2014) and items for Perceived Usefulness were adapted from Lin et al. (2021).

6. Analysis and findings

Partial least squares structural equation modeling (PLS-SEM; Guenther et al., 2023; Henseler et al., 2016) was used in the present study as it is well suited for exploratory studies and provides a convenient method to estimate relationships of all constructs concurrently. A two-step approach to data analysis was adopted: the measurement model was assessed in step 1 followed by the evaluation of the structural model in step 2. WarpPLS software (Kock, 2022a) was used for measurement and structural model evaluation. We followed best practices for evaluating and reporting PLS-SEM results as recommended in the literature (Henseler et al., 2016; Kock, 2022b). The following subsections report the results of the measurement and structural model.

6.1. Assessment of the measurement model

Measurement model validation helps to verify the validity and reliability of the study's construct measures. Table 1 presents model fit statistics; we find that the data fit the model well (Kock, 2022b). We inspected the individual item loadings, composite reliability, average variance extracted, and discriminated validity. Table 2 provides the measurement scale characteristics, which were assessed against recommended thresholds (Henseler et al., 2016; Kock, 2022b). Item reliability was established as the loadings of all items exceeded 0.70 (loading values not meeting the threshold value of 0.70 were removed). Composite reliability coefficients of the measures exceeded the threshold value of 0.70, providing an indication of adequate internal consistency reliability. Convergent validity of the constructs was established as all average variance extracted (AVE) values exceeded the threshold value of 0.50.

Table 1
Model fit statistics

Measure	Values	Recommended Criterion
Average path coefficient (APC)	0.183, $p = 0.027$	Acceptable if $p < 0.05$
Average R-squared (ARS)	0.530, $p < 0.001$	Acceptable if $p < 0.05$
Average adjusted R-squared (AARS)	0.494, $p < 0.001$	Acceptable if $p < 0.05$
Average block VIF (AVIF)	2.137	Acceptable if <= 5
Average full collinearity VIF (AFVIF)	2.065	Acceptable if <= 5

Table 2
Measurement scale characteristics

Construct	Items	Loadings	Composite reliability (CR) coefficients	Average variance extracted (AVE)
Behavioral intention (BIN)	BIN1	0.939	0.964	0.900
	BIN2	0.960		
	BIN3	0.946		
Attitude toward behavior (ATT)	ATT1	0.949	0.950	0.864
	ATT2	0.959		
	ATT3	0.878		
Subjective norm (SNM)	SNM1	0.948	0.946	0.898
	SNM2	0.948		
Perceived behavioral control (PBC)	PBC1	0.727	0.826	0.614
	PBC2	0.816		
	PBC3	0.805		
Outcome expectancy (OEY)	OEY1	0.861	0.877	0.704
	OEY2	0.835		
	OEY3	0.820		
Perceived usefulness (PUF)	PUF1	0.781	0.854	0.661
	PUF2	0.866		
	PUF3	0.789		

Discriminant validity—to test whether each construct is unique and different from other constructs—was assessed by the Fornell-Larcker criterion (Fornell & Larcker, 1981). All the diagonal values are greater than the off-diagonal numbers in the corresponding rows and columns (Table 3); thus, established discriminant validity. In summary, the model displays good measurement properties.

Table 3
Discriminant validity test

	BIN	ATT	SNM	PBC	OEY	PUF
BIN	0.949	0.627	0.456	0.251	0.503	0.644
ATT	0.627	0.929	0.358	0.209	0.644	0.681
SNM	0.456	0.358	0.948	0.290	0.131	0.466
PBC	0.251	0.209	0.290	0.783	0.156	0.223
OEY	0.503	0.644	0.131	0.156	0.839	0.675
PUF	0.644	0.681	0.466	0.223	0.675	0.813

6.2. Assessment of the structural model

After evaluating the measurement model, we estimated the structural model. We examined the variance inflation factor (VIF) values and found that there was no indication of multicollinearity issues as VIF values were below 5; as per Kock (2022b), "it is recommended that VIFs be lower than 5; a more relaxed criterion is that they be lower than 10" (p. 98). There was an acceptable level of predictive relevance as Q2 coefficient values exceeded zero (Kock, 2022b). In terms of the target endogenous variable variance, we note the following from Fig. 2: the coefficient of determination, R2, is 0.53 for BIN. Thus, the antecedent variables explain 53 % of the variance in BIN.

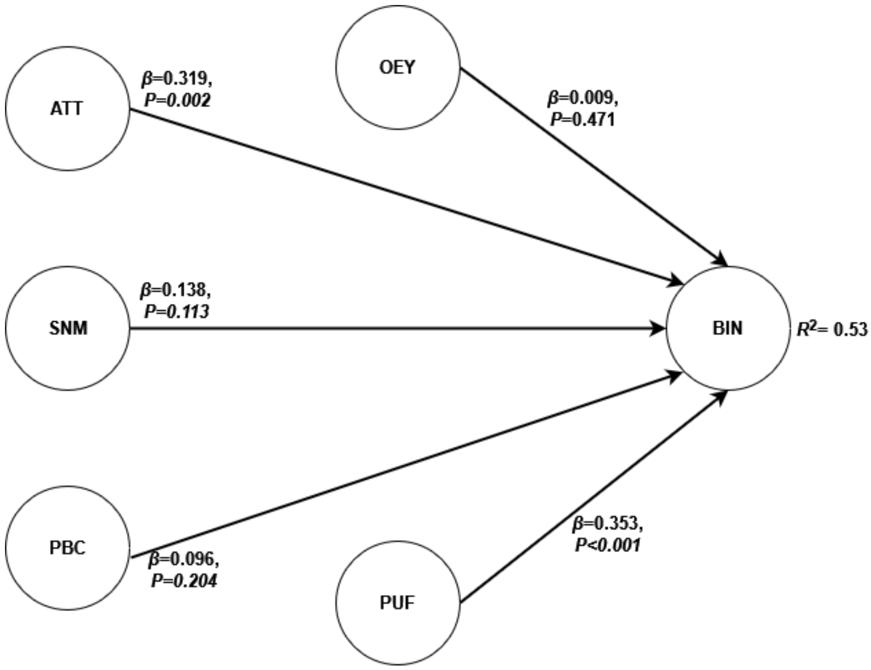

Fig. 2. Structural model results

Table 4
Hypothesis testing

Hypothesis	Path	Path coefficient (*β*)	*p* value	Effect size (f^2)	Result
H1	ATT→BIN	0.319	p = 0.002	0.202	Supported
H2	SNM→BIN	0.138	p = 0.113	0.064	Not Supported
H3	PBC→BIN	0.096	p = 0.204	0.027	Not Supported
H4	OEY→BIN	0.009	p = 0.471	0.005	Not Supported
H5	PUF→BIN	0.353	p < 0.001	0.233	Supported

We provide a summary of the results of hypothesis testing in Table 4 and include the following elements: path coefficients (β, path significance (p-value), and effect size (f^2). We use the guidelines proffered in the literature apropos assessment of f^2: values of 0.35, 0.15, and 0.02 indicate large, medium, and small effect sizes, respectively (Cohen, 1988). When we examine Table 4 and Fig. 2, we note that not all hypotheses were empirically supported. We glean several insights from our analysis, which we summarize below:

- ATT (medium effect size) and PUF (medium effect size) are positively related to BIN
- The native constructs from the theory of planned behavior (SNM and PBC) are not significantly related to BIN
- The association between OEY and BIN is not significant

- The constructs in the research model explain 53% of the variance in BIN

We found that ATT (medium effect size) and PUF (medium effect size) were positively related to BIN but no other factors were found to be significantly related to BIN. The native constructs from the theory of planned behavior, SNM and PBC, were not significantly related to BIN. Further, the association between OEY and BIN was not significant. All together the constructs in the research model explained 53% of the variance in BIN.

7. Discussion

The importance and relevance of data science raises the question: what motivates students to learn data science? To address this question, we modeled students' intentions to learn data science using the theory of planned behavior (Ajzen, 1985, 1991) as a guiding framework to examine the factors influencing students' intentions to learn data science.

Out of the five hypotheses, only two were supported: H1 and H5. That is, among the constructs in the research model, the findings indicate that only attitude toward learning data science and perceived usefulness are positively related to behavioral intentions. Recent work on investigating the factors that influence students' intentions to learn artificial intelligence found support for the two links: (1) attitude and behavioral intentions and (2) perceived usefulness and behavioral intention (Sing et al., 2022). Constructs that did not influence behavioral intentions, for example, subjective norm, highlight the need to further scrutinize such constructs when investigating links to behavioral intentions. Findings from a meta-analysis on the theory of planned behavior suggest that subjective norm tends to be a weak indicator of intentions (Armitage & Conner, 2001). It is important to note that the explained variance of behavioral intentions is in line with previous research undergirded by the theory of planned behavior (Sing et al., 2022).

The findings of the present study are particularly interesting as it suggests that the core factors are not always central to planned behavior. In learning data science, we seemingly act for reasons that do not have to do with subjective norm or perceived behavioral control or outcome expectancy. Thus, neither means nor ends but favorable attitudes towards an activity may suffice. These confirm observations of the incompleteness of TPB (Chen & Tung, 2014). We may explain these findings by having recourse to the concepts of intrinsic and extrinsic motivation from self-determination theory (Ryan & Deci, 2000). Intrinsic motivation refers to "the inherent tendency to seek out novelty and challenges, to extend and exercise one's capacities, to explore, and to learn (Ryan & Deci, 2000, p.70)", whereas extrinsic motivation refers to performing "an activity in order to attain some separable outcome (Ryan & Deci, 2000, p.71)". These concepts help to understand how individuals may sustain the motivation for learning data science over the long term.

Data science is not inherently simple, it requires a specific determination; and we see that in the strong association between attitude and perceived usefulness. To want to learn data science, requires a favorable attitude and a view of the utility of the activity, as our results demonstrate. However, the notion of utility is wrapped up in the individual's perceptions of the activity (Lemay et al., 2019 a and b). Given this, it will be interesting to study the relation of goal orientation to behavioral intentions to learn data science, as it is concerning that models of antecedents to behavior are limited to explaining less than half of the variance (Venkatesh et al., 2003). Previous studies (Keong & Hirst, 2010; Tan,

2001) suggest that goal orientations are positively related to behavioral intention for innovation adoption (Keong & Hirst, 2010). It is possible that many antecedents to important decisions requiring a long-term commitment are much too idiosyncratic to model, but it is likely that our syncretic model has not considered other factors or sources of motivation. Motivation researchers have advanced numerous typologies of motivational behavior (Eccles & Wigfield, 2002), from expectancy-value theory to goal orientation and achievement motivation, and self-determination theory invoked earlier. Thus, it is likely that individuals find motivation for learning data science from intrinsic and extrinsic sources, from personal interest to professional advancement.

7.1. Limitations and future directions

Understandably, our research has limitations, which open avenues for future research. First, the small convenience sample is a limitation. In addition, the current study relied on a sample of STEM students. It may be fruitful for researchers to replicate the findings using larger samples from other groups. Second, while we restrict our work to the theory of planned behavior as the core theoretical driver of our work, we invite future studies to explore other salient theoretical orientations. On the same note, we acknowledge that in seeking additional determinants of behavioral intentions, consideration was given to only two additional frameworks—technology acceptance model and social cognitive theory. There may be value in seeking other frameworks, including expectancy-value theory (Wigfield & Eccles, 2000) and self-determination theory (Ryan & Deci, 2000), for drawing salient constructs that may influence behavioral intentions. This provides another compelling opportunity for more research. Third, our study examines behavioral intention and finds no support for the usual factors beyond attitude and perceived usefulness. This points to the need to examine relationships to other motivational constructs such as expectancy value and goal orientation to investigate their relationships to the core factors of planned behavior. Fourth, while we focused on modeling behavioral intentions, future research could explore deep qualitative inquiry to offer a new perspective. Fifth, we examined behavioral intentions as it is deemed a key antecedent to actual behavior; however, we acknowledge that there may be value in exploring other behavioral factors including outcomes, goals, and goal orientations. Future research could consider addressing this issue to offer additional insights. Sixth, there may be value in investigating the boundary conditions on the relationships between the antecedent constructs and behavioral intention and whether there is a need to uncover moderators. An additional question pertains to the specific topics in data science that most interest students and their goals. It would be interesting to conduct research that explicitly addresses these. Finally, in future research, it would be interesting to study the temporal aspects of behavior. Learning data science is a long-term commitment and studying the temporal dimension we can observe learning stages through the developmental trajectory.

Modeling intentions to learn data science helps to orient interventions in data science education. We can focus on learners' values in designing learning materials and teaching. It is unsurprising that interventions for data science have focused on the programming and technical aspects of analysis when individuals are interested in its practical utility. Perhaps as a consequence, relatively little focus has been given to research methodologies and to social theory, when so much of the data regards humans and their activities. Such training is needed to formulate research questions and conduct practical research. However, what counts as data science education and how these are related to professional outcomes is unclear at present but are important questions to ask to help learners get the most out of their data science education.

8. Concluding remarks

The present study extends and modifies the theory of planned behavior to ascertain students' behavioral intentions to learn data science. A research model was tested using PLS-SEM. The research model included attitude toward the behavior, subjective norm, perceived behavioral control, outcome expectancy, and perceived usefulness as antecedents to behavioral intentions. The findings revealed that only attitude toward learning data science and perceived usefulness are positively related to behavioral intentions. The findings are important in that they shed light on the salient factors that shape students' intentions to learn data science.

Author Statement

The authors declare that there is no conflict of interest.

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