Comparing Relations among Autonomy Support, Motivation, and Academic Success across Online and Face-to-Face STEM Learning Environments

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Table of Contents

Abstract

Students' motivational beliefs are shaped by their learning environments. The COVID-19 pandemic altered these environments significantly, forcing a shift to emergency online/remote learning in courses previously delivered in traditional classrooms. Past research has documented the critical role of students' motivational beliefs in online learning environments. However, they have not considered how perceptions of context might shape these beliefs and have not compared students' beliefs in traditional and online learning environments. The present study thus investigated how levels and relations among students' motivational beliefs (attainment value and self-efficacy) and perceptions of motivation support (autonomy support) differed across 2020 online and 2019 face-to-face contexts. Structural equation models examined attainment value as a predictor of academic achievement and career intentions; autonomy support and self-efficacy were also included as predictors of attainment value and outcomes. Using short-term longitudinal data collected from 2057 undergraduate STEM students across two cohorts (Fall 2019 and Fall 2020), analyses revealed that students' final grades and career intentions were predicted by both attainment value and self-efficacy. Multigroup analyses revealed that students reported higher STEM career intentions in face-to-face settings; structural relations appeared to not differ across learning environments. Results extend theoretical understanding of the roles of learning environments and the pandemic in shaping students' motivational beliefs.

Abrégé

Les croyances motivationnelles des étudiants sont façonnées par leurs environnements d'apprentissage. La pandémie de COVID-19 a considérablement modifié ces environnements, obligeant à passer à un apprentissage d'urgence en ligne/à distance dans des cours auparavant dispensés dans des salles de classe traditionnelles. Les recherches antérieures ont documenté le rôle critique des croyances motivationnelles des étudiants dans les environnements d'apprentissage en ligne. Cependant, elles n'ont pas pris en compte la manière dont les perceptions du contexte pouvaient façonner ces croyances et n'ont pas comparé les croyances des étudiants dans des environnements d'apprentissage traditionnels et en ligne. La présente étude a donc examiné comment les niveaux et les relations entre les croyances motivationnelles des étudiants (valeur de réalisation et auto-efficacité) et les perceptions du soutien de la motivation (soutien de l'autonomie) différaient dans les contextes 2020 en ligne et 2019 en face à face. Des modèles d'équations structurelles ont examiné la valeur d'accomplissement comme prédicteur de la réussite scolaire et des intentions de carrière; le soutien à l'autonomie et l'auto-efficacité ont également été inclus comme prédicteurs de la valeur d'accomplissement et des résultats. À l'aide de données longitudinales à court terme recueillies auprès de 2057 étudiants de premier cycle en STEM dans deux cohortes (automne 2019 et automne 2020), les analyses ont révélé que les notes finales et les intentions de carrière des étudiants étaient prédites à la fois par la valeur de réalisation et l'auto-efficacité. Les analyses multigroupes ont révélé que les étudiants ont déclaré des intentions de carrière STEM plus élevées dans les environnements en face à face ; les relations structurelles ne semblaient pas différer entre les environnements d'apprentissage. Les résultats élargissent la compréhension théorique des rôles des environnements d'apprentissage et de la pandémie dans le façonnement des croyances motivationnelles des étudiants.

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List of Tables

List of Figures

Introduction

Student motivation and learning are inextricably linked in educational environments. Zimmerman (2000) states that students who are highly motivated in the classroom are more likely to engage in scholarly behaviour that will facilitate the learning process. Reciprocally, students actively engaging in the learning process are more likely to sustain high motivation (Schunk et al., 2008). In accordance with Bandura's (1986) social cognitive theory, a triadic reciprocity exists among the learner's physical environment, cognitive processes, and learning behaviour, creating a dynamic for a motivated learning experience. Further, situated expectancy-value theory shows that students' motivational beliefs are shaped by a variety of factors such as cultural milieu, socializers, experiences, and most importantly their perceptions of these experiences (Wigfield et al., 2016a). For instance, a student will only find the instructors' message highlighting the importance of science and science careers valuable only if he or she finds that message to be relevant and true for them. Therefore, contemporary theories of motivation focus on a combination of contextual aspects and individual characteristics to examine processes shaping in motivation.

The COVID-19 pandemic caused unprecedented disruption in education systems worldwide and made online learning the only available mode of education (Daniel, 2020). Further, the growth of related technologies over the course of the pandemic has resulted in the merging of online teaching and learning into routine practices of universities (Teresevicienе et al., 2020). It is anticipated that COVID-19 will permanently normalize the use of digital technologies for education (BBC News, 2020; Woods, 2020). While distance or asynchronous learning does have its own advantages – being accessible to learners around the world and flexible to their needs – it has also placed critical importance on student motivation even more than conventional classroom models (Artino, 2008; Keller, 2008; Fong, 2021). In the face of prolonged periods of online learning, cultivating a motivationally supportive environment becomes pivotal to ensure learners achieve their goals (Bekele, 2010). However, despite its significance for learning, many researchers have noted that there is sparse literature on the functioning of motivation processes in online contexts (Artino, 2008; Bekele, 2010; Hartnett, 2016; Jones & Issroff, 2005; Miltiadou and Savenye, 2003). Understanding how students' motivational processes may differ in response to different situations will be critical in understanding the kind of programmatic design required to support students' motivation and success.

In particular, empirical evidence focusing on the functioning of motivational processes in online environments is critical in supporting the retention and production of employable university graduates. This is required especially in fields of science, technology, engineering, and mathematics (STEM) that have attrition rates documented to be as high as 48% (Chen, 2013). Students citing lack of interest along with perception of poor teaching practices as reasons for their decisions to leave STEM (Hunter, 2019) has put the spotlight on the important role of motivational beliefs in reducing attrition. Coupled with the upsurge in usage of technology in education across the world, it is important to look at achievement motivation in online programs to better STEM retention. Empirically comparing motivational processes across online and face-to-face environments would be beneficial for programmatic design of courses at university levels, including policies around curriculum and technical infrastructure, and inform teacher training programs. Furthermore, it will contribute to the scholarly community's understanding of the situated nature of motivational processes (Nolen, 2020; Eccles & Wigfield, 2020).

Literature Review

Motivation in STEM Programs

Despite countries around the world dedicating research, policy initiatives, and funds to address the problem of enrolment and retention of students in STEM programs, the issue persists. Canada has only 30% of university students taking a STEM major, and this number has increased by less than 4% between the years 2010 and 2016 (Statistics Canada, 2020). Further, during this period, Canadian STEM programs had a graduation completion rate of only 29% versus a 51% graduation completion rate in non-STEM programs (Statistics Canada, 2020). Research over the past several decades has demonstrated that factors related to motivation, such as students' perceived value and expectancies for success in STEM disciplines, are critical for explaining persistence in STEM (Anderson & Chen, 2016; Cromley et al., 2016; Seymour & Hewitt, 1997; Wigfield & Eccles, 2000). These studies provide evidence that students who find their course interesting, important, or useful (task value) and feel confident that they can succeed (expectancy for success) tend to achieve higher academic outcomes. Students with high task value and expectancy beliefs are also likelier to persist and pursue careers in STEM (Wigfield et al., 2016b).

Indeed, situated Expectancy-Value Theory (SEVT; Wigfield & Eccles, 2020) suggests that individuals value tasks that are consistent with their self-definitions or central to their identity (Wigfield et al., 2009). This type of value is termed attainment value, defined as the importance to one's identity of doing well in a task. Although the positive predictive and reciprocal relationships between students' expectancies, attainment value, and achievement outcomes are explored in theory (Eccles, 2009), empirical studies have focused mostly on utility value (Chouinard & Roy, 2008; Kosovich et al., 2017), measured importance broadly (rather than identity-related importance specifically), or used composite measures of task value (Archambault et al., 2010; Fredricks & Eccles, 2002; Jacobs et al., 2002; Musu-Gillette et al., 2015). Given that students make career-related choices based on how central they find courses to their identities (Côté, 2006; Eccles, 2009; Luyckx et al., 2006; Marcia, 1993; Roisman et al., 2004; Waterman, 1993), particularly during young adulthood, it is important to focus on attainment value to unpack the functioning of these processes.

Motivation in Online Learning

Contemporary studies such as Rosenzweig and Wigfield (2016), Lam et al. (2015), and Schenke et al. (2017) indicate that there exists an interactive relationship between learners and their learning environment is what influences students' motivational beliefs. This means that students' motivational beliefs are not an individualistic trait, but rather dynamic and change in response to their perceptions of the learning environment. However, research focused on online learning (e.g., Wighting et al.,2008; Yukselturk & Bulut, 2007; Styer, 2007) has typically viewed motivation as a personal characteristic that is consistent across contexts and situations, and particularly as a characteristic observed in successful online learners. Further, comparative studies such as Rovai et al. (2007) and Shroff and Vogel (2009) suggested that students in online learning environments are more intrinsically motivated than their counterparts who undergo face-to-face teaching. While intrinsic motivation may influence initial engagement in online environments, research that frames intrinsic and extrinsic motivation as a static dichotomy dividing successful students from unsuccessful students might show an overly simplistic view of contextual effects and dynamic motivation. Viewing motivation only as a result of a learner attribute or the learning environment contradicts the idea that individuals can have varied motivation levels in a given context and time (Turner & Patrick, 2008).

Furthermore, in their recent article Eccles and Wigfield (2020) have paved the way for expectancy-value theory to take a more situated approach by interweaving development, social cognitive, and sociocultural perspectives on motivation. This new perspective emphasizes how students' perceptions of the motivational support, their identities, goals, and personal experiences shape their motivational beliefs. Situated approaches such as this posit that the change in mode of instruction, modalities, and processes will elicit differential motivational beliefs in students. Investigating how motivational supports work in online learning environments is important to inform programmatic decisions. Despite the reciprocal relationship between learning environments and student motivation, only a few studies focusing on online environments have acknowledged this dynamic, differential, and responsive nature of motivation in online settings as compared to what was documented in traditional learning environments (Shroff et al., 2007; Xie et al., 2006). In both of these studies, the authors investigated levels of students' expectancies for success and perceptions of the context but did not measure how students' motivational beliefs relate to each other and the environment to influence other learning outcomes. Therefore, creating a gap in understanding what role student perceptions of motivational support play shaping students' levels of expectancies and values, how they might predict academic achievement, and finally how these might differ in response to different instructional contexts.

Most of the extant research (Chen & Jang, 2010; Hartnett, 2010; 2016) on motivation in online learning environments has used the self-determination theory (SDT; Ryan & Deci, 2000), which is a theory of motivation that is built on the fundamental premise of learner autonomy, arguing that all humans have an inherent need to experience a sense of agency and control. It further states that environmental conditions that support individual autonomy enhance more intrinsic forms of motivation that are central to individuals' identities and expectancy beliefs through the process of exploration (Ryan & Deci, 2002). Marcia (1993) also elaborated on how the process of exploration which arises from autonomy-supportive structures supports forms of motivation that are central to students' identities. Attainment value, as described earlier, is central to students' identities, and tends to overlap with some of the more internalized forms of the extrinsic motivation elucidated in SDT. Therefore, it is reasonable to expect that students' perceived autonomy would relate to their attainment values. Prior studies (Chen & Jang, 2010; Hartnett 2010; Shroff et al., 2007; Xie et al., 2006) have illustrated that SDT provides a useful analytical tool to understand the nuances of motivation in online learning. All these studies measured students' motivational beliefs (perceived interest, perceived competence, etc.) and concluded that students participating in online learning are more intrinsically motivated than students in traditional learning environments. However, these studies did not measure students' perceptions of motivational support, how these processes shape students' motivational beliefs, and relate to subsequent academic achievement. Accordingly, this study, the first of its kind to my knowledge, uses SDT to measure students' perceptions of climate, and how they influence students' motivational beliefs (SEVT).

Among many of the drastic changes that the COVID-19 crisis caused was the immediate shift to online learning. This led to an increase in scholars' investigation of learning mechanisms, particularly motivational processes to help grapple with the new set of competencies required to navigate these changing circumstances. For example, Chiu et al. (2021) conducted a review of nine empirical studies conducted across the Asia Pacific and the United States. Their aim was to understand students' motivation during COVID-19. Some key ideas relevant to this research are that there was an increase in overall value beliefs of students during online learning, and teachers' actions, particularly the designing of collaborative activities, related positively with online self-regulated learning. Self-efficacy or expectancy beliefs has consistently featured in most prominent motivation theories (Anderman, 2020), and given the advent of new technologies and the required competence to navigate them, researchers predicted that students would feel less efficacious during online COVID-19 learning. This assertion was indeed echoed in studies on college students (Alemany-Arrebola et al., 2020; Hilpert et al., 2021) and primary school students (Rutherford et al., 2021), where researchers saw a dip in levels of expectancies for success during the pandemic. Further, in a multi-country study conducted by Holzer et al. (2021), students' competence satisfaction was found to be a predictor of intrinsic learning motivation showing that students who feel confident in succeeding in online learning also tend to value their learning.

Other studies during the pandemic investigated students' perceived autonomy (Gruber et al., 2021; Hensley et al., 2021; Chiu, 2021). These studies were in-line with most prior research on motivation in online environments, and took to SDT to answer their research questions. Results from these studies were varied. Some studies found a dip in levels of autonomy as a function of the lack of choice in the way instruction was delivered, and the whole situation being outside of their control (Gruber et al., 2021; Hensley et al., 2021). In contrast, other studies documented increases in autonomy due to the structure of asynchronous learning activities that let students choose how their spent time be it reading activities, digital games, or project-based learning (Chiu, 2021). This finding further illustrates how instructional practices can influence motivation, bolstering the need to examine empirical proofs of motivation supports, and how these might differ in online and face-to-face settings. Specifically, more evidence is needed to investigate the differential relationship between students' perceptions of instructional context, how they shape their task values, and academic choices. Moreover, researchers have not examined other specific aspects of motivation such as identity-based-values, and the potentially differential interplay of these beliefs with expectancies and their effect on students' academic achievement. These limitations hinder the cross-environmental (online and face-to-face) development of instructional practices that are empirically proven to be motivationally supportive. Accordingly, this study integrates SEVT and SDT to examine supports for STEM students' motivation, and compare how they might differ across learning contexts.

Self-Efficacy

Self-efficacy is defined as "people's judgements of their capabilities to organize and execute courses of action required to attain designated types of performances" (p. 77, Bandura, 1986). Due to the conceptual overlap between self-efficacy and expectancy beliefs, this is the most widely used indicator of expectancy for success in current empirical studies (Rosenzweig et al., 2021). Students' confidence in their ability to learn the content in their course has been linked to performance and persistence in achievement-related tasks (Eccles, 2005), and even more so in STEM (Hutchinson et al., 2006; Rittmayer & Beier, 2009) as a lot of students struggle with issues of confidence, that could be stemming from lack of mastery experiences (Britner & Pajares, 2006). Self-efficacy is context-specific indicating that individuals' self-efficacy beliefs are likely to vary with change in the format of education (Hodges, 2008). This means learners with high self-efficacy in face-to-face settings may not function with similar levels in online settings. While there is extensive research on self-efficacy in face-to-face settings, it is sparse when it comes to online settings (Alqurashi, 2016; Hodges, 2008).

Studies on self-efficacy in online learning typically either investigated technology-related self-efficacy or self-regulated learning using the Motivated Strategies for Learning Questionnaire

(MSLQ) that contains a self-efficacy subscale which was adapted from the Patterns of Adaptive Learning Scales (PALS; Midgley et al., 2000). Although these studies were predominantly focused on self-regulated learning, the self-efficacy subscale significantly predicted higher levels of overall self-regulation in learners. Self-efficacy was studied as a mediating variable between other learning-related concepts such as intrinsic motivation and self-regulated learning (Pardo et al., 2017), help-seeking behaviour (Dayne et al., 2016) and personal epistemology (Akturk, 2014). These studies examined the technology-related self-efficacy, which deals students' confidence in using the technology, showing that students who were confident in using technology were overall more motivated and successfully regulated their learning. However, these studies did not focus on academic-related self-efficacy and how academic self-efficacy relates with academic achievement when the program is delivered online (Alqurashi, 2016; Chang et al., 2014; Wang et al., 2013). Further, these studies neither looked at how environmental supports affect self-efficacy in students, nor did they compare how these might differ from what is documented in traditional learning environments. Additionally, extant research also suggests that stronger relations are observed when self-efficacy beliefs are measured at the same domain of the outcome (e.g., Bong 2006; Valentine et al., 2004), and that competence beliefs in one domain often show negative relations to achievement in another domain (Marsh et al., 2017). Studies comparing domain specific self-efficacy, and its relation with academic success across two learning contexts is scarce, and is a gap in research that this study attempts to close.

With Bandura's establishment of self-efficacy as a significant influencer of students' learning experience, subsequent research throughout the 1980's and 1990's focusing on traditional learning environments further cemented this idea (e.g., Bouffard-Bouchard,1990; Lent et al., 1986; Pajares, 1996; Pintrich & de Groot, 1990; Risemberg & Zimmerman, 1992; Schunk, 1981, 1983, 1984a, 1984b, 1991; Schunk & Hanson, 1985; Zimmerman, 1989; Zimmerman & Ringle, 1981). For example, self-efficacy is shown to relate with performance positively and reciprocally (Bandura, 1997; Pajares, 2005), and lead to high interest and engagement (Schunk & Pajares, 2002). Current studies continue to confirm a positive correlation between academic self-efficacy with academic performance in traditional college environments (e.g., Alyami et al., 2017; Bartimote-Aufflick et al., 2015; De Clercq et al., 2013; Domenech-Betoret et al., 2017; Farchi, Cohen, & Mosek, 2014; Fong & Krause, 2014; Hoigaard et al., 2015; Macaskill & Denovan, 2013; Trigwell et al., 2013; Zientek et al., 2017). Additionally, self-efficacy as an important predictor of STEM career outcomes have also been documented (Lent, 2005; Robinson, Perez et al., 2022b). Yet, academic self-efficacy has not been sufficiently studied in relationship with online learning (Alqurashi, 2016). Furthermore, studying and comparing correlates of self-efficacy longitudinally is rare. Evidence from studies documenting students' self-efficacy processes is not only important in making programmatic and instructional changes to support students' motivation in STEM fields, but in also expanding our understanding of the situated nature of efficacious beliefs.

Attainment Value

Task value is defined as the "quality of the task that contributes to the increasing or decreasing probability that an individual will select it" (Eccles, 2009, p. 82). It consists of interest value (enjoyment in engaging in the activity itself), utility value (valuing a task based on its ability to fulfil a personally central goal), and attainment value. The concept of attainment value pertains to the importance of a task to an individual's identity or central to their aspects of self (Wigfield et al., 2009). Individuals place higher importance on tasks that are closer to their self-definitions.

There is a significant body of literature emerging that focuses on the role of task values in academic achievement in traditional learning environments among students across age groups that illustrate the positive relationship between bolstering values and student achievement (Acee & Weinstein, 2010; Bong, 2001; Chen & Liu, 2009; Durik et al., 2006; Eccles, 1987; Hulleman et al., 2010; Luttrell et al., 2010; Neuville, Frenay, & Bourgeois, 2007; Simpkins et al., 2006; Sullins, Hernandez, Fuller, & Tashiro, 1995). Furthermore, there are studies that also illustrate this positive relationship in STEM disciplines specifically (Chow et al., 2012; DeBacker & Nelson, 1999; Meece et al., 1990; Watt, 2006; Watt et al., 2012). For example, Robinson and colleagues explored the positive relationship between identity beliefs and academic and career-related outcomes in STEM (Robinson et al, 2018; 2019; 2020). However, there exists sparse literature focusing specifically on the relationship of attainment value with other learning-related concepts and outcomes. As highlighted by Rosenzweig et al. (2020), most intervention studies have mostly focused on utility value as they are more easily malleable. They also urge researchers to investigate attainment value as it is more central to long term motivation outcomes such as persistence. Moreover, despite broader psychological literature conceptualizing attainment value as a key indicator of identity (Ashmore et al., 2004), contemporary studies (e.g., Musu-Gilette et al., 2015) use the composite measures combining multiple forms of value, or value beliefs as a whole.

Identity processes are salient in influencing career and academic choices in students (Eccles, 2009; Cote, 2006) making it crucial to unpack the underlying mechanisms that foster these beliefs and investigate their roles in determining students' behavior. Further advocating the need to look at identity-related attainment value in isolation from other task beliefs, is the finding that attainment values are relatively stable when compared with other values, and expectancies (Eccles, 2009; Robinson et al., 2019). Largely what was seen is that while other constructs showed declines, and costs showed patterns of increase, attainment value remained significantly more stable. Perhaps more important to the present inquiry is that attainment value was the most important predictor of retention in a STEM major (Robinson et al., 2019), and can be shaped in autonomy supportive environments when students have the freedom to explore what interests them (Marcia, 1993; Robinson et al., 2022). Available evidence suggests that attainment value is relatively stable (Eccles, 2009), but can decline over years (Hernandez et al., 2013; Robinson et al., 2018) or even over a semester (Robinson et al., 2019). Declines over a semester are seen in introductory STEM courses suggesting that smaller declines are seen over college for students who have come to value science as a key part of their identity. However, evidence exists that even small shifts in students' attainment or identity beliefs have major implications for academic and career outcomes. Further, it should be taken into consideration that expectancy and value beliefs are intertwined; waning self-efficacy beliefs can prompt declines in students' valuing of a given task (Jacobs et al., 2002; Marsh et al., 2005). Therefore, it is important to examine the interconnected levels of both these constructs along with how they influence other learning outcomes.

In the case of online learning environments, studies investigated task value beliefs as a whole (e.g., Uzuner, 2007). Findings from these studies indicate that task value beliefs in online environments significantly predict social ability, intrinsic goal orientation, and self-efficacy (Lin et al., 2008); predict social navigation, perceived peer and instructor social presence (Yang, Tsai, Kim, Cho, & Laffey, 2006); and directly affect academic achievement and persistence (Joo et al., 2013). Chiu and Wang (2018) conducted one of the few studies solely investigating subjective task values (interest, utility, attainment) individually and found that all three of them had significant direct effects on learners' choice behaviour, specifically in courses conducted online. However, these studies were not conducted in a higher education setting in STEM, and did not add understanding of how motivational beliefs relate to the learning environment. However, there are not enough studies focusing on task values in online learning environments, specifically looking at how students' attainment beliefs in such settings might differ from those in face-to-face environments.

Taken together, learning experiences in undergraduate gateway courses affect students' beliefs and career-related choices, and hence it is important to investigate how expectancies and values are shaped, and in-turn predict learning outcomes in both online and face-to-face environments.

Self-Determination Theory (SDT)

Self-determination is defined by Deci and Ryan (1985) as "quality of human functioning that involves the experience of choice… the capacity to choose and have those choices… be the determinants of one's actions" (p. 38). This theory posits that humans have three needs: autonomy (sense of control and agency), competence (feeling confident with tasks and activities that is in broader alignment with expectancy beliefs), and relatedness (feeling like they belong with others). Fulfilment of these needs leads to overall psychological well-being and an elaborated sense of self. One of the advantages of the SDT is that it also provides detailed insights in enhancing the motivation process, by identifying strategies to create motivationally supportive environments. One of the first of its kind was Reeve and Jang's (2006) paper detailing autonomy-supportive behaviour exhibited by teachers which led to a rise in autonomy-supportive interventions. Several of these interventions were successful in (a) decreasing autonomy frustration (e.g. Cheon et al., 2019; Tilga et al., 2019), and autonomy dissatisfaction (Reeve et al., 2020); (b) increasing autonomous motivation (Abula et al., 2020; Fin et al., 2019); (c) increasing classroom engagement (Cheon et al., 2016; Cheon & Reeve, 2013, 2015); (d) increasing agency and initiative (Reeve et al., 2020); and (e) increasing academic achievement (Cheon et al., 2012, 2020; Cheon & Reeve, 2013; deCharms, 1976; Cheon, Reeve, & Ntoumanis, 2019; Ulstad et al., 2018).

Early SDT research in online learning environments was conducted by Xie et al. (2006). A positive correlation was found between three SDT-based indicators (perceived interest, value, choice) and student' course attitude and engagement and gave an insight into the environmental factors that affect motivation along with individualistic traits as described by SEVT. Chen and Jang (2010) found a direct relationship between contextual support and self-determination which was mediated by need satisfaction. A set of diverse findings in Hartnett (2010) showed the complex and intricate ways that intrinsic and extrinsic motivation function, further illuminating that motivation is indeed multi-faceted, complex, and contextually rooted. However, constructs from SDT and SEVT are not typically measured together. But given the direction motivation literature is headed with SEVT getting traction (Nolen, 2020; McCaslin, 2009; Eccles & Wigfield, 2020), this combination will help us understand and empirically measure how students' expectancy and values are shaped by their perceptions of contexts, and how they differ in face-to-face and online learning environments.

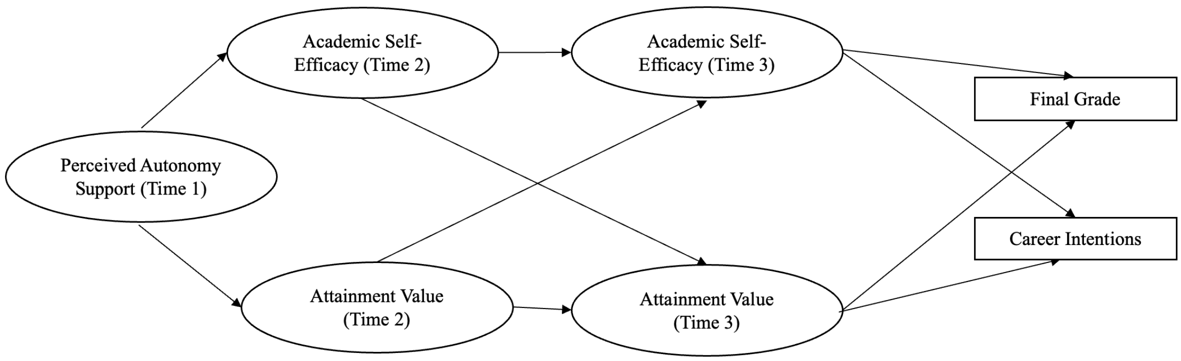
The Present Study

There is limited evidence for relationships among autonomy support, attainment value, self-efficacy, and academic outcomes. However, prior research supports the hypothesis that beliefs such as self-efficacy and attainment value may relate with autonomy supportive environments and subsequently influence learning outcomes. Given the criticality of finding insights to improve STEM retention, the current study adopts a situated expectancy-value framework (SEVT; Eccles & Wigfield, 2020) to examine students' attainment values, self-efficacy beliefs, academic achievement, and career intentions across online and face-to-face learning environments. This was done by contextually examining their relationship with perceptions of autonomy support in the two delivery methods before and during the pandemic. Accordingly, this study investigates these relationships over the course of a semester for two cohorts of students in undergraduate chemistry courses.

The research questions are: (a) What is the role of autonomy support, self-efficacy, and attainment value in predicting students' academic achievement and career intentions? (b) What role does program delivery method (face-to-face before the pandemic versus online during the pandemic) play in predicting levels of students' self-efficacy, attainment value, and perceived autonomy support? (c) Is there a difference in the relation among variables of motivational beliefs and outcomes across the two delivery methods? The figure below illustrates the models that hypothesize the relationships among the variables.

Figure 1

Theorized Model for Relations among Variables.



Note. Time 1 = beginning of semester; Time 2 = mid-semester; Time 3 = end-of-semester.

The first research question focused on how students' perceptions of autonomy and expectancies for success (self-efficacy) predict their attainment value and subsequent academic achievement. For the overall group, it was expected that self-efficacy would predict academic achievement as illustrated by prior research (Hutchinson et al., 2006; Rittmayer & Beier, 2009). In-line with findings from Robinson et al. (2022), I expected that students' perceptions of autonomy support would predict their attainment value beliefs. The intertwining relationship between expectancies and values, particularly self-efficacy predicting differential, heterogenous trajectories in attainment values (Robinson et al., 2018; 2019) would suggest that similar findings – self-efficacy predicting attainment value – can be expected. Putwain et al. (2019) positioned attainment value to work in addition to students' self-efficacy to predict academic achievement. Robust existing evidence supports the prediction of a positive directional relationship between self-efficacy and grades (Hutchinson et al., 2006; Rittmayer & Beier, 2009); and between attainment value and career intentions (Côté, 2006; Eccles, 2009; Robinson et al. 2018; 2019). Eccles (2009) also posits that attainment value acts as a mediator between students' expectancy and achievement outcomes. Hence, it was expected that both attainment value and self-efficacy would predict students' final grades and career intentions.

The second research question focused on differences in mean levels of students' perceptions of context, expectancies, values, and final grades. Given that the sudden shift to remote instruction was one of the most drastic changes for students, studies have seen complex shifts in students' motivation and learning (Chiu & Hew, 2018; Chiu et al., 2021; Lin, 2021). Because of the shift to a new learning environment, coupled with their limited experience in using these online systems and opportunities, it was expected that students' expectancy beliefs would be lower in 2020 compared to 2019. These patterns are shown by studies such as Alemany-Arrebola et al. (2020), Hilpert et al. (2021), and Rutherford et al. (2021). Further, according to SEVT and SDT, when students perceive themselves to be less competent, their perception of how the task is important to them (attainment value) could diminish too. The way students perceive autonomy was expected to go one of two ways. First, the lack of control on the modalities of their learning could cause their autonomy perceptions to diminish (Hensely et al., 2021). Second, students could feel more autonomous with the independence to use their time flexibly and to nurture other motivational resources through reading activities, projects, or digital games (Holzer et al., 2021).

The third research question focused on students' perceptions of autonomy support relating to self-efficacy, and attainment value and how, in turn, these two motivational constructs relate to academic and career outcomes across face-to-face and online contexts. It was expected that perceived autonomy support would positively predict self-efficacy and attainment value by facilitating the process of exploration (Ryan & Deci, 2002; Marcia, 1993; Robinson et al., 2022) in face-to-face settings. Further, prior research has also highlighted how autonomy-supportive environments can lead to increased performance as students identify with the task, and have more internalised or rather intrinsic reasons to engage in the task (Taylor et al., 2014; Frland & Worrell, 2016; Ryan and Deci, 2020). This relationship can differ in online settings based on if and how students feel autonomous. Further, these beliefs have predicted academic outcomes in the past (Kuo et al., 2013), as was expected from the model. Moreover, a significant body of research pioneered by Jang and colleagues (Jang et al., 2010) states that autonomy without structure can be overwhelming for students. The lack of structure during the pandemic, and other factors such as stress and anxiety which were heightened might alter the role of students' perceived autonomy. Further, attainment value might exert more pronounced effects as students might need to dig deeper to find intrinsic, personal reasons to persist under such adverse conditions. Based on recent studies showing evidence for diminishing levels of motivational constructs during the pandemic because of the reasons stated above, it was expected that motivation and its relationship with outcomes would be overall more positive in face-to-face settings.

Method

Participants

The sample consisted of undergraduate students enrolled in two introductory undergraduate chemistry courses (general chemistry and organic chemistry) at a research-intensive Canadian university. The participants were from two different cohorts – Fall 2019 (face – to-face setting) and Fall 2020 (online setting due to COVID-19). The courses were taught by a combination of instructors: two team instructors for general chemistry, one for organic chemistry in 2019, and two team instructors both for general chemistry and organic chemistry in 2020. The curriculum and course content across the two years were the same, with the difference being in their delivery methods. In Fall 2019, the teaching was conducted in a large lecture hall with a capacity of 650 students. The instructors gave a collective total of 33 lectures across the two courses, each lasting approximately an hour. The lectures typically started with a brief review of content previously learned, announcements about the course and related opportunities, followed by newer material. While teaching, instructors provided examples, gave students time to practice, and students had the opportunity to interact synchronously, whenever they wanted to, with their peers and instructors. The instructors also recorded these face-to-face lectures using an automated system provided by the university that the students could access through the online learning management system.

The same general course format was delivered entirely via Zoom in Fall 2020, with no avenue for in-person interaction between students and instructors. Lectures (or concept videos, as the instructors termed it) were pre-recorded and uploaded to the learning management system so that the students could watch asynchronously during the week. The instructors also hosted short weekly synchronous problem-solving sessions, where students could familiarise themselves with more rigorous content and interact with the instructors and their peers. These were not mandatory, and students who did not want to attend these had the choice of getting their questions addressed asynchronously via email. Both years had similar assessments, where the final grade was a cumulation of periodic quizzes, two mid-term exams, and a final exam.

The sample consisted of a total of 1060 and 997 participants in Fall 2019 and Fall 2020, respectively (64.1% female; 33.5 % male; 42.5% Asian, 40% white, 3.2% Hispanic/Latino, 1.75% Black, 1.35% Indigenous, 8.5% multi-racial). The surveys were disseminated by the course instructors at the beginning, middle, and end of semester to capture students' motivational beliefs and perceptions of motivational support. In both years, the surveys were sent out during weeks 4 (Time 1; T1), 8 (Time 2; T2), and 12 (Time 3; T3) of the semesters. The students received extra credit at the end of the semester for completion of the surveys. Students provided consent for their responses and course grades to be used in the study. Anyone under the age of 18 was not eligible to participate in the study.

Measures

The surveys were conducted as part of a larger study on motivational experiences among STEM students, and included items that measured students' motivation (e.g., interest value, academic self-efficacy, utility value, etc.), and perceptions of motivational support (e.g., perceived competence support, perceived teacher control, perceived autonomy support, etc.). The students also answered questions on their demographics and STEM career intentions. Motivation and autonomy support perceptions were measured on a typical 5-point Likert-type scale (e.g., 1 = *strongly disagree*; 5 = *strongly agree*). A full list of survey items used in this study is provided in Appendix A.

Academic Self-Efficacy

Academic self-efficacy items were used as indicators of students' expectancies for success using a measure adapted from the Patterns of Adaptive Learning Scales (PALS; Midgley et al., 2000; 5 items; α = .86 -.89). The items focused on students' confidence to learn and master coursework in chemistry (e.g., "I'm certain I can master the skills taught in chemistry") and for this study, were assessed when students were in the eighth (T2) and twelfth (T3) weeks of the semester.

Attainment Value

Attainment value assessed how important students found their chemistry coursework to be for their identities. This scale was adapted from Conley (2012; 7 items; α = .87; e.g., "Being good in chemistry is an important part of who I am"). Attainment value data from weeks 8 (T2) and 12 (T3) of the semester were used for this study.

Perceived Autonomy Support

This scale was adopted from Jang et al. (2016) and Patall et al. (2018), and consisted of 5 items ($\alpha = .80$ -.81) that were used to ascertain if students viewed the instructors' actions as supporting their autonomy (e.g., "My instructor provides me with choices and options"). Data from the fourth week (T1) of the semester was used for this measure.

Course Grades

The course instructors provided a cumulative final grade to each of the students that encompassed their scores on quizzes, laboratory assignments, and exams.

Career Intentions

In the T3 survey, students reported their STEM career intentions ("To what extent do you intend to pursue a career in science, technology, engineering, and mathematics?"; Estrada et al., 2011).

Analytic Plan

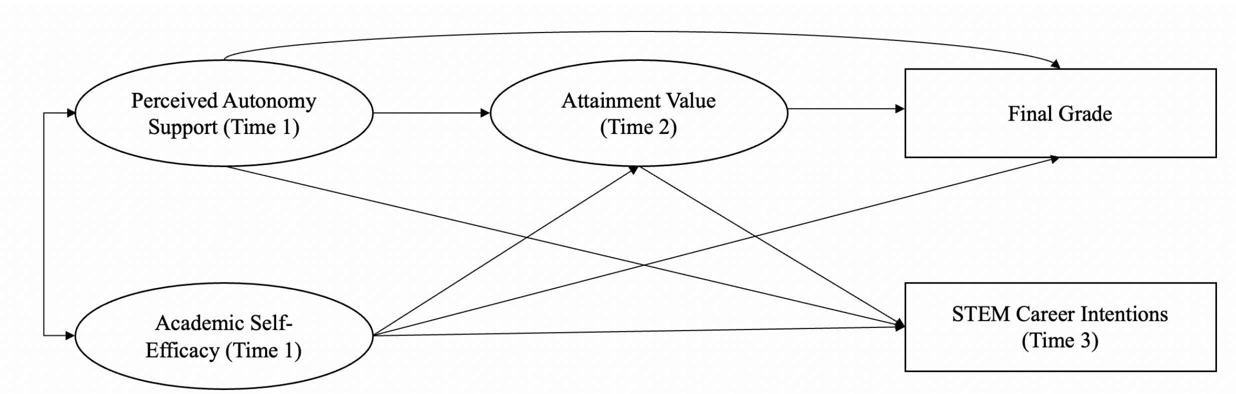
Preliminary analyses included descriptive statistics, correlations, and missing data analysis were done using IBM SPSS Statistics Version 26. Confirmatory factor analyses were conducted using the lavaan package in RStudio (v2022.02.1; Rosseel, 2012). Structural equation modeling in lavaan (Rosseel, 2012) was used to examine autonomy support as a predictor of self-efficacy and attainment value, the interplay between self-efficacy and attainment value, and their relationship with students' final grades and career intentions. Multigroup models were used to compare mean and structural differences in students' motivational beliefs, and their relationships with achievement outcomes across online and face-to-face settings. Model fit was determined by multiple fit indices including comparative fit index (CFI) and Tucker Lewis Index (TLI; > .90 for acceptable fit; >=.95 for excellent fit), RMSEA (<.08 for acceptable fit; <.06 for excellent fit; Hu & Bentler, 1999), and SRMR (<.08 for good fit; Hu & Bentler, 1999). All models included gender and race/ethnicity (underrepresented racial/ethnic group vs. overrepresented racial/ethnic group) predicting all the variables in the models to control for potential demographic differences in these processes.

Results

Initial CFAs revealed a very high correlation ($r = .997$, $p < .01$) between the attainment value and self-efficacy measures from the same time points. Consequently, the initially hypothesized model produced an uninterpretable non-positive definite covariance matrix due to collinearity issues as a result of this high correlation between the latent variables. This should be considered a limitation of the study. An alternative model that could still address the core research questions about how the variables of autonomy support, self-efficacy, and attainment value relate to each other and learning outcomes, as well as how they differed across 2019 and 2020, was proposed as follows:

Figure 2

Revised Model for both Online and Face-to-Face Settings.



Note. Time 1= beginning of semester. Time 2 = mid-semester; Time 3 = end of semester.

The larger dataset already contained students' responses on items measuring their academic self-efficacy at week 4 (T1), so I used that along with the other original variables of interest.

Confirmatory Factor Analyses

The structural model consisted of a three-factor measurement model of perceived autonomy support (T1), academic self-efficacy (T1), and attainment value (T2). This model showed excellent fit to the data, χ^2 (51) = 200.133***, RMSEA = .044, CFI = .981, TLI = .975, SRMR = .029.

Measurement Invariance

Because my interest was in comparing learning environment groups, I also conducted measurement invariance tests across the face-to-face (2019) and pandemic online (2020) groups for the latent variables. The configural model assumed the same model structure across groups. The weak invariance model assumed factor loadings to be equal. I then specified the item intercepts to be equal which made up the strong invariance model. Invariance was inferred when the change in CFI when comparing consecutive models was equal to or less than .01 (Cheung & Rensvold, 2002). Results presented in Table 1 support strong measurement invariance for the latent variables across the two learning environment groups. This shows that students in 2019 and 2020 interpreted the survey items similarly, and so any observed mean differences can be attributed to true differences in the study variables rather than measurement differences (Widaman & Reise, 1997). The strong measurement invariance constraints were retained in the multigroup models.

Table 1

Year Group Measurement Invariance for Latent Variables

Model	χ^2	df	RMSEA	CFI	ΔCFI	TLI	SRMR
Configural	238.338	102	.042	.982	-	.977	.032
Weak	259.791	111	.042	.980	-.002	.977	.036
Strong	311.799	120	.046	.975	-.005	.972	.038

Preliminary Analyses

Correlations and descriptive statistics are represented in Tables 1 and 2. The following results indicated that all study variables were positively and significantly correlated. The relations were consistent with expectations from theory and prior research. Separate course-wise (Fall 2019 and Fall 2020) descriptive and correlation statistics for the study variables can be found in Appendix B.

Table 2

Descriptive Statistics for Study Measures

Scale	*n*	*M*	*SD*	α
Academic Self-Efficacy (Time 1)	1817	3.68	0.69	.89
Perceived Autonomy Support (Time 1)	1804	3.78	0.72	.81
Attainment Value (Time 2)	1641	3.49	0.79	.87
STEM Career Intentions (Time 3)	1597	7.20	2.79	
Final Grade	2014	85.15	13.36	-

Note. Computed using composite scores in SPSS

Table 3

Zero-Order Correlations among Study Variables

	1	2	3	4	5
1. Academic Self-Efficacy (Time 1)	-				
2. Perceived Autonomy Support (Time 1)	.267**	-			
3. Attainment Value (Time 2)	.343**	.275**	-		
4. STEM Career Intentions (Time 3)	.106**	-.050	.118**	-	
5. Final Grade	.255**	.165**	.282**	-.173**	-

**$p < .01$
Note. Computed using composite scores in SPSS

Main Results

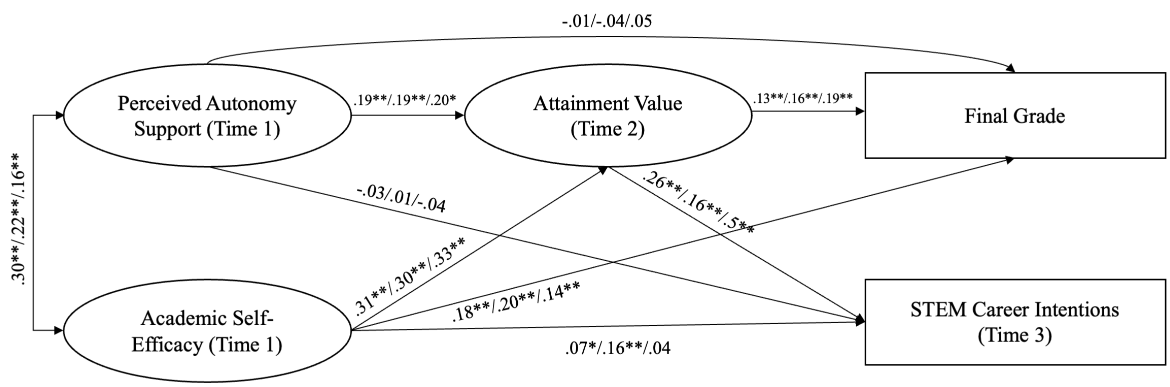
My first research question focused on the relations among students' perceived autonomy support, academic self-efficacy, attainment value, final grades, career intentions. The specified model for the overall sample used latent factors and fit the data well, χ^2 (87) = 282.292***, RMSEA = .041, CFI = .975, TLI = .965.

Consistent with our hypotheses, both attainment value and self-efficacy predicted students' final grade ($\beta_{\text{attainment}} = .132$, $p < .001$; $\beta_{\text{self-efficacy}} = .179$, $p < .001$). and career intentions

($\beta_{attainment} = .261$, $p < .001$; $\beta_{self\text{-}efficacy} = .070$, $p = .01$), when controlling for other paths. No significant direct paths were found between students' perceived autonomy support and their grades or career intentions. Students' attainment value was significantly predicted by both perceived autonomy support ($\beta = .195$, $p < .001$), and academic self-efficacy ($\beta = .306$, $p < .001$).

Figure 3

Model-Estimated Relations among Study Variables



Note. Standardized path coefficients for each model labeled in the following order: overall/face-to-face settings (2019)/online settings (2020).

My next research questions focused on mean and relational differences in students' beliefs across the two learning environments. Using latent factors, multigroup models were created. In the baseline model, parameters were constrained to be equal across groups (Table 4, Model 0), in line with the null hypothesis where the models would not differ across online and face-to-face groups. The next model allowed only the means of the model variables to be free across groups (Model 1). This was followed by a model estimation where only the regression coefficients were allowed to be free across the two groups (Model 2). Next, each of these models were compared to the baseline all constrained model, and significant differences in the model were evaluated using chi-square difference tests. The results of these (Table 4) indicated that model parameters differed significantly across groups; the means-free (Model 1) and regression-free (Model 2) models fit the data significantly better than the all constrained model (Model 0). Therefore, a final model was specified with both means and regression coefficients freely estimating (Table 4, Model 3).

Table 4

Fit Indices for Multigroup Model Comparisons

	Model	χ^2	df	$\Delta\chi^2$	Δdf	RMSEA	CFI	TLI
0	Means and regression coefficients equal across groups	520.07	213	-	-	.047	.955	.950
1	Means freely estimating; regression coefficients equal across groups	501.27	210	-18.81	-3	.046	.958	.953
2	Means equal across groups; regression coefficients freely estimating	415.86	195	-104.21	-18	.041	.968	.962
3	Means and regression coefficients free across groups	412.39	192	-107.68	-21	.042	.969	.961

All difference tests were significant for $p < .001$.

The means and standard errors of attainment value, self-efficacy, perceived autonomy support, final grades, and career intentions were retrieved from R. First, as evidenced by overlapping confidence intervals, means of students' attainment value in 2019 (M = 3.83, SE = .25, 95% CI [3.00, 4.00]) and 2020 (M = 3.63, SE =.3, 95% CI [3.03, 4.21]) did not significantly differ. Means of self-efficacy also did not significantly differ for face-to-face (M = 3.50, SE = .12, 95% CI [3.36, 3.75]), and online (M = 3.62, SE = .06, 95% CI [3.49, 3.74]) settings.

Students' perceptions of autonomy support were not significantly different across the two cohorts: 2020 (*M* = 4.14, *SE* = .06, 95% CI [4.01, 4.26]), and 2019 (*M* = 3.83, *SE* = .12, 95% CI [3.58, 4.06). Students' final grades across the two years were not significantly different: 2020(*M* = 92.95, *SE* = 2.02, 95% CI [88.99, 96.91]), and 2019 (*M* = 80.90, *SE* = 4.27, 95% CI [72.52, 89.28]). Significant differences were observed in STEM career intentions with students' reporting higher career intentions in 2019 (*M* = 8.62, *SE* = 0.61, 95% CI [7.42, 9.81]) than in 2020 (*M* = 5.51, *SE* = 0.89, 95% CI [3.76, 7.26]). Overall, only students' STEM career intentions differed across the two years.

None of the paths under investigation were significantly different across the two cohorts. When controlling for other paths, attainment value significantly predicted final grades of students in 2019 (β = .16, *SE* = .68, *p* < .001, 95% CI [-1.17, 1.49]), and in 2020 (β = .19, *SE* = .36, *p* < .001, 95% CI [-.52, 0.91]). Additionally, as shown by overlapping confidence intervals, the coefficients did not differ across the two groups. The relationship between students' academic self-efficacy and final grades also did not significantly differ across the two years. Self-efficacy was a predictor of students' grades both in 2019 (β = .20, *SE* = .77, p < .001, 95% CI [-1.31, 1.71]), and in 2020 (β = .13, *SE* = .46, *p* = .02, 95% CI [-.77, 1.04]). After controlling for other paths, attainment value (β = .16, *SE* = .09, *p* < .001, 95% CI [-.03, .35]) and self-efficacy (β = .16, *SE* = .11, *p* < .001, 95% CI [-.05, .37]) both predicted students' career intentions in 2019, but in 2020 only attainment value (β = .5, *SE* = .16, *p* < .001, 95% CI [.17, .82]) predicted career intentions. As seen by overlapping confidence intervals, the relationship between attainment value and career intentions was not significantly different across the two cohorts.

In both learning environments, students' perceived autonomy support (β_{2019} = .19, *SE* = .05, *p* < .001, 95% CI [.09, .28]; β_{2020} = .20, *SE* = .26, *p* < .001, 95% CI [.05, .34) and self-efficacy (β_{2019} = .30, *SE* = .04, *p* < .001, 95% CI [.21, .38]; β_{2020} = .33, *SE* = .06, *p* < .001, 95% CI [.20, .45]) significantly predicted attainment value when controlling for other paths. The confidence intervals were observed to be overlapping meaning that the relationship between the variables did not significantly differ across these two contexts.

Taken together, results showed that students' academic achievement was significantly positively predicted by their self-efficacy and attainment value across both cohorts. Further, their career intentions were influenced by both variables in face-to-face settings, but only attainment value was a predictor in online settings. Students' perceptions of autonomy support did not predict outcomes in either setting. Additionally, students' academic self-efficacy and their perceptions of autonomy support significantly predicted their attainment value in both learning environments.

Discussion

The challenging demands of STEM courses can lead to high attrition rates (Chen, 2013). Students citing lack of interest among reasons to drop out put the spotlight on motivation research specifically in STEM courses (Hunter, 2019). Prior research has highlighted that factors related to students' perceived value and expectancies for success in STEM disciplines are critical for explaining persistence in these fields (Anderson & Chen, 2016; Cromley et al., 2016; Seymour & Hewitt, 1997; Wigfield & Eccles, 2000). Studies have suggested that students' attainment value, which is defined as the importance of a task to one's identity, is more important in predicting long term motivational outcomes compared to other task values (Robinson et al., 2019; 2022). Despite this assertion, most extant research has focused on supports for utility value. Further, in line with SEVT (Eccles & Wigfield, 2020), expectancy beliefs such as self-efficacy are strong predictors of students' attainment value, meaning that students who expect to succeed in a task are also likely to place personal importance on the task.

Given the recent shift in contemporary research to viewing motivation as a function of the contextual factors or perceived supports, it is important to investigate the motivational supports that can influence these beliefs. SDT (Ryan & Deci, 2000) highlights how when students feel like they are in control of their learning or are in environments where they perceive that their choices matter, students are more intrinsically engaged in a task, and perform better. Hence, measuring how autonomous students perceive their learning environment to be could be key in understanding why or how students' expectancies and values are shaped.

The COVID-19 pandemic disrupted education systems and increased the usage of technology in learning environments. These changes have been predicted to slowly be inculcated in learning environments after the pandemic, meaning that technology's role in designing learning environments is only going to be more important. In the light of these newer contexts, it is important to understand how motivational processes might stay the same or differ. This will be particularly important in informing programmatic decisions in educational institutions to ensure that instructors and learning environments continue to foster student motivation. The increasing rate at which technology is being incorporated in learning environments, coupled with the criticality of creating supportive motivational climates in STEM settings, makes it urgent for researchers to focus specifically on online motivation. Accordingly, this study attempted to illuminate how some of these key motivational constructs differ across different learning environments, how they relate with each other, and predict achievement outcomes.

The overall hypotheses were partially supported where both attainment value and self-efficacy positively predicted students' final grades in the overall sample. Prior research (Wigfield et al., 2016a; Bong, 2001) highlights that expectancy beliefs influence short-term achievement and value beliefs are stronger predictors of long-term choice outcomes such as career intentions. The findings for this sample align with this idea, where self-efficacy appeared to be a stronger predictor of grades, and attainment value appeared to be a stronger predictor of students' STEM career intentions. Both grades and career intentions did not relate to perceived autonomy support when controlling for self-efficacy and attainment value. It appears that if perceived autonomy support predicts these outcomes, it's indirectly via motivation. When controlling for those potential indirect effects, a significant direct effect is not seen. This could allude to other factors such as instructor enthusiasm, approachability, or students' task values and achievement emotions as factors that more directly influence students' achievement-related behavior. Further, this non-significant relationship between perceived autonomy support and outcomes could be explained by Jang and colleagues' (2010) work on how students need structure along with autonomy for them to adopt achievement-oriented behavior. Especially in online settings, the lack of a timetable or extrinsic factors that help students structure their day may have been missing, which explains why the relation was not significant despite students' perceiving their instructor to be supportive of their autonomy.

Means and Structural Relations by Learning Environments

The findings of the overall model contribute to our understanding of the relationships among students' perceived autonomy support, self-efficacy, and attainment value. They also illuminate how these beliefs predict students' learning outcomes. However, these findings were qualified by learning environment differences in mean levels of career intentions for students in online and face-to-face settings, as well as differential significance (though not magnitude) of relations between self-efficacy and career intentions.

First, in contradiction to my initial hypotheses, no cohort differences were seen in students' perceptions of autonomy support and academic self-efficacy. Theory would suggest that students might find online settings more autonomy supportive because of the flexibility in how they can spend their time. Theory also predicted that students' self-efficacy might decrease due to the introduction of new modalities. However, the results hint that for their motivation, students were familiar and comfortable with the technology or were able to adapt well to the new mode of instruction. Attainment value has been documented to be relatively stable compared to other forms of motivation (Perez et al., 2014; Robinson et al., 2018; 2019), which is echoed by results from this sample that show differences in learning environments do not necessarily lead to variable perceptions of congruency between tasks and students' identities.

Although the difference was not significant, students' overall grades appeared to be higher in 2020, which could be due to a variety of reasons. Lenient grading structures due to the pandemic, the lack of social activities, and being able to organize time available the way they want to, could be a few of the many reasons for higher achievement. In contrast, students reported higher STEM career intentions in 2019. Results suggested this was not due to differing levels of autonomy support in the two semesters, so this could instead be a result of lost extra-curricular opportunities due to pandemic-related disruptions. These experiences, such as summer research internships and shadowing opportunities, are an important contributor to retention in STEM (Thiry et al., 2011).

Second, the overall model showed that academic self-efficacy and attainment value were predictors of final grades and career intentions when other paths in the model were controlled.

Indeed, multigroup findings further support existing evidence on the relationships among these constructs, however we add new and important evidence that these processes unfold similarly in different contexts. The significant positive relationships between students' final grades and their self-efficacy and attainment value align with prior research that emphasizes that students who are believe they are capable; and perceive academic tasks to be central to their identity tend to achieve higher academic outcomes. Attainment value predicted students' STEM career intentions in both settings, which is in alignment with prior research (Hernandez et al., 2013; Robinson et al., 2018).

Third, the overall model showed that students' self-efficacy and their perception of opportunities for autonomous learning were significantly associated with their attainment value. This was indeed reflected in the multi-group analyses as well, showing that students who believe they are capable and that their choices matter in their learning environment tend to find the academic tasks they engage in more central to their identity regardless of the mode of instruction or learning environment they are in. Self-efficacy appeared to be a stronger predictor in both settings, which aligns and extends past findings of how students' feeling competent in a domain are more likely to identify with that domain (Robinson et al., 2019; Perez et al., 2014). Taken together, the results overall extend past findings by providing evidence of similar relationships existing in online learning environments.

Limitations and Future Directions

One factor that may limit my study is that most of the variables consisted of self-report measures. Because most measures were self-reported, there is a chance that hindsight bias, or common method bias, or even social desirability may have influenced student responses. For example, students may have felt uncomfortable reporting actual measures of support and responded in an idealized or stereotypical manner.

Concerning limitations involving the study sample, because study participation was voluntary it is possible that selection bias may have impacted the results. For instance, STEM students who are academically successful or motivated already may have been likelier to respond to surveys concerning their learning experiences than students who are overwhelmed. Relatedly, generalizing the findings from this study to students in STEM degree programs at other universities must be done with caution, as the present institution is research intensive and highly competitive, with rigorous admission requirements. Student experiences in this context may not be representative of students at other post-secondary institutions. Moreover, as program demands and gender ratios/inclusiveness can vary widely among STEM disciplines, future research examining similar constructs within other STEM degree programs (e.g., biology, chemistry, computer science) are encouraged to better assess generalizability of study findings.

Extant empirical research has shown situated expectancy-value theory to be one of most pertinent frameworks to examine students' achievement-related behavior. However, given the context of COVID-19, and the sudden shift to remote instruction, there were other needs of students that may have been more directly impacted or salient. For example, with heightened isolation, students' belongingness with their peers, professor, and university were likely affected. Further, students had to bear the emotional cost of having to perform academically in a new environment. Relatedly, negative affect such as anxiety and stress are more commonly experienced in a time of global crisis (Fruehwirth et al., 2021; Giuntella et al., 2021). Focusing on such constructs (belongingness, cost, emotions) that were more central to the change in the learning environment could have illuminated differences in how students' motivational beliefs are influenced in times like these.

The present study cannot afford any causal relations between the variables. Although the study measures and analytical methods were based on existing research supporting the directional relationships assessed, further studies focusing on other more direct variables that could explain students' achievement are warranted. For example, students' technological self-efficacy, distance from negative social climate at university, or peer and parental motivational supports could explain higher achievement in online settings (Klootwijk et al., 2021). Therefore, further research using experimental methods in particular is necessary to explore alternate associations and directional causality.

Conclusion

The main purpose of this study was to empirically compare mean and structural differences in students' perceptions of context, their expectancies and values, academic achievement, and STEM career intentions. Contemporary motivation research highlights the pivotal role that students' perceptions of support and context play in shaping their motivational beliefs. Technology and online learning environments became the norm during the COVID-19 pandemic and are here to stay (Teresevičiene et al., 2020; Woods, 2020). However, how differently students' motivational beliefs are shaped, and how they relate with achievement has not been investigated. The present study contributed to this growing body of research by empirically showing that students' perceptions of support and motivation are similarly shaped in online environments and traditional learning environments, which is especially remarkable considering the overall context of the pandemic and emergency remote instruction in 2020. The relationship between motivation beliefs and learning outcomes are also similar across the two learning environments. However, students reported higher intentions of pursuing STEM careers in face-to-face settings. These findings suggest that course instruction and departmental support should be re-examined to incorporate career-related opportunities in online learning environments for students to feel strongly about STEM fields. Further investigation is required, specifically into other motivational constructs such as belongingness, cost, and affect that may have been more directly impacted by the shift to emergency remote learning to illuminate other differences that may occur in students' motivation in such environments. Longitudinal research is also required to examine long-term effects of online or hybrid learning on students' academic achievement and career intentions in STEM programs.

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Appendix A

Survey Items

Academic Self-Efficacy (adapted from Midgley et al., 2000)

1. I'm certain I can master the skills taught in chemistry.
2. I'm certain I can figure out how to do the most difficult class work in chemistry.
3. I can do almost all the work in chemistry if I don't give up.
4. Even if the work in chemistry is hard, I can learn it.
5. I can do even the hardest work in chemistry if I try.

Attainment Value (adapted from Conley 2012; Robinson et al., 2018, 2019)

1. It is important for me to someone who is good at solving problems in chemistry.
2. Being someone who is good at chemistry is important to me.
3. Being good in chemistry is an important part of who I am.

Perceived Autonomy Support (adapted from Jang et al., 2016; Patall et al., 2018)

1. My instructor provides me with choices and options.
2. My instructor conveys confidence in my ability to do well in this course.
3. My instructor encourages me to ask questions.
4. My instructor listens to how I would like to do things.

STEM Career Intentions (Estrada et al., 2011)

1. To what extent do you intend to pursue a career in science, technology, mathematics, and engineering?

Appendix B

Descriptive Tables for Individual Years

Descriptive Statistics for Study Measures in 2019

Scale	*n*	*M*	*SD*	α
Academic Self-Efficacy (Time 1)	1054	3.64	0.70	.85
Perceived Autonomy Support (Time 1)	1042	3.65	0.71	.78
Attainment Value (Time 2)	973	3.35	0.82	.87
STEM Career Intentions (Time 3)	913	8.61	1.93	
Final Grade	1049	79.96	14.54	-

Note. Computed using composite scores in SPSS

Zero-Order Correlations among Study Variables in 2019

	1	2	3	4	5
1. Academic Self-Efficacy (Time 1)	-				
2. Perceived Autonomy Support (Time 1)	.201**	-			
3. Attainment Value (Time 2)	.310**	.233**	-		
4. STEM Career Intentions (Time 3)	.194**	.073*	.203**	-	
4. Final Grade	.233**	.063**	.235**	.100**	-

**$p < .01$
Note. Computed using composite scores in SPSS

Descriptive Statistics for Study Measures in 2020

Scale	*n*	*M*	*SD*	α
Academic Self-Efficacy (Time 1)	763	3.73	0.66	.87
Perceived Autonomy Support (Time 1)	762	3.94	0.69	.81
Attainment Value (Time 2)	668	3.68	0.71	.88
STEM Career Intentions (Time 3)	684	5.31	2.63	

Final Grade	965	90.79	9.05	-

Zero-Order Correlations among Study Variables in 2020

	1	2	3	4	5
1. Academic Self-Efficacy (Time 1)	-				
2. Perceived Autonomy Support (Time 1)	.347**	-			
3. Attainment Value (Time 2)	.389**	.266**	-		
4. STEM Career Intentions (Time 3)	.200**	.102*	.438**	-	
4. Final Grade	.196**	.167**	.186**	.204**	-

**$p < .01$
Note. Computed using composite scores in SPSS