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Abstract:

Distance learning, already a topic of interest among higher education administrators and faculty, took on new significance during the coronavirus disease of 2019 (COVID-19) pandemic when face-to-face classes worldwide abruptly shifted online. Many students who had never taken classes online had to either engage in distance learning or withdraw from their classes. An interesting question arises from this situation: will these students continue to take classes online when circumstances no longer require them to do so? In this paper, we investigate factors that may influence college students' intentions to continue with distance learning once they no longer have to do so. We developed a model based on social cognitive theory and social cognitive career theory and tested it using data from surveying 525 college students who took distance learning classes. Results indicate that personal and environmental factors drive intentions to continue with distance learning through their impact on distance learning perceived performance and satisfaction. We discuss our findings' implications for practice and future research.

Keywords: Distance Learning, Online Learning, Continuance Intentions.

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1 Introduction

As the world has attempted to cope with the coronavirus disease of 2019 (COVID-19) pandemic, we found ourselves in a unique position: for the first time, our online classrooms contained students (and, more importantly perhaps, professors) who had to be there—not students and professors who had freely chosen the online option. Many universities had not sufficiently prepared to move online before the pandemic. After making investments and adjusting processes to facilitate distance learning, some institutions may wish to maintain their online offerings even after conditions allow returning to face-to-face instruction.

As technological capabilities have grown over the past few decades, they have given higher education institutions the ability to offer courses online—a booming market that has reached over one hundred billion U.S. dollars (Koksal, 2020). Universities can benefit from using the Internet to teach courses by saving campus spatial resources, expanding their reach to students from farther away, and so on. Distance learning[1] might also offer benefits to students such as being more compatible with a work-related lifestyle, saving resources such as costs and time on commuting to campus, and attending universities with less regard to location. Thus, universities have cared about understanding success factors related to distance learning for quite some time (Hollands & Tirthali, 2014; Kaufman, 2015). It seems possible that distance learning will continue to become more widespread (Barsotti, 2020; Dhawan, 2020; Korkmaz & Toraman, 2020; Iyer & Chapman, 2021) and even an integral part of a “new normal” (Dick, Akbulut, & Matta, 2020), although we have yet to see the long-term effects.

Although many institutions have struggled with the rapid shift to online learning and sought to return to face-to-face classes as soon as conditions allow, some institutions have attempted to leverage what they have learned from the transition to distance learning by expanding their online course offerings. While many faculty and students may find online courses objectionable, others, forced into experiencing distance learning, may find themselves more comfortable with the online modality and may shift preferences to distance learning (Goldman & Karam, 2020). In addition, some have called for universities to embrace distance education as an option rather than a replacement for face-to-face courses (Taparia, 2020). We need to acknowledge, however, that challenges and frequent missteps characterized the rapid shift to distance learning in response to pandemic restrictions. The widely reported problems with the sudden change from face-to-face to online classes provided ammunition to those who oppose distance learning, which may reduce the probability for widespread, lasting change. Although we do not know the long-term effects, distance learning clearly gained new significance during the COVID-19 pandemic as schools worldwide turned to online courses to continue their operations and to allow students to continue progressing towards their educational goals. One element that remains unclear, however, concerns the extent to which students will want to continue with distance learning once the circumstances no longer require that they do so.

Universities may be tempted to continue with large-scale distance learning based on the logic that the forced experience with online courses may make students more amenable to taking classes online. However, it would be a mistake to simply assume that they would. While some students will likely be open to continuing to take classes online, others may prefer face-to-face courses. As a result, it will be useful to understand factors that influence students’ desire to continue with distance learning. In this study, we examine this issue by investigating the following research question:

> **RQ:** What factors influence students’ desire to continue with distance learning once circumstances no longer require them to do so?

This question has particular relevance today as institutions consider how to integrate distance learning once the pandemic subsides. Many students have been exposed to online learning for the first time due to responses to the pandemic. Some institutions may seek to use this exposure to expand online courses, even after a return to campus, perhaps by offering selected courses or sections online. These institutions will need to understand students’ reactions to online courses and the factors that drive these reactions. Our study provides useful information related to these issues. We acknowledge, however, that student preferences represent only one aspect that needs attention. We also need to consider faculty and administrative preferences, but investigating such preferences falls outside our scope in this paper.

[1] We use the terms “distance learning”, “online learning”, and “online classes” interchangeably to represent taking courses in which information and communication technologies fully mediate interactions that traditionally occurred face-to-face in both the synchronous and asynchronous modalities.

To investigate this research question, we developed a research model based on social cognitive theory (SCT) and social cognitive career theory (SCCT). We tested the model using data from a surveying 525 college students who resided in the United States. We found strong support for the research model. The way students perceived support and distance learning compatibility influenced their desire to continue with distance learning through their impact on distance learning satisfaction and perceived performance as did how students perceived their distance learning self-efficacy. Satisfaction fully mediated the impact that perceived performance had on desire to continue.

Our research contributes to the literature in several ways. First, we demonstrate the efficacy of using social cognitive theory (Bandura, 1986, 1997) as a conceptual framework for studying distance learning continuance. Second, we provide three useful instantiations of social cognitive theory's main elements and demonstrate how personal and environmental factors come together as compatibility. Third, we conceptualize compatibility—an important construct—in a unique manner (i.e., as a blend of technical, environmental, and learning style compatibility). Finally, we theorize about the influence of social isolation and self-regulation on self-efficacy.

This paper proceeds as follows: in Section 2, we summarize the background and underlying theory bases. In Section 3, we present our research model. In Section 4, we develop our hypotheses. In Section 5, we outline our research methodology and present our results. In Section 5, we discuss our findings, their implications and limitations, and future research directions. Finally, in Section 6, we conclude the paper.

2 Background and Theory

2.1 Distance Learning

COVID-19 has had significant effects on the global education sector. Epidemiologists recommend social distancing to slow its spread, and social distancing guidelines have led many educational institutions to replace in-person classes with online classes either partially or totally. Allo (2020) estimates that nearly 300 million students worldwide had their school activities affected.

In an effort to combat this unprecedented situation, institutions resorted to distance learning. Distance learning allowed students to continue their education during the global pandemic due to its location flexibility (Dhawan, 2020). Distance learning refers to "teaching and planned learning where the teaching occurs in a different place than the learning" (Siemens, Gašević, & Dawson, 2015, p. 101). Thus, one can trace distance learning back to any time where a teacher instructs students from a separate location. With rises in Internet and technological capabilities, distance learning has become increasingly feasible. Instructors can now communicate with their students through email, computer conferencing, and synchronous and asynchronous discussions (Holmberg, 2005). As a result, much research has examined distance learning (Park & Shea, 2020).

Research themes related to distance education have evolved over time (Martin, Sun, & Westine, 2020). However, two recent literature reviews on distance learning show a persistent focus on online learners' characteristics and online engagement (i.e., Zawacki-Richter, Bäcker, & Vogt, 2009; Martin et al., 2020). In fact, over the last decade, nearly 50 percent of publications on online learning have focused on online engagement and learner characteristics (Zawacki-Richter et al., 2009; Martin et al., 2020). These findings demonstrate this research stream's continued importance.

Martin et al. (2020) developed a framework for online learning research themes that includes three domain levels: 1) organization, 2) course and instructor, and 3) learner. The learner domain covers student characteristics and outcomes and their interaction with specific courses. The course and instructor domain covers how instructors design and facilitate courses. The organizational domain covers the contextual influences on the course. Martin et al. (2020) note that research can cross the domains. In this paper, we focus on the learner level.

Researchers have also continued to pay attention to factors that determine students' distance learning continuance intentions over the years (e.g., Guo, Xiao, Van Toorn, Lai, & Seo, 2016; Rodriguez-Ardura & Meseguer-Artola, 2016; Panigrahi, Srivastava, & Sharma, 2018). Work that has reviewed the distance learning literature (Lee & Choi, 2011; Hart, 2012) lists several factors that lead students to drop out of distance learning courses or persisting through. These factors include psychological attributes such as locus of control, self-efficacy, and satisfaction; institutional and technical support; and students' interactions with other students and faculty.

2.2 Social Cognitive Theory

The majority of academic development research recognizes that personal and environmental factors shape student academic behaviors (Osipow, 1990). Accordingly, we surmise that unique contextual (i.e., environment) and individual factors (i.e., person) drive the desire to continue with distance learning, which ultimately leads to students' taking online classes when circumstances no longer require them to do so (i.e., behavior). Therefore, we sought theory that included both personal and environmental factors that motivate and govern a particular type of behavior—a student's decision to continue with distance learning. As a result, we developed the conceptual framework that guided our study based on social cognitive theory (SCT) (Bandura, 1986, 1997) and its derivative social cognitive career theory (SCCT) (Lent, Brown, & Hackett, 1994), which view psychosocial phenomena as mutually and reciprocally determined by personal, environmental, and behavioral factors. As Figure 1 shows, SCT posits that personal attributes, external environmental factors, and behavior all act as intertwined constructs and affect one another bidirectionally.

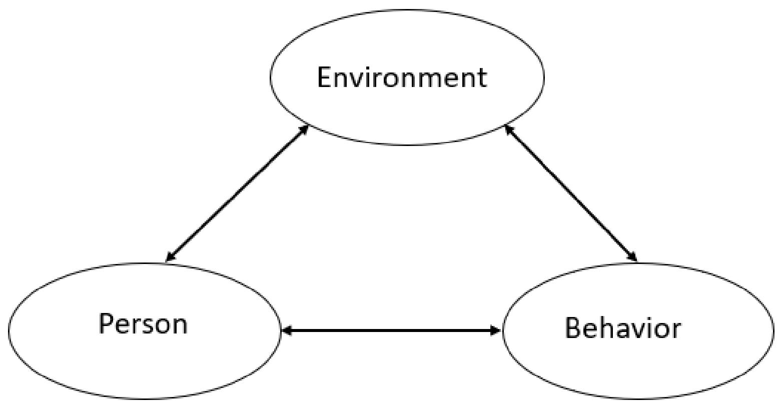

Figure 1. Social Cognitive Theory (Bandura, 1986)

According to SCT, behavior depends on the interplay between contextual and individual components that operate in a given situation. People enter contextual situations with personal attributes, such as internal cognitive and affective states, and physical attributes, such as abilities or other physical resources (Bandura, 1986, 1989). They then interact with the contextual environment. Environmental forces can include forces that support behaviors or act as barriers to certain behaviors. When considering prospective behaviors, individuals assess their ability to engage in these behaviors by integrating perceptions about themselves, the environment, and the particular behavior in question. Thus, behaviors result from interactions between an individual's personal attributes and the environment. We expect the subsequent behavior to affect one's personal attributes and environment over time, which explains the framework's bidirectionality (Bandura, 1982). Central SCT tenets include self-efficacy and outcome expectations as personal factors that interact with potential environmental factors in determining behavior (Bandura, 1997). Consistent with SCT, distance learning has fundamentally altered the learning environment by enabling new forms of behavior. When a novel action, such as taking classes online, is enabled, individuals form judgments concerning their abilities (self-efficacy) to interact with the novel environment (distance learning in this case) based on how they assess environmental factors, which may include the tools and resources at their disposal. Jointly, these factors determine their desire to continue with the behavior (continuing with distance learning).

SCT has proven to be a powerful framework in explaining, predicting, and governing behavior. Researchers have used and validated SCT extensively in numerous disciplines, such as education, psychology, communication, athletics, and organizational behavior (Looney & Akbulut, 2007). More recently, researchers have used the theory to examine the role that coping plays in higher education (Kurian & Mekoth, 2021) and to understand gender differences in science and engineering academic fields (Stewart et al., 2020).

In the IS discipline, researchers have successfully applied SCT to a broad range of topics, such as computer and software training and use, end user psychology, virtual organizations and e-commerce, and e-learning systems (Compeau & Higgins, 1995a; Staples, Hulland, & Higgins, 1999; Agarwal &

Karahanna, 2000; Hayashi, Chen, Ryan, & Wu, 2004; Looney & Akbulut, 2007; Akbulut, Looney, & Motwani, 2008). Some researchers have also suggested that future research should focus on explaining and predicting individual behavior by unlocking the SCT's full potential by leveraging it from a higher point of view that encompasses both theoretical models and constructs (Carillo, 2010).

SCCT represents a comprehensive set of variables that influence academic and career choice behaviors over time (Lent et al., 2005). Researchers developed SCCT based on multiple career development theories to provide an integrative framework that one can apply to both academic- and career-development processes, but it mainly has its roots in SCT. Leveraging the SCT's general principles, SCCT focuses on the interplay among environmental, personal, behavioral factors in order to explain and predict how individuals' academic and vocational interests will develop, the career-relevant choices they will make and pursue, and their performance and persistence in academic and vocational endeavors over time (Lent et al., 1994; Looney & Akbulut, 2007). SCCT features several variables such as self-efficacy, outcome expectations, and personal goals that influence individuals' educational or vocational development. It also incorporates how these variables interact with individuals' environment that includes various support and barrier factors in the academic- and career-development process (Lent & Brown, 1996). While SCCT covers a broad spectrum of academic- and career-related domains, such as the relationship between entrepreneurial self-efficacy and intentions (Santos & Liguori, 2020) and the relationship between self-efficacy and job satisfaction (Chang & Edwards, 2015), researchers have also successfully leveraged it in the computing domain to investigate the core factors that affect students' interest in and decisions to major in IS (Akbulut, 2015, 2016)

2.2.1 Behavior

According to SCCT, the determination to engage in a particular educational or occupational activity plays an important role in self-regulating actual behavior (Bandura, 1986; Lent & Brown, 1996). In this study, we investigate students' desire to continue with distance learning when circumstances no longer require that they do so. In this respect, students' academic plans about which learning environment to pursue, aspirations, and expressed choices serve as goal mechanisms that help students organize and guide their behavior so that they can attain their desired outcomes (Lent et al., 1994; Akbulut et al., 2008).

2.2.2 Personal Factors

SCCT acknowledges the important role that personal factors play in the educational and vocational choices that individuals make (Lent & Brown, 1996). Individuals possess certain personal factors such as traits, histories, and cognitive resources to deploy when they make decisions (Bandura, 1986; 1989). Students assess their ability to engage in prospective behaviors by integrating perceptions about themselves with what the behaviors require. Distance learning represents a major shift from the traditional face-to-face learning. Therefore, the switch to a new way to learn would cause students to evaluate their own internal cognitive, affective states, and physical attributes. In our study's context, we expect self-efficacy, social isolation, self-regulation, compatibility with students' learning style, and perceived satisfaction and performance to serve as salient personal factors that influence continuance desires with distance learning.

2.2.3 Environmental Factors

Environmental factors refer to the temporal and spatial forces beyond an individual's boundaries (Bandura, 1986). SCCT states that students do not make academic and career choices in a vacuum solely based on personal factors; they also consider their environment. Therefore, we expect environmental factors to influence every stage of the academic-development process (Lent, Brown, & Hackett, 2000). Moreover, environmental factors also influence and are influenced by both personal and behavioral factors. The literature has identified several environmental factors that individuals perceive as aiding or inhibiting their efforts to implement a particular educational or occupational goal. In our study's context, we expect support and two types of compatibility (technical and environmental) to be important as previous research has suggested (Van Slyke, Dick, Case, & Ilie, 2010; Akbulut-Bailey, 2012).

By including personal and environmental factors, SCT and SCCT provide a useful foundation for studying how personal and environmental factors come together to determine distance learning continuance intentions. As we discuss in Section 3, our research model integrates personal factors, environmental factors, and, importantly, a "coming together" of environmental and personal factors. Thus, combined with the broad support for SCT, we contend that SCT and SCCT are appropriate perspectives from which to study desires to continue distance learning.

3 Research Model and Hypotheses

Figure 2 below represents the research model we used in our study. We expect personal and environmental factors to independently and cumulatively affect student satisfaction and perceived performance in the online learning environment, which, in turn, we expect to determine students' desire to continue with distance learning. The dashed rectangles represent SCT elements, while "personal x environmental" indicates how personal and environmental factors interact. We focused on distance learning continuance as our behavior of interest. We modeled support and compatibility as second-order formative constructs as we developed them from the indicators, which we explain in Section 4.1 and show in Table 4. In this section, we describe how we developed our hypotheses in detail. Before turning to our hypotheses, however, we point out that our model proposes both direct and indirect effects of perceived support, perceived compatibility, and self-efficacy on desire to continue with distance learning. Few studies have investigated the antecedents in our model with respect to both direct and indirect effects.

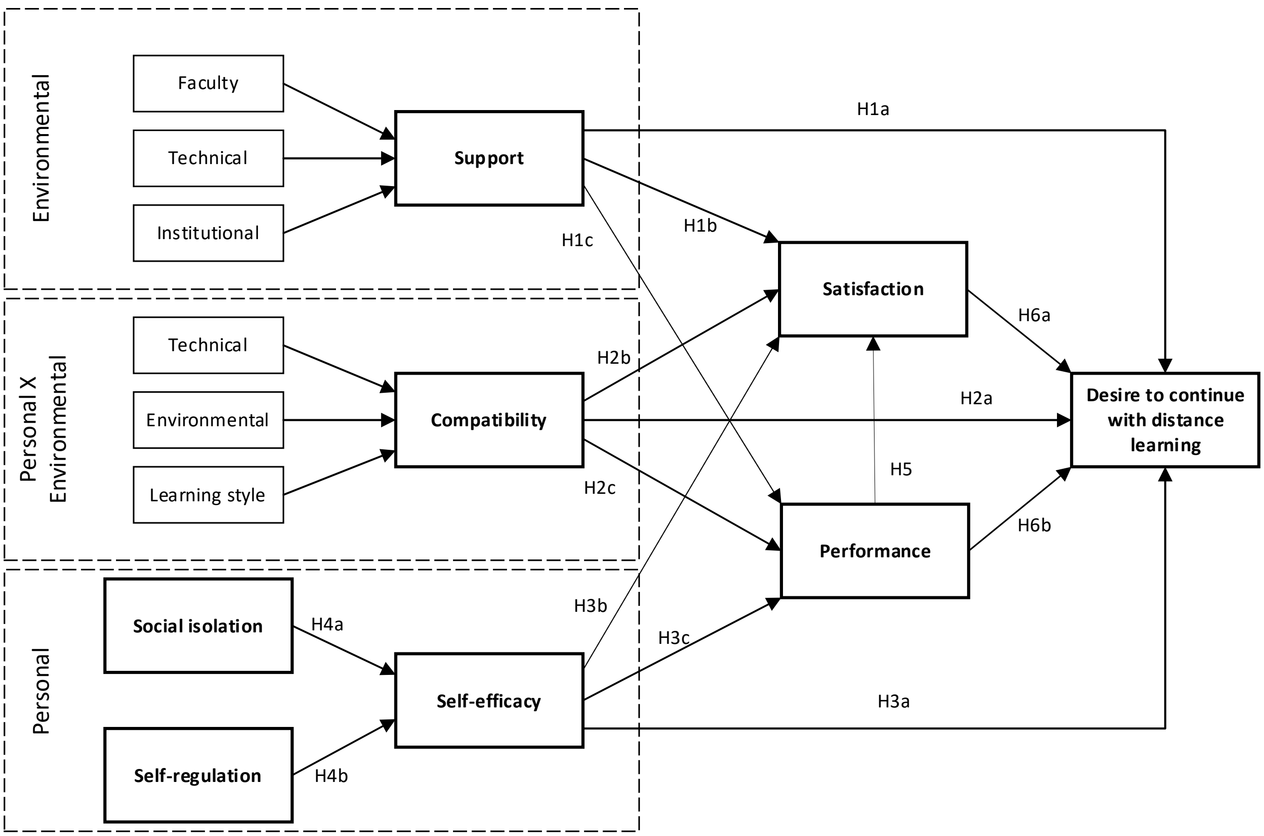

Figure 2. Research Model

3.1 Support

The literature has identified various support factors in the pursuit of academic and career choices, such as encouragement from others, role models, instrumental assistance, technology sophistication, and financial resources (Lent, Brown, & Hackett, 2002; Akbulut-Bailey, 2012). Support plays a role in students' interest in and determination to pursue a particular educational path and their retention (Heyman, 2010). Similarly, the telecommuting literature highlights that organizational support has an important role as well (Bentley et al., 2016). Moreover, research has shown technological support to be a key factor in knowledge creation and employee participation (Lee & Choi, 2003).

However, one should not take the impact that support has on distance learning outcomes as a given. Many students today (though, of course, not all) can already competently conduct their online activities and may have little need for technical support. In addition, much institutional support for distance learning may occur "behind the scenes", which students may not recognize. Further, students may not recognize the institutional support available to them. Although prior research and our own thinking led us to believe that support will be important, the question deserves further research. Furthermore, we do not know whether support directly affects desires to continue with distance learning, whether it indirectly does so through performance perceptions and/or satisfaction, or both.

In our study's context, support refers to the students' perceptions about the level of formal and informal encouragement and assistance available to them. Thus, we can categorize such support as coming from three prior sources: 1) from the professor in the sense that students feel that the professor takes an interest in their work and that the professor will be available to support them (which reflects the manager's role in an online work environment), 2) from the institution in taking steps to facilitate easy access to resources and a willingness to "be there" for students who encounter problems, and 3) providing technological assistance when required. For many universities, large-scale online learning means using unfamiliar technology, which brings inherent frustrations and often requires them to establish or expand their help desk operations to help users deal with technology challenges. So, it seems reasonable to expect that students' perceptions about the support they receive will relate to their desire to continue with distance learning. Therefore, we hypothesize:

H1a: Perceived level of support for distance learning is positively associated with desire to continue with distance learning.

There are perhaps particular challenges that surround the role of support in the helping students cope with the current environment. Researchers have long recognized that students engaging in online education assume a high degree of responsibility for their learning. One important challenge concerns problems students face in interacting with others in a distance learning environment (Ludwig-Hardman & Dunlap, 2003, p. 3). However, in this pandemic-driven environment, most students have been forced into circumstances that have not matched their expectations, desires, and, indeed, skills. In such a situation, support takes on extra importance. Without support, we can expect students to be less than satisfied with their online experience. As such, we assume that students would be more satisfied with distance learning if they believe that their professors and institution support them and that have the necessary assistive tools and aids to help them as needed. Empirical support exists for the relationship between perceived support and students' overall satisfaction with online courses (Lee, Srinivasan, Trail, Lewis, & Lopez, 2011). Therefore, we hypothesize:

H1b: Perceived level of support for distance learning is positively associated with satisfaction with distance learning.

As for satisfaction, the literature indicates a positive relationship between support and student performance. Jaggars and Xu (2016) built on previous research and showed that, by making frequent posts, inviting questions and responding quickly, soliciting and using solicited feedback, and demonstrating a sense of caring, instructors created an environment that encouraged student commitment and course performance. In another study, Looney and Akbulut (2007) showed that effective instructors bolster students' performance expectations. Earlier work has also showed that instructors increase student success when they actively participate in students' learning and create personal relationships with them (Looney & Akbulut, 2007; Jaggars & Xu, 2016) because they help motivate students succeed.

Competent "anywhere, anytime" technical support is central to providing online classes (Maddux & LaMont Johnson, 2014). However, such classes lack this central component in many cases. Many education institutions do not provide round-the-clock support, and the support they offer varies in quality. Researchers have long recognized that education institutions need to have technical support (preferably training, orientation, and documentation) in place (Davis, Little, & Stewart, 2008). Still, education institutions face difficulties in implementing such support, which can cause confusion if not overcome. In particular, these difficulties likely concern decisions about who should look after the function (e.g., the IS helpdesk or teaching unit). Wherever it ends up, the function needs to provide seamless support to students.

Likewise, research has shown that, in higher education settings, institutional support and assistance provided to students not only improves student learning but also encourages students to pursue particular academic paths (Akbulut-Bailey, 2011). Researchers have argued that a comprehensive institutional support system ameliorates student performance at least as measured in dropout and retention rates (Lee & Choi, 2011). Institutions need to provide, and be seen to provide, students with support across activities in a holistic manner, which includes advising, professional interaction, and financial support. When institutions provide students with such support in each stage of their academic career, it makes students feel that the institution, as a whole, cares about them and the barriers they face. Gaytan (2013) identified institutional support to students as one of the most important factors affecting student retention in online courses. Lee et al. (2011) found that teachers should communicate what types of support students can access and provide an easy way for them to access and use the support. Therefore, we hypothesize:

H1c: Perceived support for distance learning is positively associated with perceived performance in distance learning courses.

However, we should not take these relationships as given despite our reasoning.

3.2 Compatibility

Researchers have long recognized compatibility as central to understanding technology adoption (Tornatzky & Klein, 1982; Rogers, 2003; Van Slyke et al., 2010). The literature has identified several different compatibility dimensions. In educational settings, Van Slyke et al. (2010) empirically tested compatibility's multi-dimensionality and found that compatibility with values and preferences, which they defined as learning style compatibility, influenced distance learning intentions. They stated: "when students find that distance learning fits with the way they like to learn, they are likely to use this mode of learning" (Van Slyke et al., 2010, p. 407). Van Slyke et al. also found that prior experience and existing work practices had no significant effect on their intentions—students were more likely to make their decisions based on what they wanted rather than what they had experienced in the past. In other words, in thinking about a desire to continue with online learning, students will likely base their decision based on whether or not it fits with their idea of how one should use the technology to facilitate distance learning.

Accordingly, in this study, we expand the compatibility dimension from one essentially connected to fitting students' preferred way of learning to also include the environmental and technological compatibility that they might experience. We see this view of compatibility as particularly relevant at this time as circumstances have perhaps forced many students to use inadequate places to work and study and have access to insufficient technology (i.e., bandwidth, software, and hardware).

Students pushed from the face-to-face environment to the online one may have found the technology that they had to use unfamiliar, or even unavailable, and, therefore, as not conducive to their learning activities, which could have led to frustration and dissatisfaction. Research has long found the ease with which one can use relevant technology (i.e., their ease of use) to significantly predict satisfaction in online learning (Joo, Lim, & Kim, 2011) and behavioral intent (Venkatesh & Bala, 2008). Adapting the ease of use constructs from Ventakesh and Bala's (2008) study, we examine the extent to which compatibility with technology acts as an element of compatibility as a whole. In our context, technology compatibility deals with the extent to which students perceive the information and communications technology available to then as adequate for engaging in distance learning rather than referring to operational compatibility (e.g., whether an application will run on a student's computer).

Environmental compatibility refers to the extent to which students' have a sufficient physical environment to undertake online learning. The pandemic not only affected students in higher education but also severed whole families from traditional places of work and education; indeed, many elementary and secondary schools closed or conducted classes online. As a result, family members had to share information and communication technology (ICT) resources, such as tablets, computers, and bandwidth, in the home. The compromise arrangements that many found themselves in likely caused frustration with the learning environment students had to use in order to continue their studies. As above, a university's decision to have students study from home may not have considered the availability of a room, or even a place in the home, in which to work and concentrate. The online education literature has scarcely mentioned suitable study environments, but, drawing on the early telecommuting literature, McCune (1998) identified a separate workspace and ergonomic furniture as requirements for working at home.

We expect perceived compatibility to positively impact distance learning outcomes. However, again, we should not take these relationships as given. The IS literature has largely viewed compatibility in a simplistic manner by not accounting for its multidimensional character (Van Slyke et al., 2008). By including three compatibility dimensions that we specifically chose for the distance learning context, we more completely capture compatibility and its effects. However, because we conceptualize compatibility in a way that differs from prior research, our empirical results will add to our knowledge about this important variable's effects. Therefore, we hypothesize:

H2a: Perceived compatibility of distance learning is positively associated with desire to continue with distance learning .

When students believe that distance learning is incompatible with their learning preferences, technology or environment, they are likely to find distance learning less satisfying. In contrast, satisfaction is likely to result when individuals find that their situation supports an activity (such as distance learning) (Chan et al., 2010). Therefore, we hypothesize:

H2b: Perceived compatibility of distance learning is positively associated with satisfaction with distance learning.

In a similar fashion, we expect perceived compatibility to also affect perceived performance. Perceptions about compatibility partly reflect an individual's assessment of the extent to which a situation fits with their perceived needs. When an individual's circumstances fit well (are compatible with) what a task or tasks requires, the individual's performance will likely increase (Goodhue & Thompson, 1995). Researchers have demonstrated this relationship in the education context (e.g., McGill & Klobas, 2009). In the distance learning context, students will likely perceive their performance as lower when they believe that distance learning does not fit well with the way they prefer to learn or with their technological or physical environments. Poor compatibility in any of these areas will likely involve discomfort that individuals must deal with, which could reduce how much time and attention resources they may devote to learning. Further, in some cases, poor compatibility may represent tangible barriers to performance. For example, the lack of a quiet workspace will likely have negative performance implications. Similarly, technology compatibility problems often require considerable time and attention to overcome. Consider, for example, a student who relies on a Chromebook, which may not be able to run specialized software. That student must take time and expend effort in either acquiring another computer or in determining some workaround. In extreme cases, the student may simply fail to complete assignments that require specialized software. On the other hand, when students' living conditions and environment suit distance learning (such as having a designated area to complete their work away from distractions, the ability to organize their work area based on the needs of their courses, etc.) and they have all the technologies that they need for distance learning at their disposal and have no difficulty in using distance learning tools and technologies, they would be more likely to believe that they would perform better in their online classes. Therefore, we hypothesize:

H2c: Perceived compatibility of distance learning is positively associated with perceived performance in distance learning courses.

3.3 Self-efficacy

Self-efficacy, a core component in SCT and SCCT, refers to the "belief in one's capability to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p 3). Self-efficacy functions by providing individuals with beliefs regarding their capabilities to exercise control over their actions and the environment (Looney & Akbulut, 2007). IS research suggests that self-efficacy plays a critical role when one interacts with information technologies (Taylor & Todd, 1995; Compeau, Higgins, & Huff, 1999; Agarwal & Karahanna, 2000; Johnson & Marakas, 2000).

To accurately predict intention and behavior, self-efficacy judgments should be task specific, which means that they should capture the capabilities necessary to perform the behavior in question (Bandura, 1986, 1997). In our study's context, in coping with online classes, individuals need to be able to answer the question "can I do this?" in the affirmative. Changes in the education and training mode from face-to-face to online may affect learner self-efficacy beliefs (Hodges, 2008). These beliefs, which we define following Bates and Khasawneh (2017, p. 181), who adapted Compeau and Higgins' (1995b) definitions, as "the extent to which people feel confident in their ability to successfully use online learning technology to complete the learning task requirements of college courses", appear frequently in the literature as important in both satisfaction and performance in online classes. "Self-discipline, the ability to work alone, time management, learning independence, the ability to develop a plan for completing work, and so on" constitute a particular skill set (Ludwig-Hardman & Dunlap, 2003).

Individuals who believe that they lack the capabilities to successfully perform a behavior are unlikely to want to engage in that behavior in the future. In the distance learning context, students who believe that they have the capabilities to successfully engage in distance learning are more likely than their less confident peers to want to take classes online (Chiu & Wang, 2008). Empirical evidence exists to support the relationship between self-efficacy and distance learning continuance intentions (e.g. Gong, Xu, & Yu, 2004; Chiu & Wang, 2008). Therefore, we hypothesize:

> **H3a:** Perceived distance learning self-efficacy is positively associated with desire to continue with distance learning.

Shen, Cho, Tsai, and Marra (2013) stated that possessing the self-efficacy to complete an online course most significantly explains variances in satisfaction. They demonstrated that students' self-judgment about their capabilities to complete an online course played a critical role in their satisfaction with the course. In addition, they found instructors who used a proactive approach that promoted social interaction helped to enable students in developing the self-efficacy they needed to complete an online course.

Central to the belief that one can cope is confidence in one's ability to do so (Letcher & Neves, 2010). Alqurashi (2019) suggested that satisfaction depends on students coming to the course with a high degree of confidence in their capability to do well, overcome challenges, manage their course schedule, and achieve course objectives. Therefore, we hypothesize:

> **H3b:** Perceived distance learning self-efficacy is positively associated with satisfaction with distance learning.

Researchers have widely examined self-efficacy and its relationship with performance. Chemers, Hu, and Garcia (2001) identified "compelling support" for the role that self-efficacy plays in student success and noted both direct and indirect relationships with academic performance. Choi (2005) identified task specific self-efficacy (academic-related tasks) as a significant predictor of performance as measured in term grades. Bradley, Browne, and Kelley (2017) underlined the need to consider both self-efficacy and self-regulated learning in online educational environments in their study on undergraduate students. They found that student self-efficacy beliefs directly influenced academic outcomes.

Of course, the self-efficacy and performance constructs overlap and affect each other to a considerable degree. Talsma, Schüz, Schwarzer, and Norris (2018) conducted a meta-analysis in which they considered the relationship between the two constructs. They found a significant effect both ways but a stronger effect from performance to self-efficacy. In a later publication, the lead author described the relationship between self-efficacy and academic performance as complex and nuanced (Talsma, Norris, & Schuz, 2019). In a similar vein, Talsma (2019) noted that past academic performance affected self-efficacy beliefs in a larger way than the other way around. On the other hand, other authors have generally conducted research based on self-efficacy predicting performance (Wilson & Narayan, 2014; Yokoyama, 2019; Hwang, Choi, Lee, Culber, & Hutchison, 2015). Therefore, we hypothesize:

> **H3c:** Perceived distance learning self-efficacy is positively associated with perceived performance in distance learning courses.

3.4 Self-regulation and Social Isolation

Using a "telepresence" lens, Guo et al. (2016) examined the isolation concept in depth and demonstrated that the degree to which an individual becomes absorbed in an activity depended on a sense of "being there" and, drawing on earlier work by Csikszentmihalyi (1975), that using a computer-mediated environment in online learning greatly affected individuals' continuance intention via a state of flow—that state when one wants to continue an activity for its own sake.

Dang, Zhang, and Amer (2018) examined social presence in a blended learning environment and found support for the hypotheses that student-to-student and student-instructor networks positively influenced social presence, which, in turn, affected the learning climate and perceived academic performance. They suggested that the learning environment needs to be developed to a point where it is social and personal enough, with sufficient interactions and communications in place, to help students learn. Weidlch and Bastiaens (2017) also found support for social presence. Specifically, they found that a sociable learning environment affected the quality of the learning experience. Such a learning environment possibly takes on particular importance in distance learning when we consider how, due to the pandemic, many students found themselves isolated and away from the learning environment that they had previously sought. Shen et al. (2013) also pointed out that social isolation could contribute to diminished self-efficacy. Further, Alqurashi (2019) points out that the vicarious experience of working with and observing others (i.e., not isolated) contributes to self-efficacy.

In a study on teleworkers, Golden, Veiga, and Dino (2008) identified social isolation as a factor in lower performance and suggested that researchers had room to further investigate the relationship between social isolation and performance. Hill, Liyan Song, and West (2009) further established the role that self-efficacy and social isolation play in learning in online classes. Thus, we hypothesize:

H4a: Perceived social isolation is negatively associated with distance learning self-efficacy.

The belief that one has the ability to cope with the tasks necessary to achieve one's objective is particularly important tp effective learning online (Artino & McCoach, 2008; Lee, Choi, & Kim, 2013; Bradley et al., 2017). Self-efficacy at least partly derives from an ability to manage one's behavior and produce positive and acceptable results (self-regulation) as Lynch and Dembo (2004) and Hodges and Kim (2010) have indicated and the degree to which one can interact with colleagues and peers (social isolation) as Shen et al. (2013) and Artino and Jones (2012) have reported. Cho and Shen (2013) examined these two concepts (i.e., self-regulation and social interaction) together and found that self-efficacy affected self-regulation.

Many researchers have argued that self-regulation takes on particular importance in the online classroom. In this environment, the student assumes primary responsibility for the learning process (Dabbagh & Kitsantas, 2004). Furthermore, online students need to become self-directed (Bollinger & Martindale, 2004). Researchers have found self-regulation to predict academic success (Lynch & Dembo, 2004; Artino & Stephens, 2009) and completers versus dropouts (Lee et al., 2013).

In studying e-learning in organizations, Sharma, Dick, Chin, and Land (2007) found that intrinsic goal orientation (regulating oneself to take actions to master content, manage tasks, working to deadlines, etc.) predicted performance. They also included mastery and retention as dimensions of performance and found that performance related to learning the actual e-learning course content and materials taught.

The differences between traditional and online classrooms mean that learners need to be self-regulated; that is, they need to establish study and work schedules, be mindful of timetables, have the ability to cope with perhaps unfamiliar tasks, and work by themselves. Self-regulated learning theory perceives learning as "an activity that students do for themselves in a proactive way" (Zimmerman & Schunk, 1989, p. 1) and not something that happens outside of or to the learner. As such, they need to possess these self-regulatory attributes to perform well and continue with their learning. To compound the problem that students face, particularly in the current pandemic environment, they also lack factors that may have motivated them (Hodges, 2005), such as group pressure and the instructor's presence (e.g., instructors may chastise students for incomplete work and, in doing so, enforce deadlines). Therefore, to succeed in the online classroom, students need to rely more on their individual abilities. Therefore, we hypothesize:

H4b: Perceived self-regulation is positively associated with perceived distance learning self-efficacy.

3.5 Performance and Satisfaction

Student perceived performance and satisfaction play important roles in educational settings. Researchers have used these factors to investigate student learning, academic success, and retention in various studies that have investigated learning environment (including online learning environment) effectiveness (Alshare & Lane, 2011; Eom, Wen, & Ashill, 2006; Chen, Keys, & Gaber, 2015; Kaufman, 2015; Dick & Akbulut, 2020).

In addition to self-efficacy beliefs that we discuss in Section 3.3, SCT and SCCT also include outcome expectations in regulating human behavior. Individuals consider the potential outcomes of their activities before they undertake them. Outcome expectations refer to a priori beliefs regarding the perceived likelihood that favorable consequences will result from enacting a particular behavior (Bandura, 1986, 1997). While the literature has identified different types of outcome expectations (Compeau & Higgins, 1995a; Compeau et al., 1999), performance-related outcome expectations dominate (Venkatesh, Morris, Davis, & Davis, 2003). Thus, we focus exclusively on this form. We can define student perceived performance as students' perceptions about how well they learned in a particular learning environment (Wighting, 2011). In our study's context, performance refers to the students' judgments about how well they have performed in the online environment.

Distance learning satisfaction refers to students' judgments about the quality of their learning experience with online learning, the enjoyment they feel from it, and whether they would recommend taking other online classes to other students. Studies about the differences in student perceptions about online and face-to-face classes have found mixed results in terms of student satisfaction levels (Herbert, 2006; Mortagy & Boghikian-Whitby, 2010). Regardless, prior research has emphasized the need to design online learning environments that promote student satisfaction, particularly to ensure student retention (Herbert, 2006; Kauffman, 2015). Students who feel that they have performed well in a particular learning environment would be more likely to be satisfied with their online learning experiences. This thinking has a long history in research into academic satisfaction. For example, in studying college students, Aitken (1982) found that academic performance more strongly predicted academic satisfaction than factors related to courses, social isolation, major, instructors, or advisors. More recently, Hatcher, Kryter, Prus, and Fitzgerald (1992) described student satisfaction as a function of perceived performance. One way to view distance learning satisfaction reflects the extent to which students believe that their investments in time and effort yield performance returns (Weerasinghe & Fernando, 2017). Students who believe that their investments have resulted in high performance will likely be more satisfied than their peers who perceive lower performance returns. This relationship between distance learning performance and satisfaction has been demonstrated empirically (de Melo Pereira, Ramos, Gouvêa, & da Costa, 2015). However, despite the thinking provided above, other antecedents may be more important than perceptions about performance in determining satisfaction with distance learning. It may be, for example, that perceived compatibility could lead students to be satisfied with distance learning even when they believe they have performed poorly. However, considering the factors above together, we hypothesize:

H5: Perceived distance learning performance is positively associated with satisfaction with distance learning.

Student's satisfaction with online learning can directly influence their desire to use online learning. Researchers have found satisfaction, an intrinsic motivation, to significantly influence individuals' usage intentions and behavior in various settings (e.g., Bhattacherjee, 2001; Limayen & Cheung, 2008). Researchers have commonly used satisfaction as an indicator to evaluate the effectiveness of learning environments in both academic and business settings (Alavi, 1994; Alavi, Wheeler, & Valacich, 1995). For example, researchers have found that users' satisfaction level with initial IS as the strongest factor that predicts IS continuance intentions in online banking (Bhattacherjee, 2001). As for students in an educational setting, Chao (2019) found student satisfaction with m-learning to significantly determine their intentions to use m-learning in the future. As such, students who exhibit higher satisfaction with a particular learning method would plausibly develop a stronger desire to continue with it. Learner satisfaction has significantly predicted persistence, which suggests that online universities need to focus on increasing learner satisfaction in order to maintain high levels of learner persistence (Joo et al., 2011). Therefore, we hypothesize:

H6a: Satisfaction with distance learning is positively associated with desire to continue with distance learning.

Similar to satisfaction, students' perceived performance can affect their desire to continue with online learning directly. People develop intentions and goals in part based on the positive outcomes they expect to obtain (Akbulut-Bailey, 2012). The higher the likelihood that they will do well in the online environment, the more likely that students will want to continue with online classes. Empirical results indicate a relationship between performance expectations and distance learning intentions (Tarhini, El-Masri, Ali, & Serrano, 2016; El-Marsi & Tarhini, 2017). Such results should not be surprising. Students who feel they perform well in a distance learning environment should be more likely to want to take distance learning courses in the future. Despite this thinking, perceived performance may only matter to continuance desires to the extent that these perceptions affect satisfaction. If so, the direct relationship would not hold in the way we expect. However, we do expect perceived performance to have both direct and indirect effects on desire to continue with distance learning. Therefore, we hypothesize:

H6b: Perceived distance learning performance is positively associated with desire to continue with distance learning.

In Section 4, we discuss the method we used to test our hypotheses and our results.

4 Method and Results

This study grew from a small pilot study (n = 36) from two courses running in a metropolitan university, which moved to fully online due to the pandemic. As a result, we gained the opportunity to test some of the adapted scale items. Although small, our sample size had sufficient size such that we could conduct reliability checks on the survey questionnaire. We found satisfactory results for these checks and so proceeded with the study proper.

In order to test the research model, we administered a survey that comprised previously validated scales to adult higher education students who took at least one online course prior to the current term (ending by June, 2020); in effect, this requirement ensured that participants had some experience with distance learning prior to the mandated distance learning brought about in response to the COVID-19 pandemic. We measured scale items on a seven-point scale (strongly agree to strongly disagree). We provide the scale items and their sources in Appendix A. When possible, we used existing scales that prior studies had validated. In some cases, we adapted items for our research context. In order to capture the underlying theoretical dimensions comprehensively, we used multiple indicators to measure each construct.

We limited our data to students who resided in the United States at the time we conducted the study. The survey panel company Qualtrics solicited survey participants based on the aforementioned criteria. We secured a pilot sample with 50 participants and analyzed their responses for survey administration and scale reliability problems. Finding none, we proceeded with the data collection. We rejected responses if they failed either of the two attention check items included in the survey. After we met an initial target of 500 responses, we examined responses for data quality by checking for straight-line responses and nonsense answers to text questions. We defined straight-line responses as more than 66 percent of responses to Likert-type scale items being at either endpoint of the scale (1 or 7). We rejected and replaced two responses. When we stopped collecting data, our final sample contained 525 responses.

Approximately 90 percent of the participants classified themselves as full-time students. The sample skewed toward female participants with approximately 60 percent of the respondents identifying as female. The sample comprised 86.5 percent undergraduate students. The mean age was 22.1 years. We show the respondent demographic data in Table 1.

Table 1. Sample Demographic Characteristics

Sex	Female: 314 (59.8%) Male: 208 (39.6%) Non-binary: 3 (0.6%)
Age	Mean: 22.1 years Standard deviation: 5.6 years
Country of birth	USA: 473 (90.1%) Other: 52 (9.9%)
Classification	Undergraduate: 454 (86.5%) Graduate: 71 (13.5%)
Number of prior classes taken online[2]	Mean: 3.6 Standard deviation: 5.0

4.1 Measurement Model Results

We used SmartPLS 3.0 to analyze the measurement and structural models that we derived from our research model. We found acceptable reliability and validity of all scales based on our measurement model. All scale items loaded as we expected with all path coefficients from indicator variables to latent variables significant at $p < 0.001$. Appendix B shows loadings and cross-loadings for all indicators. Although we found some relatively high cross-loadings, in all cases, indicators loaded more strongly on the intended latent variable than on other latent variables.

[2] We asked participants the number of online courses taken prior to the term ending by June.

We confirmed the reliability and convergent and discriminant validities of the scales. First, we examined the reliability of items that comprised each construct to ensure the items collectively measured their intended construct consistently (Gefen, Straub, & Boudreau, 2000). We show the reliability statistics in Table 2. In this respect, we calculated Cronbach's alpha coefficients and composite reliabilities to assess internal consistency reliability (Nunnally, 1978). Cronbach's alpha coefficients ranged from 0.799 to 0.970 (except for one lower score). Composite reliabilities were even higher and ranged from 0.767 to 0.978. The Cronbach's alpha score for social isolation was low (0.580), but the composite reliability score for it was 0.767. Because the composite reliability was acceptable, we decided to retain all items in the social isolation scale.

Table 2. Internal Consistency

Scale	**Cronbach's alpha**	**Composite reliability**
Desire to continue	0.949	0.967
Performance	0.867	0.901
Satisfaction	0.930	0.950
Support		
Faculty support	0.923	0.945
Technical support	0.921	0.950
Institutional support	0.897	0.936
***C*ompatibility**		
Environmental compatibility	0.799	0.878
Technical compatibility	0.831	0.888
Learning style compatibility	0.970	0.978
Personal characteristics		
Self-efficacy	0.879	0.925
Social isolation	0.580	0.767
Self-regulation	0.840	0.893

We assessed convergent validity both at the individual item and construct levels by examining the individual item loadings and the average variance extracted (AVE), respectively (Fornell & Larcker, 1981). In order to claim convergent validity at the item level, items should load significantly on their intended constructs (Gefen & Straub, 2005). All of our scales satisfied this criterion. In addition, as Appendix B showed, all scale items loaded more strongly on their intended factor than on any other factor. No undesirable cross-loadings emerged.

In order to claim convergent validity at the construct level, AVE values should equal or exceed 0.50 (Fornell & Larcker, 1981), which demonstrates that a construct as a whole shares more variance with its indicators compared to error variance. As Table 3 shows, the AVE values for each construct exceeded the recommended threshold value 0.50, which confirms the items collectively demonstrated convergent validity (Fornell & Larcker, 1981; Gefen et al., 2000).

Table 3 provides information related to discriminant validity as well. We show inter-scale correlations in the off-diagonal elements, and the diagonal elements show the square root of the average variance (AVE) that each scale explained. In all cases, the square root of the AVE exceeded the absolute value of the associated inter-scale correlations, which indicates acceptable discriminant validity (Fornell & Larcker, 1981). As we mention above, all indicator items loaded much more highly on their indicated scale than on any other scale, which further evidences discriminant validity. To investigate potential multicollinearity, we examined variance inflation (VIF) factors for each scale. The maximum value was 2.688 (for performance and continuance), which indicates multicollinearity did not pose a serious problem (Hair, Black, Babin, & Anderson, 2018).

Table 4 provides statistics related to the second-order latent variables. We modeled the second-order latent variables as formative primarily because we had no theoretical or practical reason to expect the first-order latent variables to correlate highly. For example, we had no theoretical basis to assume that technical barriers and environmental compatibility would highly correlate with each other. We found a highly significant relationship between the first- and second-order latent variables in all cases with path coefficients in the direction we expected.

Table 3. Discriminant Validity

	1	2	3	4	5	6	7	8	9	10	11	12
1) Desire to continue	**0.95**											
2) Performance	0.58	**0.78**										
3) Satisfaction	0.69	0.79	**0.91**									
4) Fac. support	-0.02	0.13	0.18	**0.90**								
5) Tech. support	0.26	0.28	0.37	0.45	**0.93**							
6) Inst. support	0.06	0.17	0.22	0.59	0.59	**0.91**						
7) Tech. comp.	-0.30	-0.42	-0.41	-0.20	-0.37	-0.24	**0.82**					
8) Env. comp.	0.31	0.42	0.46	0.28	0.37	0.34	-0.47	**0.84**				
9) Learn. style comp.	0.70	0.67	0.75	0.06	0.29	0.12	-0.36	0.37	**0.96**			
10) Self-efficacy	0.35	0.57	0.55	0.34	0.42	0.33	-0.42	0.49	0.48	**0.90**		
11) Soc. isolation	-0.43	-0.54	-0.58	-0.10	-0.21	-0.13	0.30	-0.41	-0.53	-0.34	**0.73**	
12) Self-regulation	0.14	0.29	0.21	0.16	0.35	0.28	-0.24	0.31	0.21	0.41	-0.15	**0.82**

Note: Diagonal elements are the square root of the average variance explained. Off-diagonal elements show the inter-scale correlations.

Table 4. Results for Second-order Latent Variables

Path	Path coefficient	P-value
Faculty support -> support	0.477	< 0.001
Technical support -> support	0.396	< 0.001
Institutional support -> support	0.360	< 0.001
Technical compatibility -> compatibility	0.313	< 0.001
Environmental compatibility -> compatibility	0.234	< 0.001
Learning style compatibility -> compatibility	0.706	< 0.001

To control for common method variance, we varied the response order with some items having strongly agree as 1 and others having that response as 7. Despite this control, problematic common method variance could still have existed. Thus, we performed a marker variable test for common method variance using the blue attitude scale (Miller & Chiodo, 2008). The mean correlation between this latent variable and the others in the model was 0.022—values under 0.10 indicate a low threat of common method bias (Malhotra, Kim, & Patil, 2006). Having established our measurement model's acceptability, we turn attention to the results from the structural model.

4.2 Structural Model Results

Table 5 shows the R^2 values for the endogenous latent variables in our model. Our model accounted for a large portion of the variance in desire to continue (48.3%), perceived performance (53.9%), and satisfaction (71.4%) and a smaller but still significant portion of the variance in perceived self-efficacy (24.7%)[3].

Table 6 provides statistics related to the paths in our research model. Figure 3 shows the results diagrammatically. Results indicate general support for the model in that seven of the 11 paths had p-values less than 0.001. One additional path (support to satisfaction) was significant at $p < 0.05$, and one

[3] We included several control variables (sex, age, number of previous online courses taken, and student classification (undergraduate or graduate)) in our initial analysis. None had a significant impact on desire to continue with distance learning courses, so we removed them from the model. All reported results exclude these control variables.

path was significant at $p < 0.10$. Two paths (self-efficacy to satisfaction and performance to desire to continue) were clearly nonsignificant. Two paths were significant (support to desire to continue, $p < 0.001$, and support to performance, $p = 0.066$) but in the opposite direction from what we hypothesized. In Section 5, we discuss these results further.

In complex mediated models, one can find it instructive to examine total effects of important variables as Table 7 shows. Because we had an overarching interest in understanding desire to continue with distance learning, we examined the total effects of this outcome. As expected, satisfaction, perceived performance, and compatibility had a significant positive total effect on desire to continue. In particular, compatibility had a particularly strong effect (0.699). Contrary to our expectations, self-efficacy had virtually no total effect on desire to continue. (Note that, because self-efficacy had a nonsignificant total effect, so too did social isolation[4] and self-regulation.) Further, we expected support to positively affect desire to continue, but we found a significant negative total effect. We discuss these results further in Section 5.

Table 5. Results for Second-order Latent Variables

	R^2 value
Desire to continue	0.541
Performance	0.543
Satisfaction	0.717
Self-efficacy	0.247

Table 6. Structural Model Results

Path	Hypothesis	Path coefficient	P-value	Support
Support -> desire to continue	H1a	-0.120	0.001	No*
Support -> satisfaction	H1b	0.068	0.015	Yes
Support -> performance	H1c	-0.076	0.066	No**
Compatibility -> desire to continue	H2a	0.364	< 0.001	Yes
Compatibility -> satisfaction	H2b	0.389	< 0.001	Yes
Compatibility -> performance	H2c	0.575	< 0.001	Yes
Self-efficacy -> desire to continue	H3a	-0.081	0.064	No**
Self-efficacy -> satisfaction	H3b	0.003	0.940	Marginal
Self-efficacy -> performance	H3c	0.267	< 0.001	Yes
Social isolation -> self-efficacy	H4a	-0.282	< 0.001	Yes
Self-regulation -> self-efficacy	H4b	0.369	< 0.001	Yes
Performance -> satisfaction	H5	0.500	< 0.001	Yes
Satisfaction -> desire to continue	H6a	0.495	< 0.001	Yes
Performance -> desire to continue	H6b	0.001	0.991	No

Yes: $p < 0.05$ and in hypothesized direction
Marginal: $p < 0.10$, > 0.05 and in hypothesized direction
* Significant path at $p < 0.01$ but with a negative rather than positive path coefficient as we hypothesized.
** Significant path at $p < 0.10$ but with a negative rather than positive paths coefficient as we hypothesized.

[4] Due to an anonymous reviewer's suggestion, we analyzed the direct effect that social isolation had on perceived performance, satisfaction, and desire to continue post hoc. Social isolation had a negative effect on performance (-0.543) and satisfaction (-.192) but not on continuance (-0.045, < 0.240).

Table 7. Total Effects

Variable	Total effect	P-value
Support -> desire to continue	-0.104	0.011
Compatibility -> desire to continue	0.699	< 0.001
Self-efficacy -> desire to continue	-0.013	0.784
Satisfaction -> desire to continue	0.495	< 0.001
Performance -> desire to continue	0.248	< 0.001

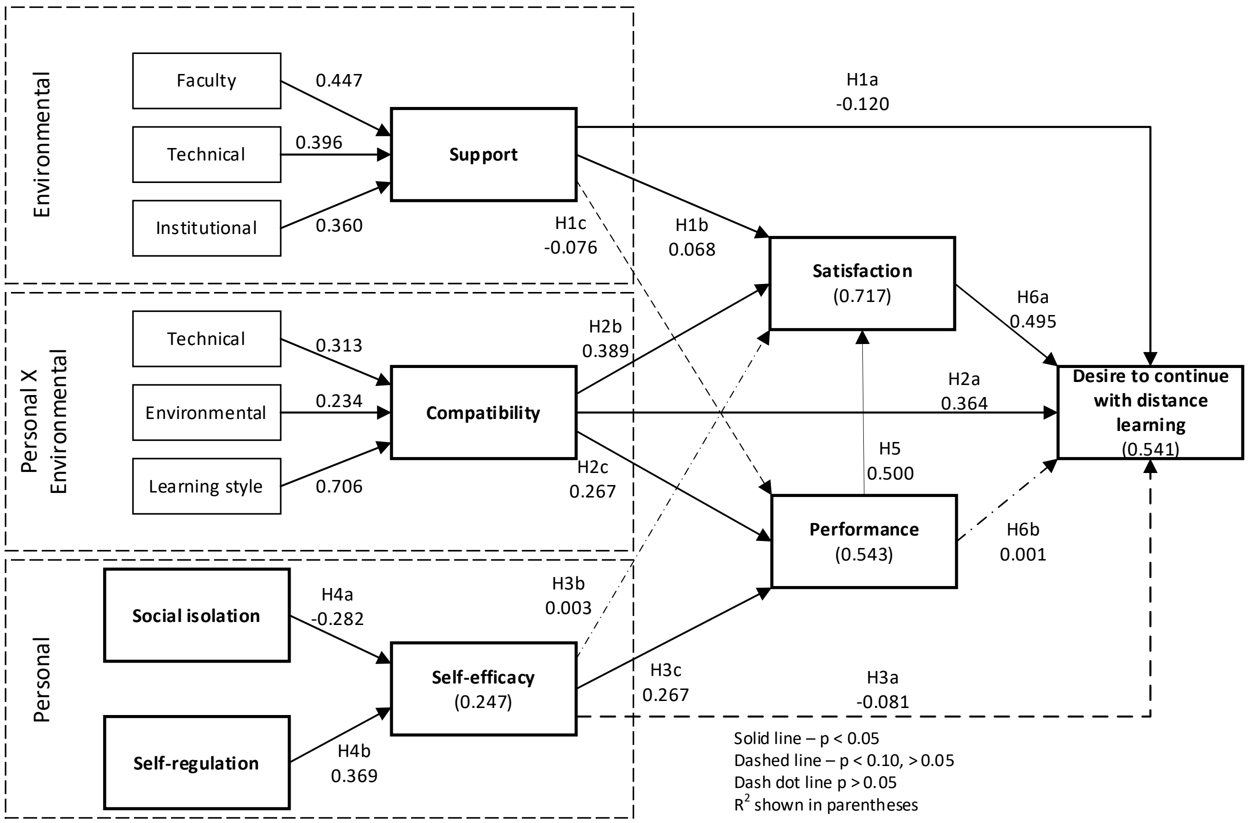

Figure 3. Research Model with Results

5 Discussion

Our results show strong support for our research model, which indicates that social cognitive theory and social cognitive career theory represent useful theoretical foundations for understanding students' desire to continue with distance learning (once no longer required to use distance learning). As SCT predicts, factors related to the person and factors related to the environment in which a behavior occurs affected behavioral intentions through their impact on perceived performance and satisfaction. Distance learning satisfaction had a strong positive effect on desire to continue with distance learning. Perceived performance had a positive impact on desire to continue as well, but satisfaction fully mediated this Impact. Our model accounted for a large portion of the variance in distance learning satisfaction (71.4%), perceived performance (53.9%), and desire to continue (48.3%). The two self-efficacy predictors (social isolation and self-regulation) accounted for 24.7 percent of the variance in self-efficacy.

Interestingly, we found both direct and mediated effects from our antecedent factors. Support, compatibility, and self-efficacy all had significant direct and mediated effects; although self-efficacy had a nonsignificant total effect. These results indicate that the relationships among personal factors, environmental factors, and behavioral intentions are complex. These results also indicate that one needs to consider satisfaction and perceived performance when evaluating continuance desires.

According to our results, compatibility represents the most important factor in determining distance learning outcomes and desire to continue with distance learning. Among support, compatibility, and self-efficacy, compatibility had the strongest effect on perceived performance, satisfaction, and, through these, desire to continue. The total effect that compatibility had on desire to continue (0.468) was second in effect size only to satisfaction (0.635). On reflection, we do not find this result surprising. In our model, compatibility represents how technical, environmental, and an individual's preferred learning style come together; essentially, compatibility represents a confluence of personal and environmental factors. SCT predicts that this confluence determines behavior, so it should not be a surprise that it also strongly influences desires to continue with distance learning.

We found another interesting insight from examining the results related to compatibility: among the three first-order latent variables that comprised compatibility (technical compatibility, environmental compatibility, and learning style compatibility), compatibility with preferred learning style had by far the largest path coefficient. This finding supports other research that demonstrates the important role that such compatibility plays in technology adoption and continuance intentions (e.g., Van Slyke et al., 2010). This finding suggests that the fit of distance learning with a student's preferred way of learning plays a more important role than the fit with other environmental factors in determining continuance desires.

We found the results related to self-efficacy surprising. We expected self-efficacy to impact desire to continue through its impact on perceived performance and satisfaction. While self-efficacy did have an impact on perceived performance, it effectively had a nonexistent direct impact on satisfaction ($p = 0.946$), although it did have a mediated impact through perceived performance. In retrospect, this finding makes some sense. One potential explanation for this surprising result comes from realizing that self-efficacy indicates a person's assessment of their capabilities rather than their preferences. Therefore, someone who believes they can deal with distance learning may prefer face-to-face classes. Future research should explore this possibility.

We found that social isolation had a negative impact on self-efficacy and indirectly on desire to continue; in contrast, self-regulation positively affected self-efficacy and desire to continue (indirectly). However, these factors (social isolation and self-regulation) had small and nonsignificant effects on desire to continue due to the fact that self-efficacy, performance, and satisfaction mediated them.

We recommend caution regarding these nonsignificant results, however. Recall that compatibility had a strong effect on desire to continue; it affected this outcome directly and indirectly through compatibility's effects on perceived performance and satisfaction. As for why, the effects from compatibility possibly effectively trumped the effects from the personal factors that we included in our study. In other words, compatibility may have rendered self-efficacy moot in our study due to the former's importance.

As expected, we found that support positively impacted student satisfaction with online classes. The effect, however, was small. In addition, we found the negative relationship between support and perceived performance surprising. We hypothesized that this relationship would be positive. As for why we found this unexpected result, students with performance concerns are possibly more likely to seek support than those without such concerns. These may make beliefs regarding support more salient, which could affect the level of perceived support. Students who already perform well may have little need to seek out support. Additional research needs to test this explanation's efficacy. Another potential explanation for the negative effect that support had on desire to continue concerns self-efficacy. It may be that self-efficacy moderates the relationship between support and desire to continue such that individuals high in self-efficacy find support less important in determining continuance desires. We could make a similar argument for compatibility's moderating effect. However, post hoc analyses indicated that neither self-efficacy nor compatibility significantly moderated relationship between support and desire to continue.

Among the three first-order latent variables that comprised support (faculty support, technical support, and institutional support), faculty support had by far the largest path coefficient. This finding supports prior research on the important role faculty plays in students' academic choices, interest in, and aspirations to pursue a particular academic path (Akbulut et al., 2008). As we hypothesized, we found that students' satisfaction with the online environment had a significant positive impact on their desire to continue with distance learning. This finding concurs with prior research that has used satisfaction as a parameter to evaluate learning environment effectiveness in both educational and academic settings (Piccoli, Ahmad, &

Ives, 2001). Given that previous experience serves as an important factor that determines future attitudes and behaviors, universities interested in promoting distance learning should promote student satisfaction with distance learning environments.

However, as opposed to our expectations, we did not find support for the relationship between performance and desire to continue. In this context, the fact that satisfaction fully mediated the impact that perceived performance had on desire to continue represents an interesting finding. It seems to indicate that an attitudinal factor (satisfaction) more than a utilitarian factor (performance) drives desire to continue with distance learning. Beliefs about performance matter to continuance but only to the extent that they impact satisfaction.

5.1 Implications for Research

Our findings offer several implications for research. Our primary contribution to research concerns our confirming social cognitive theory and social cognitive career theory as a useful foundation for building distance learning outcome models.

The model we used in this study may serve as a starting point for investigating other distance learning aspects. For example, we studied distance learning in general. However, our model may provide a perspective from which to study distance learning as it relates to specific disciplines, courses, or types of courses (e.g., conceptual versus applied courses). Other contextual factors, such as culture, may also be interesting to study using our model.

Although our model accounted for a significant portion of the variance in desire to continue (48.3%), other factors may also affect continuance desires. Our model did not include hedonic factors, such as enjoyment, that may affect continuance. It may also be interesting to consider negative affective factors, such as stress, anxiety, or factors that reflect the demands of online learning, such as work overload or role ambiguity and conflict. In addition, other utilitarian factors likely affect distance learning continuance, such as convenience and relative advantage. Future research should consider these and other relevant factors as they relate to distance learning continuance desires.

We found our results related to support somewhat surprising due to 1) the small effect sizes and 2) the negative relationship between support and perceived performance. The small effect sizes may be due to nonlinear relationships between support and perceived performance. For example, a ceiling effect may occur whereby support matters to perceived performance up to a point but not above that point. Future research should investigate the relationship between support and perceived performance more closely.

The results related to self-efficacy may warrant further investigation. We found a strong relationship between self-efficacy and performance—an important finding because some other studies have not found major differences between students with high or low self-efficacy and their perceived performance (Kauffman, 2015; Tladi, 2017; Yokoyama, 2019). However, we should note that those studies focused on generic computer self-efficacy rather than task specific online learning self-efficacy.

We also hypothesized that self-efficacy would have a positive relationship with distance learning satisfaction. At the same time, we found that, in our model, self-efficacy had essentially no direct impact on satisfaction ($p = 0.946$), although it did impact satisfaction indirectly through perceived performance. To further investigate this issue, we ran an exploratory post hoc analysis that modified the research model by removing the path from compatibility to satisfaction. We eliminated this path because both compatibility and self-efficacy reflect one's beliefs about how well they fit with distance learning. In analyzing the revised model, we found that self-efficacy had a significant positive effect on satisfaction ($b = 0.089$, $p = 0.024$) once we removed compatibility's effect. From this analysis, we seemingly found an overlap in the portion of the variance in satisfaction that compatibility and self-efficacy accounted for. Future research should investigate this exploratory finding further.

Researchers could use the research model that we present in this paper to examine group-based differences. For example, researchers could compare our results, which we identified based on a sample from the United States, with samples from other countries. They could also apply the model to examine how gender affects desires to continue with distance learning. Although gender did not have a significant direct impact on desires to continue, it could still moderate the relationships in the research model. Understanding these relationships would also have practical implications as this understanding would guide educators and administrators to develop more targeted strategies for promoting distance learning.

Also, researchers have conducted little research on suitable study environments. We do not exhaustively list factors related to improving one's study environment. We do, however, demonstrate the need for students to have a suitable study environment. Further research might investigate different types of study environments along with their effect on student satisfaction and performance and, hence, on desire to continue with distance learning.

We viewed environmental compatibility in a limited way and focused only on students' physical learning environments. However, for many students, the higher education experience more holistically includes their entire campus. For such students, the environment in which they take classes tells only part of the tale; the social environment tells the other. However, the social environment may be less important for commuter, part-time, or nontraditional students. Future research should consider extending our model by broadening how we conceptualize the learning environment and by testing the extent to which different learning environment aspects differ in their effects by student type.

Finally, we treated distance learning in general and did not specify particular disciplines or course types when asking about continuance desires. However, students' desires to continue to could conceivably vary by discipline or course type. For example, students may better accept taking conceptual courses online but prefer face-to-face courses for more applied courses (or vice versa). Researchers could apply our model to specific courses or disciplines by appropriately adapting some of the measurement scales. Of course, they would need to undertake additional theorizing as well.

5.2 Implications for Practice

Our findings hold several implications for practice. First, institutions that want to promote distance learning should carefully consider the impact that compatibility (especially with preferred learning style) has on it. Compatibility had the strongest total effect on satisfaction and the second largest total effect (after satisfaction) on desire to continue. Compatibility with preferred learning style had a stronger effect on overall compatibility than its other components (environmental compatibility and technical compatibility). Thus, efforts to promote distance learning's compatibility will likely pay benefits with respect to continuance. Removing technical barriers may also be effective in improving compatibility and, thus, increasing students' desires to continue. Measures to ensure that students can access the hardware and software that they need may help. For example, making specialized software available online should increase technical compatibility, which may enhance satisfaction and performance and desire to continue. Schools should also consider ways that allow students to access learning materials effectively through their smartphones to increase perceptions of compatibility. However, they should consider fitness of use. Smartphones may be fine for some uses but not for others. Environmental compatibility may be harder for schools to influence. However, providing tips and training on how to set up effective learning spaces (even when shared or limited) may help increase environmental compatibility.

The results related to compatibility with preferred learning style also have important practical implications. Students will differ with respect to this aspect of compatibility, and these differences have strong effects on desires to continue with distance learning. As such, institutions should perhaps take a flexible and potentially quasi-customized approach to offering online courses. In some cases (prior to the COVID-19 pandemic), institutions often separated their face-to-face and online offerings (e.g., focused on face-to-face classes with residential and full-time students and restricted online offerings to part-time students). This approach seems practical, but, given the predominance of full-time, traditionally aged students in our sample, it seems that it may make sense to offer options to full-time students. Those who find that online courses fit well with their preferred ways of learning may gravitate towards online courses. In addition, it may be useful to put some aspects of classes online while putting others face-to-face (as with blended learning courses). Researchers need to conduct more work to test the effectiveness of such an approach and to determine what course aspects may be the best fit with distance learning. However, our results suggest that researchers should examine this avenue further. We note, however, that some institutions may find such flexibility infeasible due to resource constraints.

We also offer a warning regarding our results related to support. Given the relatively weak effect that support had on satisfaction and performance, it might be tempting to conclude that support lacks importance. However, we do not believe that to be so. For instance, support may have more importance when not present than when present (i.e., a floor effect). Thus, when support drops below some minimum level, it may be that satisfaction and performance perceptions (and, by extension, desire to continue) suffer. Future research should investigate this potential explanation.

While less important than compatibility, reducing social isolation and increasing self-regulation perceptions with respect to distance learning will likely affect self-efficacy and, therefore, performance perceptions. Although our results suggest that social isolation and self-regulation will not affect satisfaction directly, they do suggest that social isolation and self-regulation will indirectly affect desire to continue with distance learning indirectly through performance. Ultimately, reducing social isolation and increasing self-regulation will have positive effects on desire to continue.

Finally, our model provides some direction for university administrators who want to better understand to whom they should be promoting distance learning. When circumstances no longer require students to engage in distance learning, they will self-select into online classes. Our model may help explain which students will choose to take classes online. According to our results, the best results will come from promoting distance learning to students who find distance learning compatible with their learning style and environmental and technological environments. These students are the most likely to be more satisfied with distance learning, to perceive their performance in distance learning courses as being higher, and, as a result, to want to continue with distance learning courses. One challenge, however, will involve identifying these students. Instructors might overcome this challenge by adjusting their online classes to meet different learning styles. We acknowledge, however, that overworked faculty may find such a task impractical. Another approach would involve encouraging students with high compatibility to continue taking select classes online. We found that compatibility had a significantly high effect on perceived performance (0.571), so students who perceive distance learning as compatible are also likely to perceive that they perform well in these classes. Institutions should possibly direct students with low perceived compatibility from online classes when alternatives exist.

5.3 Limitations

This study has several limitations. First, we did not measure actual distance learning continuance. Although intentions typically strongly predict actual behaviors, especially when individuals can engage in the focal behavior, intentions do not necessarily lead to behaviors. As a result, future research should extend our model by adding actual continuance behaviors. Longitudinal studies would be especially interesting.

Second, the sample we used comprised students who resided in a single country (the United States). We made this choice to control for potential confounding effects from country or culture. As we mention in Section 5.1, future research could test our model in other contexts or by using multi-country samples. These studies may reveal interesting differences or may confirm our model's efficacy across countries and cultures.

Third, even though our research model incorporated important factors that could affect students' desire to continue with distance learning, we could not include all potential factors. In order to better understand students' desire to continue with distance learning, researchers need to consider and validate additional factors using more comprehensive models that incorporate both direct and indirect effects.

Fourth, we focused on students' desires to continue with distance learning in this study. However, we also need to consider faculty desires. As with students, many faculty had their first exposure to fully online courses when the pandemic forced them to deliver their courses online. Future research should investigate factors that might affect faculty members' desires to continue with distance learning. A troubling possibility exists for some institutions: what happens when one group, students or faculty, wants to continue with distance learning and the other does not?

Fifth, this study's cross-sectional nature limits our ability to draw inferences about causality. While we found our design useful to identify the relationships among constructs, it does not provide conclusive evidence for temporal precedence. According to SCT and SCCT, person, behavior, and environment factors reciprocally determine one another as time progresses. Although our findings support the predicted directionality, these relationships will likely evolve over time (Bandura, 1997). Therefore, future studies should adopt longitudinal designs.

Sixth, since we used self-reported, single-source data, we cannot rule out common response bias. In order to address this limitation, we carefully structured the survey instrument and performed a blue marker variable test for common method variance. Even though all the measures exhibited sufficient reliability and validity, a very low possibility that bias inflated the relationships among the constructs still exists.

Therefore, future studies using complementary methods, such as collecting data from multiple resources (e.g., from instructors) and using experimental designs and longitudinal studies, would prove beneficial.

Finally, we acknowledge that our research took place during a unique time in which a pandemic brought about rapid changes in higher education. Although we based our research model on theories and investigations that researchers developed prior to the pandemic, we could have obtained different findings under other circumstances. In addition, if the pandemic lingers, students who normally (per our model) would be disinclined to continue with distance learning may choose to continue taking classes online due to health concerns. We encourage others to replicate our study to see if they can identify differences that they can attribute to the COVID-19 context.

6 Conclusions

We have seen a spike in distance learning as institutions at all education levels have shifted to online instruction during the COVID-19 pandemic. Many higher education students that had never taken online courses suddenly had to engage in distance learning or withdraw from their academic programs. However, we do not expect the pandemic to last forever. This rapid (and hopefully temporary) shift provoked our research question: what factors influence students' desire to continue with distance learning once circumstances no longer require them to do so?

We found that personal factors and environmental factors influenced students' intentions to continue with distance learning through their impact on distance learning perceived performance and satisfaction. In our model, compatibility represents how technical, physical, environmental, and an individual's preferred learning style interact. We identified compatibility as the most important factor in determining distance learning outcomes and continuance desires (other than distance learning satisfaction). Overall, we found strong support for our research model, which evidences social cognitive theory and social cognitive career theory as useful theoretical foundations for understanding students' desire to continue with distance learning (once circumstances no longer require them to use distance learning).

As it has in the past, distance education will continue to evolve as new technologies emerge and as faculty and students learn new ways to leverage technology to achieve learning at a distance. Given these constant changes, we need to understand what drives students' decisions regarding whether to engage in distance learning. This understanding may help administrators better understand how to make their institutions' online courses and program opportunities meet students' needs. The results that we present here can help administrators understand how environmental and personal factors interact to drive distance learning continuance intentions. In addition, our model and results provide a foundation for further work on these intentions.

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Appendix A

Table A1. Scale Items

Scale	Items	Source(s)
Desire to continue with distance learning	When no longer required to do so, I would take distance learning classes in the future.	Van Slyke et al. (2010)
	Taking distance learning classes is something I would do when no longer required to do so.	
	I could see myself taking distance learning classes when no longer required to do so.	
Performance	Online classes enhance my effectiveness when learning.	Dick & Akbulut (2020) Eom et al. (2006)
	Online classes improve the quality of my learning.	
	Overall, taking online classes improves my learning.	
	I expect to do at least as well by taking online classes as I would have on campus.	
	I will get similar grades by taking online classes to what I would have face to face.	
	I will do well in online classes.	
Satisfaction	I would recommend online classes to other students.	Dick & Akbulut (2020) Eom et al. (2006)
	I am satisfied with the quality of the learning experience via the online class.	
	I enjoyed online classes	
	Online classes were a good way to learn	
Support		
Faculty support	My professors really care about me.	Bentley et al. (2016)
	My professors are willing to help me when I need it.	
	I can rely on my professors.	
	When I have questions, my professors are available.	
Technical support	Adequate technical support is available from my school.	Lee & Choi (2003)
	The technical support provided by my school is good.	
	When I need technical support, I am able to get it.	
Institutional support	Help is available from my school when I have a problem.	Bentley et al. (2016)
	My school really cares about my well-being.	
	My school is concerned about me as a person.	
Compatibility		
Environmental compatibility	My living conditions during the term were suitable for online classes	New
	I can organize my room/work area to facilitate online learning	
	I have no trouble learning in my home environment	
Technical compatibility	I believe that it is easy to get online learning technologies to do what I want them to do.	New
	Overall, I believe that distance learning technologies are easy for me to use.	Venkatesh & Bala (2008)
	I have no trouble with the technology	
	I have all the technology I needed for distance learning	
Learning style	Taking distance learning classes fits my preferred way of learning.	Van Slyke et al. (2010)
	Distance learning enables me to learn in the way I prefer.	

Table A1. Scale Items

compatibility	Distance learning fits well with the way I like to learn.	
	Distance learning fits my preferred method for learning.	
Personal characteristics		
Self-efficacy	I am confident I have the ability to cope with online classes	Looney & Akbulut (2007)
	I know that I will achieve what I need to in online classes	
	I can deal with any problems that arise in online classes	
Self-regulation	Work under my control is well organized	Sharma et al. (2007)
	I complete tasks by the deadlines I set myself	
	I manage all of the things I need to in my life	
	I establish a study schedule and stick to it	
Social isolation	I feel less integrated with other students and faculty when taking classes at home.	Weinert, Maier, Laumer, & Weitzel (2014)
	I feel poorly informed about relevant school issues when taking classes at home.	
	I have a lot of contact with other students and faculty when taking classes at home.*	
Demographics	Age	
	Gender	
	Class (freshman … graduate student)	
	Major	
	Computer expertise (self-rated): What is your expertise with information technology?	
	Distance learning experience: How many online classes have you taken?	
Blue attitude (marker)	I prefer blue to other colors.	Miller & Chiodo (2008), Simmering, Fuller, Richardson, Ocal, & Atinc (2015)
	I like the color blue.	
	I like blue clothes.	

Appendix B

Table B1. Cross Loadings

Item/Scale	LSCom	DesCont	EnvCom	FacSup	InstSup	Perf	Sat	SelfReg	SelfEff	SocIso	TecCom	TechSup
LSCom1	**0.952**	0.682	0.344	0.067	0.127	0.634	0.729	0.206	0.454	-0.498	0.324	0.302
LSCom2	**0.951**	0.653	0.361	0.081	0.120	0.642	0.708	0.218	0.476	-0.488	0.345	0.287
LSCom3	**0.963**	0.656	0.358	0.041	0.097	0.651	0.718	0.200	0.440	-0.487	0.360	0.254
LSCom4	**0.965**	0.676	0.339	0.056	0.104	0.654	0.712	0.191	0.457	-0.536	0.332	0.277
DesCont1	0.679	**0.944**	0.291	-0.042	0.072	0.543	0.656	0.127	0.326	-0.433	0.282	0.239
DesCont2	0.640	**0.955**	0.295	-0.022	0.057	0.544	0.645	0.143	0.328	-0.404	0.286	0.251
DesCont3	0.670	**0.958**	0.292	-0.002	0.051	0.559	0.679	0.116	0.345	-0.400	0.279	0.256
EnvCom1	0.163	0.126	**0.794**	0.255	0.277	0.170	0.220	0.167	0.323	-0.173	0.353	0.273
EnvCom2	0.210	0.174	**0.849**	0.23	0.267	0.279	0.298	0.268	0.369	-0.289	0.360	0.310
EnvComr3	0.467	0.400	**0.876**	0.226	0.31	0.522	0.548	0.324	0.504	-0.484	0.455	0.345
FacSup1	0.059	-0.023	0.236	**0.881**	0.552	0.131	0.179	0.153	0.279	-0.118	0.103	0.367
FacSup2	0.023	-0.052	0.222	**0.919**	0.513	0.117	0.133	0.144	0.333	-0.064	0.168	0.397
FacSup3	0.039	-0.030	0.248	**0.925**	0.524	0.096	0.144	0.132	0.279	-0.076	0.186	0.408
FacSup4	0.109	0.023	0.294	**0.878**	0.518	0.123	0.201	0.142	0.338	-0.113	0.243	0.447
InstSup1	0.130	0.087	0.377	0.533	**0.875**	0.18	0.241	0.279	0.344	-0.151	0.319	0.617
InstSup2	0.104	0.043	0.286	0.553	**0.939**	0.151	0.19	0.235	0.295	-0.115	0.153	0.492
InstSup3	0.084	0.041	0.264	0.509	**0.917**	0.137	0.179	0.246	0.259	-0.087	0.170	0.488
Perf1	0.598	0.534	0.298	0.027	0.068	**0.830**	0.661	0.171	0.372	-0.459	0.303	0.172
Perf2	0.655	0.552	0.306	0.033	0.086	**0.862**	0.738	0.180	0.348	-0.537	0.301	0.192
Perf3	0.653	0.561	0.295	0.047	0.080	**0.879**	0.737	0.202	0.375	-0.530	0.320	0.214
Perf4	0.443	0.357	0.371	0.153	0.209	**0.742**	0.530	0.280	0.524	-0.377	0.363	0.228
Perf5	0.346	0.276	0.373	0.199	0.195	**0.640**	0.432	0.339	0.532	-0.286	0.322	0.266
Perf6	0.365	0.333	0.376	0.222	0.229	**0.681**	0.533	0.259	0.633	-0.281	0.375	0.275
Sat1	0.693	0.665	0.398	0.12	0.173	0.715	**0.912**	0.157	0.470	-0.500	0.311	0.305
Sat2	0.651	0.603	0.431	0.163	0.217	0.728	**0.908**	0.192	0.502	-0.534	0.396	0.343
Sat3	0.709	0.657	0.424	0.194	0.216	0.718	**0.908**	0.219	0.524	-0.513	0.393	0.371
Sat4	0.667	0.592	0.407	0.187	0.207	0.719	**0.907**	0.201	0.487	-0.549	0.395	0.333
SelfEff1	0.442	0.313	0.441	0.286	0.316	0.525	0.500	0.365	**0.895**	-0.288	0.408	0.359
SelfEff2	0.448	0.348	0.429	0.339	0.305	0.520	0.514	0.358	**0.915**	-0.325	0.345	0.394
SelfEff3	0.392	0.279	0.453	0.293	0.265	0.495	0.454	0.388	**0.882**	-0.296	0.383	0.385
SelfReg1	0.195	0.094	0.285	0.172	0.277	0.250	0.192	**0.800**	0.359	-0.137	0.261	0.323
SelfReg2	0.132	0.109	0.227	0.085	0.17	0.200	0.122	**0.821**	0.315	-0.105	0.131	0.238
SelfReg3	0.111	0.070	0.233	0.131	0.244	0.181	0.115	**0.833**	0.342	-0.080	0.193	0.280
SelfReg4	0.257	0.172	0.285	0.127	0.218	0.327	0.263	**0.835**	0.337	-0.177	0.186	0.298
SocIso1	-0.358	-0.301	-0.247	0.025	-0.029	-0.376	-0.391	-0.061	-0.169	**0.708**	-0.207	-0.118
SocIso2	-0.487	-0.391	-0.398	-0.124	-0.137	-0.505	-0.547	-0.153	-0.354	**0.908**	-0.313	-0.195
SociIso3*	-0.266	-0.241	-0.188	-0.092	-0.096	-0.268	-0.266	-0.099	-0.144	**0.526**	-0.050	-0.147
TechCom1	-0.332	-0.273	-0.379	-0.113	-0.179	-0.384	-0.381	-0.258	-0.380	0.257	**-0.851**	-0.279
TechCom2	-0.324	-0.256	-0.400	-0.172	-0.188	-0.394	-0.389	-0.191	-0.391	0.259	**-0.873**	-0.320
TechCom3	-0.281	-0.252	-0.381	-0.179	-0.172	-0.330	-0.321	-0.147	-0.299	0.276	**-0.827**	-0.305
TechCom4	-0.211	-0.178	-0.391	-0.182	-0.249	-0.238	-0.234	-0.175	-0.302	0.164	**-0.704**	-0.300

Table B1. Cross Loadings

TechSup1	0.289	0.262	0.332	0.402	0.538	0.254	0.357	0.319	0.405	-0.22	0.357	**0.924**
TechSup2	0.286	0.233	0.333	0.406	0.536	0.289	0.359	0.346	0.403	-0.204	0.333	**0.941**
TechSup3	0.204	0.232	0.373	0.443	0.559	0.236	0.322	0.306	0.370	-0.170	0.333	**0.922**

We show the highest loading in bold.
Key: LSCom: learning style compatibility, DesCont: desire to continue with online classes, EnvCom: environmental compatibility, FacSup: faculty support, InstSup: institutional support, Perf: perceived performance, Sat: distance learning satisfaction, SelfReg: self-regulation, SelfEff: self-efficacy, SocIso: social isolation, TecCom: technical compatibility, TechSup: technical support

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