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Emotional Intelligence, Self-Directed Learning, and Online Success in Adult Learners: A Mediation Model

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This is to certify that the doctoral dissertation by

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Walden University
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Abstract

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MS, Nova Southeastern University, 2006

BA, Saint Leo University, 2000

Dissertation Submitted in Partial Fulfillment

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Abstract

Online education has been established as a viable option for adult learners. More recently, it has been adopted by many institutions as a critical component in their long-term planning and success. Despite consistent growth rates in online enrollment, and the advantages to online learning, attrition rates for online courses remain higher than traditional (ground) courses. Bar-On's theory of emotional intelligence (EI) and Knowles' self-directed learning (SDL) theory have been positively linked with online academic performance and identified as predictors of learning online and life success. The purpose of this quantitative, cross-sectional study was to explore EI and SDL as predictors of online success (OS) and to test whether SDL mediated the relationship between EI and OS. Adult learners (N = 345) were recruited from a fully online university's research participant pool and from social media sites (i.e., Facebook, LinkedIn). After giving their consent, participants completed an anonymous online questionnaire hosted by an online survey platform. SPSS and the PROCESS macro were used to test the proposed mediation model. Statistically significant bivariate correlations were found among EI, SDL, and OS. Multiple regression analysis revealed that SDL predicted EI and OS. Using bootstrap resampling with replacement as the mediation method, the path coefficients indicated a weak, but statistically significant, indirect effect of SDL on the relationship between EI and OS. This study has implications for positive social change; these results may improve online course design, instruction, and alternative online education options to better meet the needs of adult online learners.

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Dedication

To Bill, my best friend, handsome husband, and the love of my life ~ thank you so much for encouraging, supporting, and loving me through this arduous dissertation journey. And most especially, for not letting me give up.

To Tiger, my sweet tortie, and good kitty ~ thank you so much for purring, wanting snuggles, and laying down on my notes and hands while I worked.

Thank you both for keeping me company during long hours sitting at my computer and for encouraging me to smile, laugh, and take standup breaks.

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Chapter 1: Introduction to the Study

Introduction

For over a decade, overall higher education enrollment rates have declined, with one exception: online education (National Center for Education Statistics, 2017; Seaman, Allen, & Seaman, 2018). Online enrollment rates for higher education have steadily increased since 2002, and they continue to remain 10% higher than traditional enrollment rates (NCES, 2017; Seaman et al., 2018). Online education has been established as a viable option for adult learners who are balancing work, family, and school (Bawa, 2016; Choi & Park, 2018; Doe, Castillo, & Musyoka, 2017). More recently, many institutions have adopted online education as a critical component in their long-term strategy planning (de los Santos & Zanca, 2018). Adult learners and professionals across the globe seek out online courses, training, and degree programs to improve life circumstances, skills, and employment opportunities (Hassan, Abiddin, & Yew, 2014; Song & Bonk, 2016; Vayre & Vonthron, 2017). The advantages to online learning include flexibility, accessibility, and greater access to learning resources, especially to populations that may not otherwise have the opportunity to earn a degree, such as working adults, parents, veterans, disabled individuals, and lifelong learners (Doe et al., 2017; Song & Bonk, 2016; Sumuer, 2018; Vayre & Vonthron, 2017). Despite consistent online enrollment growth rates, and the advantages to online learning, attrition rates for online courses remain higher than traditional (ground) courses (Bawa, 2016; Choi & Park, 2018; Doe et al., 2017; Kauffman, 2015; Peck, Stefaniak, & Shah, 2018).

Most of the research on online education has focused on the relationships between learner characteristics, retention, student satisfaction, and online learning and success (Bawa, 2016; Kauffman, 2015; Lee & Choi, 2011; Vayre & Vonthron, 2017). In this way, learner characteristics such as motivation, self-efficacy, online readiness, self-directed learning (SDL), and emotional intelligence (EI) have been positively linked with online academic performance, retention, and student satisfaction, and also identified as being critical to online learning and success (Bawa, 2016; Doe et al., 2017; Engin, 2017; Goodwin, 2016; Han & Johnson, 2012; Hobson & Puruhito, 2018; Kauffman, 2015; Song & Bonk, 2016; Vayre & Vonthron, 2017). The United States Department of Education (USDOE; 2014), as well as researchers of online education (i.e., Broadbent & Poon, 2015; Choi & Park, 2018; Kauffman, 2015; Majeski, Stover, Valais, & Ronch, 2017; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017), have called for more research into the online environment to better understand the processes of online learning, adult learner characteristics related to learner outcomes and online success (OS), and how best to improve online course design and instructional strategies.

This study was an answer to the above call for more research into the online learning environment and fills a gap in the literature by examining both EI and self-directed learning (SDL) as predictors of OS as well as the indirect effects of SDL on the relationship between EI and OS. It was also a response to the research recommendations of Cazan and Schiopca (2014), Koc (2019), and Zhoc, Chung, and King (2018), in that this study explored the possibility of SDL having an indirect (mediated) effect on the relationship between psychological traits (e.g., EI) and online learning success. For this to be tested, SDL served as a predictor and mediator variable in this study. Hayes (2018) described a mediator as an intervening variable and conceptualized it as “the mechanism through which X influences Y” (p. 7). The findings of this study may help to support EI and SDL as predictors of OS (e.g., GPA) and help to establish SDL as a mediator, or intervening variable, in the relationship between EI and OS. This research may also help to improve the understanding of adult learner characteristics in the online learning environment, such as EI and SDL, and the role they play in OS. These findings could also be used to improve online faculty training, course design, and alternative online education options (e.g., blended, web-facilitated) to better meet the learning needs of adult learners and help increase their OS (Bakia, Shear, Toyama, Lasseter, & USDOE, 2012; Bawa, 2016; Broadbent & Poon, 2015; Doe et al., 2017; Kauffman, 2015; Majeski et al., 2017; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017).

Chapter 1 includes a broad overview of existing research on the high enrollment and attrition rates in online courses, how online learning compares to traditional (ground) learning, and the role of EI and SDL as predictors of success in online education. The chapter also includes the research problem, purpose, research questions with hypotheses, theoretical framework and conceptual model, nature of the study, definitions, assumptions, scope and delimitations, limitations, and significance of the study.

Background

With the increase in online delivery of instruction in higher education during the past 14 years, researchers of online education (i.e., Allen & Seaman, 2011, 2017; Bakia et al., 2012; Choi & Park, 2018; Kerr, Rynearson, & Kerr, 2006; Lee & Choi, 2011;

Majeski et al., 2017; Peck et al., 2018; Vayre & Vonthron, 2017) have sought to understand the characteristics of online learners, the online learning process, and the predictors of online student success. After more than a decade of research, most researchers agree that the online environment is comparable to the traditional classroom environment in terms of learning outcomes, but it is different in design, instruction, and learning strategies (Allen & Seaman, 2011, 2017; Bakia et al., 2012; Bawa, 2016; Broadbent & Poon, 2015; Choi & Park, 2018; Hassan et al., 2014; Kauffman, 2015; Kerr et al., 2006; Peck et al., 2018). Some researchers have found that students ranked the traditional learning environment higher in peer and instructor interaction and the online learning environment higher in convenience and flexibility (e.g., Allen & Seaman, 2011, 2017; Bakia et al., 2012; Clayton, Blumberg, & Auld, 2010; de los Santos & Zanca, 2018; Peck et al., 2018). Other researchers have concluded that high attrition rates in online education are due to ineffective course design, pedagogy, and training (e.g., Bawa, 2016; Doe et al., 2017; Majeski et al., 2017).

Most researchers have found learner characteristics to be the main factors in predicting student persistence, dropout, and OS (e.g., Berenson, Boyles, & Weaver, 2008; Choi & Park, 2018; Clayton et al., 2010; Goodwin, 2016; Han & Johnson, 2012; Hobson & Puruhito, 2018; Kerr et al., 2006; Peck et al., 2018; Vayre & Vonthron, 2017). Considering this, the characteristics and learning strategies of student success may not be the same for online courses as for traditional classroom courses (Bakia et al., 2012; Berenson et al., 2008; Broadbent & Poon, 2015; Han & Johnson, 2012; Kerr et al., 2006; Peck et al., 2018; Vayre & Vonthron, 2017). For instance, research supports learning strategies such as rehearsal, elaboration, critical thinking, time management, and organization as predictors of success for traditional classroom environments, but not necessarily for online learning environments (Bakia et al., 2012; Broadbent & Poon, 2015; Kerr et al., 2006; Lee & Choi, 2011; Peck et al., 2018). Kerr et al. (2006) pointed out the lack of empirical investigations in online learning, student characteristics, and predictors of student success in comparison to traditional learning environments; this call for more research was later reemphasized in Kauffman's (2015) review of predictive factors in OS and in Doe, Castillo, and Musyoka's (2017) study on assessing online readiness and student success. Several researchers (e.g., Doe et al., 2017; Kauffman, 2015; Kerr et al., 2006) have concluded that students who achieve OS are self-directed learners; they learn independently and actively, and they engage in the learning process effectively (Broadbent & Poon, 2015; Kauffman, 2015; Kerr et al., 2006; Peck et al., 2018; Song & Bonk, 2016). Researchers of online learning agree that more exploration of predictors for OS is needed as more students elect to take advantage of online opportunities (Broadbent & Poon, 2015; Doe et al., 2017; Kauffman, 2015; Kerr et al., 2006; Knight, 2019; Kruger-Ross & Waters, 2013; Peck et al., 2018; Vayre & Vonthron, 2017).

EI has been identified as a predictor of student success in both traditional and online learning environments (Berenson et al., 2008; Brown, Williams, & Etherington, 2016; Buzdar, Ali, & Haq Tariq, 2016; Engin, 2017; Goodwin, 2016; MacCann, Jiang, Brown, Double, Bucich, & Minbashian, 2019; Noor & Hanafi, 2017; Zhoc et al., 2018). Bar-On (2006) defined EI as an interrelated set of intrapersonal and interpersonal competencies, skills, and facilitators that combine to determine human behavior. In other words, higher levels of EI correspond to more effective skills in communication, rapport building, and in coping with life's daily demands (Ackley, 2016; Bar-On, 2006; Brown et al., 2016; MacCann et al., 2019; Noor & Hanafi, 2017). Correlational links between EI and other psychometric properties (e.g., motivation, self-efficacy) within traditional and online learning environments have been established, and EI is now considered a primary predictor of student success in both traditional and online courses (Berenson et al., 2008; Brown et al., 2016; Buzdar et al., 2016; Engin, 2017; Kauffman, 2015; MacCann et al., 2019; Noor & Hanafi, 2017).

Researchers have also identified SDL as a significant predictor of academic success in both traditional and online learning environments (Cazan & Schiopca, 2014; Chan, 2018; Lai, 2011; Schulze, 2014; Zhoc et al., 2018). Knowles' (1975) defined SDL as a process where adult learners "take the initiative without the help of others [during] their own learning experiences," especially those outside of the traditional classroom (p. 18). Like EI, SDL has been found to improve motivation, self-awareness, and academic performance in both traditional and online learning environments (Cazan & Schiopca, 2014; Chan, 2018; Lai, 2011; Schulze, 2014; Song & Bonk, 2016; Zhoc et al., 2018).

To date, researchers have found that EI predicted student success better than personality in both traditional (e.g., Brown et al., 2016; Bukhari & Khanam, 2016) and online learning environments (e.g., Berenson et al., 2008; Han & Johnson, 2012). Other researchers have found that SDL predicted student success better than personality in both traditional (e.g., Cazan & Schiopca, 2014) and online learning environments (e.g., Lai, 2011). In addition, some researchers have found that EI and SDL are strongly correlated in either the traditional (e.g., Koc, 2019; Muller, 2007; Zhoc & Chen, 2016; Zhoc et al., 2018) or online (e.g., Buzdar et al., 2016; Engin, 2017) learning environments. In the traditional environment, some of these researchers (i.e., Zhoc & Chen, 2016; Zhoc et al., 2018) found that EI predicted SDL as well as academic learning outcomes (e.g., GPA). In the online learning environment, Buzdar, Ali, and Haq Tariq (2016) found that EI predicted online learner readiness (OLR), and Engin (2017) found EI predicted SDL as a subscale of OLR. However, there is little research exploring both EI and SDL as possible predictors of student success in either the traditional (Koc, 2019; Zhoc & Chen, 2016; Zhoc et al., 2018) or online (Engin, 2017) learning environments.

The relationship between EI and academic achievement has been directly and indirectly studied in the traditional learning environment, with mediating factors such as academic engagement, self-motivation, and coping (Koc, 2019; Noor & Hanafi, 2017; Zhoc et al., 2018). In a pioneer study using EI as a predictor and a mediator, Noor and Hanafi (2017) reported that EI predicted academic success in adult learners and that it fully mediated the relationship between emerging adulthood and academic achievement in the traditional classroom environment. In other words, EI positively correlated with emerging adulthood and academic achievement and indirectly influenced the positive relationship between emerging adulthood and academic achievement in the traditional learning environment.

Koc (2019), Zhoc and Chen (2016), and Zhoc et al. (2018) found that EI positively correlated with SDL. Zhoc and Chen (2016) as well as Zhoc et al. (2018)

found that EI significantly predicted SDL in the traditional learning environment. Zhoc et al. (2018) further explored the relationship between EI, SDL, and academic achievement and found that SDL indirectly influenced the relationship between EI and academic achievement. In her dissertation, Schulze (2014) found that SDL predicted online course completion and that learner demographics mediated the relationship between SDL and online course completion. These findings help support SDL as a predictor and mediator variable that influences relationships between psychological traits (e.g., EI) and academic success in both learning environments. Because both EI and SDL have been supported as predictors of online student success, and found to correlate with each other, then it is possible for a mediation relationship to exist between them (Baron & Kenny, 1986; Field, 2018).

Cazan and Schiopca (2014), Koc (2019), and Zhoc et al. (2018) suggested that SDL could be a mediator between psychological traits (e.g., EI, self-efficacy) and academic achievement (e.g., GPA). EI and SDL have been found to be positively associated in both the traditional (Koc, 2019; Muller, 2007; Zhoc et al., 2018) and online (Buzdar et al., 2016; Engin, 2017) learning environments. Zhoc et al. (2018) discovered that SDL mediated the relationship between EI and academic success in first year undergraduates. In this study, EI and SDL are explored as predictors of OS, and SDL is tested as a mediator of the relationship between EI and OS in adult learners (undergraduates and graduates) taking online courses.

Problem Statement

In 2002, Allen and Seaman conducted their first survey to better understand the state of online learning in the United States (Allen & Seaman, 2011, 2017). For the past 14 years, they have found, overall, that higher education enrollments are declining, and that online enrollment growth is steadily increasing (Allen & Seaman, 2011, 2017). From 2002 to 2012, higher education enrollments overall averaged 2.7% (Allen & Seaman, 2011, 2017; NCES, 2017). Since then, it has decreased to less than 2% (Camera, 2019, May 30; Seaman et al., 2018). In contrast, the percentage of higher education students taking at least one online course was 9.6% in 2002, but by 2016, the percentage was 31.6% (Allen & Seaman, 2011, 2017; NCES, 2017).

In their longitudinal study, Allen and Seaman found the number of students taking at least one online course a year, or a combination of online courses and ground courses, has continued to rise, as well as the number of higher education institutions offering distance education courses and degree programs (Allen & Seaman, 2011, 2017). For example, in the Fall semester of 2015, over six million students took at least one online course and just under half of those (47.2%) were taking all their courses online (Allen & Seaman, 2017; NCES, 2017). Online learning has become a viable option for adult learners who are balancing the demands of work, family, and school (Bawa, 2016; Choi & Park, 2018; Kauffman, 2015; Vayre & Vonthron, 2017). More recently, it has been considered a critical component in many institutions' long-term strategy planning (de los Santos & Zanca, 2018). Online learning provides adult learners with greater access to learning resources alongside the benefits of convenience and flexibility found within an asynchronous learning environment (Broadbent & Poon, 2015; de los Santos & Zanca, 2018; Hassan et al., 2014; Knight, 2019; Peck et al., 2018; Song & Bonk, 2016; Vayre & Vonthron, 2017). Working professionals and adult learners continue to seek out online courses, training, and degree programs to improve their life circumstances, skills, and employment opportunities (Bawa, 2016; Goodwin, 2016; Hassan et al., 2014; Knight, 2019; Vayre & Vonthron, 2017).

The demand for online courses, training, and degree programs remains 10% higher than traditional ground courses (Allen & Seaman, 2017; Knight, 2019; Seaman et al., 2018). Unfortunately, attrition rates for online courses have also remained higher than traditional ground courses, with online student failure and/or dropout rates running 40–80% higher than traditional courses (Bawa, 2016; Hobson & Puruhito, 2018; Kauffman, 2015; Knight, 2019; NCES, 2017; Peck et al., 2018). In this way, higher education and global, lifelong learning opportunities (e.g., MOOCs) for adult learners have been "compromised" (Van Doorn & Van Doorn, 2014, p. 325), and there is a need for an improved understanding of online learning and successful student characteristics to better direct students to the most appropriate learning environment for their learning needs to improve course completion, retention, and graduation rates for adult learners.

Researchers have explored self-efficacy, motivation, OLR, SDL, and EI as predictors of OS (i.e., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016; Kerr et al., 2006; Lai, 2011; Peck et al., 2018; Schulze, 2014; Song & Bonk, 2016; Vayre & Vonthron, 2017). Previous research supports EI and SDL as predictors of OLR (i.e., Buzdar et al., 2016; Engin, 2017; Lai, 2011) and OS (i.e., Berenson et al., 2008;

Goodwin, 2016; Lai, 2011; Schulze, 2014). However, research that includes both EI and SDL in the literature is scarce (Koc, 2019). Buzdar et al. (2016) and Engin (2017) found EI and SDL (as a subscale of OLR) were positively correlated and that EI predicted OLR and SDL in the online learning environment. The current study addresses a meaningful gap in the literature by examining both EI and SDL as predictors of online student success and the indirect nature of SDL on the relationship between EI and OS.

Previous research supports EI and SDL as predictors and/or mediators in both learning environments (e.g., Engin, 2017; Noor & Hanafi, 2017; Schulze, 2014; Zhoc et al., 2018). In the traditional environment, Noor and Hanafi (2017) found EI mediated the relationship between emerging adulthood and academic success. Zhoc et al. (2018) found EI predicted SDL and discovered that SDL mediated the relationship between EI and academic achievement. Engin (2017) found EI predicted SDL in the online learning environment. Schulze (2014) found that SDL predicted online course completion and that learner characteristics (e.g., English speaking ability) mediated, or influenced, the relationship between SDL and online course completion. If both EI and SDL are predictors of OS for adult learners, and they correlate with each other, then it is possible for an indirect relationship to exist between them. In other words, one variable (mediator) could influence the relationship between two other variables (predictor and outcome). In this study, the indirect effects (e.g., mediation) of SDL on EI and online student success were explored.

Purpose of the Study

The purpose of this quantitative study was to explore EI and SDL as predictors of OS and to test whether SDL mediated the relationship between EI and OS. Age, gender, and education level (undergraduate, graduate) were controlled for as the covariates (Hayes, 2018; Slater, Cusick, & Louie, 2017). OS was operationalized as grade point average (GPA) and was self-reported (e.g., Berenson et al., 2008; Goodwin, 2016; Zhoc et al., 2018). EI was measured using an online version of Petrides' (2009) Trait Emotional Intelligence Questionnaire – Short Form (TEIQue-SF; e.g., Engin, 2017). SDL was measured using Fisher, King, and Tague's (2001) Self-Directed Learning Readiness Scale for Nursing Education (SDLRSNE), adapted for online general education as the Self-Directed Learning Readiness Scale (SDLRS; Chan, 2018; Fisher & King, 2010; Schulze, 2014).

Participants in the study were adult learners recruited from a fully online university's participant pool and from social media websites. They were surveyed on their demographics (age, gender), current level of education (undergraduate or graduate), total number of online courses taken for their degree program, and GPA. Informed consent was obtained electronically. The demographic survey and two questionnaires (SDLRS, TEIQue-SF) were administered online through a survey platform service (i.e., freeonlinesurveys.com). These recruitment sources were comprised of both undergraduate and graduate adult learners who had taken online courses, to promote the generalizability of the study. Regression analysis was used to predict OS from EI and

SDL. Mediation analysis was used to test the indirect effects of SDL on the relationship between EI and online student success.

If EI and/or SDL are found to be predictors of OS, then this would help support the need for design modifications to the online learning environment (e.g., student self-assessments, orientation courses) to better assist students and faculty in the content and delivery of online courses In this way, the findings and design modifications may help direct students to the appropriate learning environment for their learning needs and increase student course completion, retention, and graduation rates in the online learning environment (Bawa, 2016; Berenson et al., 2008; Choi & Park, 2018; Doe et al., 2018; Goodwin, 2016; Kerr et al., 2006; Knight, 2019; Koc, 2019; Lai, 2011; Majeski et al., 2017; Vayre & Vonthron, 2017; Zhoc et al., 2018).

Research Questions and Hypotheses

The research questions and hypotheses for this study are as follows:

RQ1 - Does emotional intelligence (EI) relate positively and significantly to OS?

Ho_1: EI does not positively nor significantly relate to OS.

Ha_1: EI does positively and significantly relate to OS.

RQ2 - Does self-directed learning (SDL) relate positively and significantly to EI?

Ho_2: SDL does not positively nor significantly relate to EI.

Ha_2: SDL does positively and significantly relate to EI.

RQ3 - Using regression analysis, does EI and/ or SDL predict OS?

Ho_3: EI and/or SDL does not significantly predict OS.

Ha_3: EI and/or SDL does significantly predict OS.

RQ4 - If EI and SDL are both predictors of OS, then does SDL mediate the relationship between EI and OS? In other words, does SDL significantly influence the relationship between EI and OS.

$H\text{o}_4$: The relationship between EI and OS is not mediated by SDL.

$H\text{a}_4$: The relationship between EI and OS is mediated by SDL.

Theoretical Frameworks for the Study

The theoretical frameworks for this study are Bar-On's (2006) mixed model of EI and Knowles' (1975) theory of SDL. The conceptual model for this study (see Figure 1 below), demonstrates the relationships between EI, SDL, and OS, and the proposed mediation effect of SDL on the relationship between EI and OS.

EI. There is no one empirically agreed upon definition of EI (Ackley, 2016; Bar-On, 2006; Koc, 2019; Mayer, Salovey, & Caruso, 2008; Petrides & Mavroveli, 2018). However, there are common elements, such as recognizing and understanding emotions, managing and controlling emotions, and empathy (Ackley, 2016; Bar-On, 2006; Goleman, 1995/2005; Mayer et al., 2008; MacCann et al., 2019; Petrides & Mavroveli, 2018). After a decade of research, Bar-On (2006) described individuals who are emotionally intelligent as being able to do the following effectively: "understand and express themselves, understand and relate to others, and successfully cope with the demands of daily life" (p. 3). In addition, previous research has demonstrated that individuals with higher EI tend to have better physical health, psychological well-being, and interpersonal relationships (Ackley, 2016; Bar-On, 2006; Goodwin, 2016; Mayer, Caruso, & Salovey, 2016; MacCann et al., 2019; Noor & Hanafi, 2017; Petrides &

Mavroveli, 2018; Zhoc et al., 2018). They also tend to be smarter (e.g., higher GPAs), accomplish more of their goals, stay on task, and can actualize their fullest potential (Ackley, 2016; Bar-On, 2006; Buzdar et al., 2016; Ford & Tamir, 2012; Goodwin, 2016; Koc, 2019; MacCann et al., 2019; Zhoc et al., 2018).

Currently, there are two empirical models of EI: ability EI and mixed (trait) EI. Mayer, Salovey, and Caruso's (2008) "four branch model" is the only ability model of EI. These authors posited that emotional intelligence (EQ) is the emotional equivalent of cognitive intelligence (IQ) and cannot be taught or improved (Mayer, Caruso, & Salovey, 2016; Mayer et al., 2008). However, mixed (trait) EI models (i.e., Bar-On,2006; Goleman, 1995/2005; Petrides, 2009) combine competencies, skills, and personality traits, which is why they are known as mixed (or trait) models of EI. Bar-On (2006) and Goleman (1995/2005) posited in their mixed models of EI that EI skills can be taught and improved and that EI is a stronger predictor of success than IQ in terms of how individuals relate to others, their school and work performance, and in how they cope with daily life.

SDL. Knowles (1975) defined SDL as a process where adult learners take initiative, diagnose their own learning needs, formulate goals, identify resources, select and implement appropriate learning strategies, and evaluate their own learning outcomes (p. 18). According to his andragogical model of adult learning theory, adults' motivation to learn is internal, and they approach learning with a purpose, such as meeting a need or improving some aspect of their lives (Knowles, 1984). In this way, it is important that learning outcomes be of immediate value to adult learners both personally and professionally. Like EI, there are two approaches to SDL in the research: as a process or as a personality trait. For the purposes of this study, SDL was approached as a process (Chan, 2018; Fisher et al., 2001; 2010; Knowles, 1975, 1984; Rager, 2009; Schulze, 2014) because more recent research has found that SDL should not be categorized as a personality trait (e.g., Cazan & Schiopca, 2014; Lai, 2011; Slater & Cusick, 2017; Song & Bonk, 2016; Zhoc et al., 2018).

A conceptual model. As mentioned earlier, EI has been established as a primary predictor of student success in the online learning environment (Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016). Other researchers have linked SDL with online learning (e.g., Chan, 2018; Lai, 2011; Song & Bonk, 2016; Sumuer, 2018) and online course completion (e.g., Schulze, 2014). In alignment with the theoretical frameworks of this study (Bar-On, 2006; Knowles, 1975, 1984), both EI and SDL include cognitive, metacognitive, and affective skills that can be taught and improved with increased self-awareness and practice (Bar-On, 2007; 2010; Berenson et al., 2008; Buzdar et al., 2016; Cazan & Schiopca, 2014; Goodwin, 2016; Knowles, 1975, 1984; Lai, 2011; Schulze, 2014; Zhoc et al., 2018).

A search of the research literature yielded little research on EI and SDL as predictors of OLR (e.g., Buzdar et al., 2016; Engin, 2017) and the OS (e.g., GPA) of adult learners. This study examined EI and SDL as predictors of OS. The findings may strengthen EI as a primary predictor of online student success and support SDL as a predictor of student success in the online environment. If EI and SDL are found to be significant predictors of OS, and positively correlated with each other, then mediation analysis would be used to test the indirect effects of SDL on the relationship between EI and OS.

A mediation refers to when a relationship between a predictor variable and an outcome variable can be explained by their relationship to a third variable, known as the mediator (Field, 2018; Hayes, 2018). The proposed mediation model for this study (see Figure 1 below) was based on Baron and Kenny's (1986) classic (or triangle) mediation model and Hayes (2018) simple mediation model (No. 4) in PROCESS. The mediation model for this study (see Figure 1 below) demonstrates how one predictor variable (i.e., EI) influences an outcome variable (i.e., OS) through a single intervening variable, known as the mediator (i.e., SDL; Field, 2018; Hayes, 2018). Figure 1 (below) demonstrates the conceptual model for the relationships between the variables in this study: EI and SDL as the predictor variables; SDL as the proposed mediator variable; age, gender, and level of education as the covariate variables denoted as C; and OS as the outcome variable (GPA).

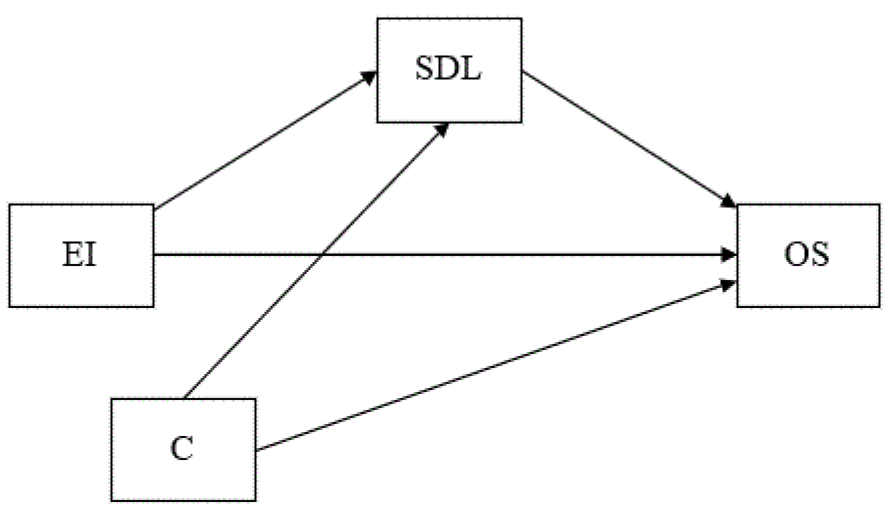

Figure 1: Proposed mediation model.

According to the causal step approach by Baron and Kenny (1986), there are four conditions necessary for statistical mediation. These were used as the research questions for this study. Specifically, employing Pearson's simple bivariate correlation coefficient (r): (a) the predictor variable (i.e., EI) must be significantly correlated with the outcome variable (i.e., OS); (b) the predictor variable (EI) must be significantly correlated with the mediator variable (i.e., SDL). Next, using multiple regression analysis in which EI and SDL are the predictor variables and OS is the outcome variable, and after controlling for the relationship between the mediator and the outcome variable, (c) the relationship between EI and OS must be reduced substantially (partial mediation) or to a non-significant finding ($p > .05$; full mediation level); and (4) while the relationship between the mediator (SDL) and outcome variable (OS) remains statistically significant.

In Figure 1 above, EI and SDL each predict OS as supported by previous research on OLR and OS (i.e., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017). In this way, EI and SDL were hypothesized to be positively and significantly correlated, just as previous researchers found them to be in the traditional learning environment (e.g., Koc, 2019; Zhoc et al., 2018) and online (e.g., Buzdar et al., 2016; Engin, 2017) learning environment. Next, multiple regression was conducted to explore EI and SDL as predictors of OS. Then, mediation analysis was used to determine if SDL mediated the relationship between EI and OS, while controlling for age, gender, and level of education.

Nature of the Study

The nature of this study was quantitative, with a nonexperimental, cross-sectional survey design (Creswell & Creswell, 2018). A quantitative approach was used since this study tested for relationships between variables, whether one variable predicts another, and for the indirect effects of a mediator variable (Creswell & Creswell, 2018; Field, 2018). The predictor variables were EI and SDL. SDL was also the mediator variable because previous research has indicated positive links between EI and SDL with OLR (i.e., Buzdar et al., 2016; Engin, 2017). Even though age and gender have also been found to positively correlate with EI (e.g., Berenson et al., 2008) and SDL (e.g., Lai, 2011), in this study they were controlled for as covariates (see C in Figure 1) in the mediation model because there were mixed findings in the literature on whether age or gender predict student success (e.g., Knight, 2019; Rahafar, Randler, Vollmer, & Kasaeian, 2017), EI (e.g., Nasir & Masrur, 2010; Noor & Hanafi, 2017), and/or SDL (e.g., Slater & Cusick, 2017; Zhoc & Chen, 2016). Participants' level of education (undergraduate, graduate) was also a covariate (see C in Figure 1) in the mediation model because of mixed findings in the literature on whether level of education predicts student success and/or SDL in either the traditional (e.g., Slater & Cusick, 2017) or online (e.g., Hsu & Shiue, 2005) learning environments. OS was the outcome variable and operationalized as GPA (e.g., Berenson et al., 2008; Zhoc et al., 2018).

The target population consisted of adult learners (ages 18 and older) taking online courses as part of a degree program (undergraduate or graduate). Nonprobability, convenience sampling was used to recruit participants from a fully online university's participant pool and from social media websites. Informed consent was obtained electronically, and all data were self-reported. Three surveys were administered online through an online survey platform service (i.e., freeonlinesurveys.com): Fisher, King, and

Tague’s (2001) Self-Directed Learner Readiness Scale for Nursing Education, adapted for online higher education as the SDLRS (Chan, 2018; Fisher & King, 2010; Schulze, 2014); Petrides (2009) Trait Emotional Intelligence Questionnaire – Short Form (TEIQue-SF; Engin, 2017); and a demographics survey. The demographics survey consisted of questions on participants’ age, gender, level of education (undergraduate or graduate), total number of online courses taken for the degree program, and GPA. The psychometric measurements (TEIQue-SF and SDLRS) aligned with using Bar-On’s (2006) mixed model of EI (e.g., Bukhari & Khanam, 2016; Engin, 2017) and Knowles’ (1975) theory of SDL (e.g., Chan, 2018; Schulze, 2014) as theoretical frameworks. Figure 1 above demonstrated the mediation model for this study and the relationships tested between the variables EI, SDL, C, and OS.

There is little in the literature on power and sample size selection in mediation analysis (Hayes, 2018, 2020). In following with a recommendation by Hayes (2018), I used Fritz and MacKinnon’s (2007) table of sample sizes needed to detect an indirect effect (at .80 power) when using mediation analysis methods. The mediation analysis method I chose to use was Hayes’ (2018) PROCESS macro in SPSS, which is a bootstrap resampling method with replacement. Fritz and MacKinnon (2007) found the bootstrap resampling method to be one of the more powerful mediation tests across conditions. They also discovered that it requires smaller sample sizes than the other methods (Fritz & MacKinnon, 2007). According to Fritz and MacKinnon (2007), the minimum sample size recommended for a mediation study using a bootstrap resampling method with a priori alpha level of .05 and medium effect size of .15 was $N = 71$.

Informed consent and all data were collected electronically through an online survey platform service (i.e., freeonlinesurveys.com) and then transferred to IBM SPSS 25 for statistical analysis (Field, 2018; Hayes, 2018). Data were interval/ratio (age, total number of online courses taken for the degree program, GPA, TEIQue-SF total score, and SDLRS total score), with two dichotomous variables (gender, level of education). Previous research relating to EI and/or SDL and OS used a quantitative, cross-sectional approach (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016; Lai, 2011; Schulze, 2014; Sumner, 2018). After data collection and input are complete, then descriptive analyses were run on the predictor and outcome variables to determine their means, standard deviations, and range of scores (Field, 2018; Hayes, 2018). Next, preliminary data screening was conducted. Scatterplots and histograms were run to identify linearity, outliers, normality, and multicollinearity to determine if the data met the assumptions for multiple regression analysis (Field, 2018; Frankfort-Nachmias & Leon-Guerrero, 2015). If the data met the assumptions, then multiple regression analyses were conducted to determine if EI and/or SDL predicted online student success. In following with Cazan and Schiopca's (2014), Koc's (2019), and Zhoc et al.'s (2018) future research recommendations, this study also investigated the indirect effects of SDL on the relationship between EI and OS. If a significant regression was found, then the mediation model was further tested using Hayes' (2018) PROCESS macro in SPSS.

Definitions

Adult learners: The term adult can be defined as "a maturing human being" who has taken on the role of spouse and/or parent or "who has arrived at a self-concept of being responsible for one's own life" (Knowles, 1975, p. 19; 1984, p. 9). In the current study, adult learner refers to undergraduate and graduate students who are 18 years or older, taking online courses as part of their degree program, and who have completed at least one semester/quarter of their degree program.

Andragogy: Literally translated, this term means "the art and science of helping adults" (Knowles, 1975, p. 19). It originally referred to how adults learn, but now it is often viewed as a model of learning that may be applied to self-directed learners of all ages (Knowles, 1984; Knowles, Holton, & Swanson, 2015).

Attrition rate: In higher education, attrition rate refers to the percentage of students who did not complete and/or pass a course or program or who withdrew at any point during the course (Bawa, 2016; Choi & Park, 2018; Peck et al., 2018). In the research literature, definitions of attrition have not been consistent (Lee & Choi, 2011). In the present study, attrition rate refers to adult learners in higher education who dropped out, failed, and/or withdrew from a course or degree program.

Distance (or online) education: An educational course, program, or institution that uses "one or more technologies to deliver instruction to students" who are physically and/or geographically separated from the instructor in order to support instruction and interaction either synchronously and/or asynchronously (Allen & Seaman, 2017, p. 6). The technologies may include Internet, audio conferencing, and wireless communication devices (Allen & Seaman, 2017). All coursework is typically completed online; however, there may be requirements for coming to campus for orientation, exams, and/or academic services (Allen & Seaman, 2017).

Emotional intelligence (EI): There is no universally agreed-upon definition for EI. However, there are common elements, such as recognizing and understanding emotions, regulating emotions, and empathy (Ackley, 2016; Bar-On, 2006; Koc, 2019; Mayer et al., 2008; Petrides, 2009). Bar-On (2006) defined EI as “a cross-section of interrelated emotional and social competencies, skills, and facilitators” that determine how effectively individuals can understand and express their emotions, understand and relate to the emotions of others, and cope with the daily demands of life (p. 3). He later explained how all EI models (i.e., ability, mixed, trait) are “mixed” because they consist of a “cross-section of bio-psycho-social” competencies and traits to explain human behavior (Bar-On, 2006, p. 11). In the same way, Petrides and colleagues (2016, 2018) have posited that all EI models can be considered trait models because they are assessing people’s self-perceptions of their emotions and emotionally-related personality traits. In the current study, Bar-On’s (2006) mixed model of EI is used as the EI theoretical framework. To measure EI in the online learning environment, participants completed an online version of Petrides (2009) TEIQue-SF (e.g., Engin, 2017).

Fully online learning: A type of distance education where all instruction, coursework, exams, and requirements for completion are carried out through Internet-based delivery (Bakia et al., 2012).

Mediation: This statistical term refers to when a relationship between a predictor variable and an outcome variable can be explained by their relationship to a third intervening variable known as the mediator (Field, 2018; Hayes, 2018).

Online (or distance) course: An online (or distance) course is one where 80% or more of the content is delivered online (Allen & Seaman, 2011). There may be requirements for coming to campus for course orientation, exams, and/or academic services (Allen & Seaman, 2017).

Online learning: This term generally describes “instructional environments supported by the Internet” and comprises of a wide variety of programs that use the Internet to provide instructional materials, facilitate instruction, and support interaction among students and teachers (Bakia et al., 2012, p. 2). For the current study, and in following with Kerr et al. (2006), online learning refers to “student learning achieved in formal university courses,” where all instruction takes place online using the Internet (p. 91).

Online success (OS): There is no one definition of OS; instead, it is probably “a combination of technical, personal, cognitive, motivational, and psychological factors (Berenson et al., 2008, pp. 2-3; Doe et al., 2017). For the present study, OS is operationalized as GPA and self-reported (e.g., Berenson et al., 2008; Zhoc et al., 2018).

Pedagogy: Literally translated, this term means “the art and science of teaching children” (Knowles et al., 1973/2015, p. 40). It has been the predominant education model, and it places sole responsibility for content and learning on the teacher (Knowles, 1984; Knowles et al., 1973/2015. It does not nurture self-directed learning because it is based on teacher-directed learning (Knowles, 1984; Knowles et al., 1973/2015).

Self-directed learning (SDL): This term is most defined as a process where learners take initiative, diagnose their own learning needs, formulate goals, identify resources, select and implement appropriate learning strategies, and evaluate their own learning outcomes (Knowles, 1975, p. 18). It is a key principle and motivating factor in the andragogical model of adult learning theory (Knowles, 1984). For the current study, SDL is operationalized as self-directed learning readiness (e.g., Fisher et al., 2001; Guglielmino, 1977; Hsu & Shiue, 2005; Knowles, 1984).

Self-directed learning readiness (SDLR): Readiness for self-directed learning, or self-directed learning readiness (SDLR), has been identified in the literature as a key learner characteristic in OS (e.g., Lai, 2011; Schulze, 2014; Song & Bonk, 2016; Sumner, 2018). SDL researchers (e.g., Fisher et al., 2001; Guglielmino, 1977; Hsu & Shiue, 2005; Knowles, 1984) have defined SDL as a level of readiness, or capacity for self-directed learning readiness (SDLR). In this sense, SDLR indicates an individual has the capacity to develop SDL skills. In the present study, participants completed an online version of the SDLRS (Fisher et al., 2001) to measure their SDL in the online environment.

Traditional (or ground) course: A traditional (or ground) course is where most of the content is delivered face-to-face in lectures and/or writing, with little to none of the content delivered online (Allen & Seaman, 2011; Bakia et al., 2012; Kauffman, 2015).

Assumptions

Given that the study’s assessment battery used self-report as the data collection method, I assumed that the members of the fully online university’s participant pool and adult learners on social media websites, who met the designated criteria (18 years or older, had taken at least one online course as part of their degree program, and had completed one quarter/semester in their degree program), would agree to participate in the study. I also assumed that they would follow through with completion of the study, by completing the assessment battery (demographics survey, SDLRS, TEIQue-SF) thoroughly, honestly, and without bias.

Scope and Delimitations

With the demand for online education remaining steady, but attrition rates for online courses remaining higher than traditional courses (Bawa, 2016; Knight, 2019; Peck et al., 2018), more research is needed into online student success. When examined in both traditional and nontraditional (online) learning environments within the context of higher education, EI and SDL have been shown to be predictors of student success outcomes (Berenson et al., 2008; Buzdar et al., 2016; Cazan & Schiopca, 2014; Engin, 2017; Goodwin, 2016; Lai, 2011; MacCann et al., 2019; Noor & Hanafi, 2017; Schulze, 2014; Sumuer, 2018; Zhoc et al., 2018). To date, the indirect relationship between EI and SDL, and how it impacts OS in adult learners, has yet to be examined. Koc (2019) and Zhoc et al. (2018) examined the relationships between EI, SDL, and academic achievement within a traditional learning environment. Zhoc et al. (2018) discovered that SDL mediated, or influenced, the relationship between EI and academic achievement as well as generic learning outcomes (e.g., critical thinking).

Adult learners are part of the population who seek out online learning to better their life circumstances, skills, and/or employment opportunities (Bawa, 2016; Hassan et al., 2014; Knight, 2019; Vayre & Vonthron, 2017). They also may not have had the opportunity to earn a degree without the availability, and flexibility, of online education (Doe et al., 2017; Peck et al., 2018; Vayre & Vonthron, 2017). This research focused on adult learners who were either members of a fully online university's participant pool or taking online courses and recruited via social media websites. Previous researchers who examined the relationships between EI and/or SDL and OS (as GPA or OLR) did not target adult learners who attended fully online institutions of higher education and/or adult learners/groups on social media (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017). In consideration of the growing demand for online education, and open access courses (e.g., MOOCs), it seemed more applicable to examine this population.

Limitations

Validity was limited in several ways. First, recruitment for the study focused on one fully online university's participant pool and social media sites, so the generalizability of the study was limited to online adult learners. In addition, because of the nonexperimental nature of the study, causality was not determined. Correlational, regression, and mediation analyses can only help support claims for associations between variables and how these may be causal in nature (Hayes, 2018). Finally, it was possible that an unknown variable not included in the mediation model, nor controlled for in the study, contributed to any relationship found. According to Hayes (2018), the best way to address this in regression and mediation analysis is to check data for quantity (i.e., representing real numbers instead of categories) and to control for the variables that other researchers have argued might be responsible for the relationships being tested (in this case, age, gender, and level of education) in the statistical analyses.

Biases that may have impacted the findings of this study include self-report and research bias. It is possible that survey questions might be answered by participants in ways that they believed the questions should be answered for the researcher or for the sake of social desirability (Cox, 2016). It is also possible, due to the nature of self-report, that participants would have trouble accurately assessing themselves when they completed the psychometric evaluations of EI and SDL. The first source of bias was addressed by making it clear to participants that the results were anonymous and confidential (Cox, 2016). As the researcher, I would not know which participant was associated with which data set. The second source of bias was addressed by using valid and reliable instruments to assess EI (i.e., Petrides' TEIQue-SF) and SDL (i.e., Fisher et al. SDLRS), and by modeling the demographic survey questions from examples in previous, peer-reviewed, research (e.g., Berenson et al., 2008; Zhoc et al., 2018). Lastly, all questions on each survey (demographics, SDLRS, TEIQue-SF) were made to be mandatory responses to help ensure that no questions were skipped and no data were missing.

Significance of the Study

Although the demand for online learning remains higher than traditional courses, attrition rates for online courses have also remained higher than campus courses, with 40–80% of online students failing and/or dropping out (Bawa, 2016; Choi & Park, 2018; Kauffman, 2015; Peck et al., 2018). Enrollment growth for higher education and global, lifelong learning opportunities for adult learners have been "compromised," with lower retention rates in online programs and lower completion and academic success rates for online courses (Van Doorn & Van Doorn, 2014, p. 325).

The USDOE (2014), along with online education researchers (e.g., Allen & Seaman, 2017; Bawa, 2016; Broadbent & Poon, 2015; Kauffman, 2015; Peck et al., 2018) have emphasized the need for an improved understanding of online learning to increase retention and graduation rates, and ultimately, the profitable employment of all students. There are gaps for identifying learner characteristics to better promote online student performance, completion, and success (Broadbent & Poon, 2015; Choi & Park, 2018; Kauffman, 2015; Kerr et al., 2006; Knight, 2019; Peck et al., 2018; USDOE, 2014; Vayre & Vonthron, 2017). This study examined EI and SDL as predictors of online student success, the relationship between EI and SDL, and the indirect effects of SDL on EI and OS for adult learners taking online courses as part of their degree program.

As mentioned previously, EI is now considered a primary predictor of online learning, OLR, and OS (Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016; Han & Johnson, 2012; Majeski et al., 2017). In addition, SDL has also been linked with online learning outcomes and academic success (Chan, 2018; Lai, 2011; Schulze, 2014; Song & Bonk, 2016; Sumuer, 2018). Studies including both EI and SDL as variables are scarce in the literature (Koc, 2019). Few studies were found that examined EI and SDL as predictors, the relationship between them, and the role their relationship plays in student success in the traditional learning environment (i.e., Koc, 2019; Zhoc & Chen, 2016; Zhoc et al., 2018). No studies were found that examined both EI and SDL as predictors of OS within the online learning environment. This research addresses a clear gap in the literature by examining EI and SDL as predictors of online student success and their relationship to one another. If EI and SDL were found to be significant predictors of online student success, and correlated with each other, then mediation analysis would be used to test the indirect effects of SDL on the relationship between EI and OS.

Last, this study answers the call for more research on learner characteristics in the online learning environment to improve online course design, delivery, and online instructor training (Bakia et al., 2012; Bawa, 2016; Broadbent & Poon, 2015; Kauffman, 2015; Kerr et al., 2006; Majeski et al., 2017; USDOE, 2014; Vayre & Vonthron, 2017). The findings of the study could lead to positive social change through online course reform in design and instructional strategies, by helping to better direct students to a learning environment more appropriate to their learning needs, which in turn, could increase online course completion rates and student success (Bawa, 2016; Berenson et al., 2008; Goodwin, 2016; Kerr et al., 2006; Majeski et al., 2017; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017). In addition, for students taking online courses, it may help to improve learning outcomes, skills, training, and overall course satisfaction, which in turn, could increase retention and student satisfaction with their university experience (Allen & Seaman, 2011, 2017; Bakia, et al., 2012; Bawa, 2016; Broadbent & Poon, 2015; Hassan et al., 2014; Hobson & Puruhito, 2018; Kauffman, 2015; Vayre & Vonthron, 2017; Zhoc et al., 2018).

Summary

Online enrollment rates continue to be higher than overall enrollment rates within higher education (Allen & Seaman, 2011, 2017). Online education has become a viable option for adult learners who are seeking to better their life circumstances, improve their skills, and/or expand their career opportunities (Choi & Park, 2018; Hassan et al., 2014; Knight, 2019). However, attrition rates for online courses also remain higher than traditional courses, with a steady dropout/failure rate between 40% and 80% (Bawa, 2016; Choi & Park, 2018; Knight, 2019; Peck et al., 2018).

Adult learners taking online courses have not had a significant presence in the education and psychology literature. EI and SDL have been identified as predictors of OLR and OS as well as positively linked with course completion, retention, and course satisfaction (Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Kauffman, 2015).

Researchers have examined the relationship between EI and SDL in student success within the traditional learning environment (e.g., Koc, 2019; Zhoc & Chen, 2016; Zhoc et al., 2018). More recently, EI and/or SDL have even been explored as mediators in the traditional learning environment (e.g., Noor & Hanafi, 2017; Zhoc et al., 2018), but I could not find a study involving both EI and SDL as predictors, and SDL as a mediator, within the online learning environment. The indirect effects of learner demographics and/or characteristics on the relationship between SDL and OS have been explored (e.g., Hsu & Shiue, 2005; Schulze, 2014), and SDL has been discovered to be a mediator between EI and academic achievement in the traditional learning environment (Zhoc et al., 2018). However, SDL has not been examined as a mediator of the relationship between EI and OS (e.g., GPA).

The purpose of this study was to examine both EI and SDL as predictors of OS, their relationship to each other, and the indirect effects of SDL on EI and OS. By doing so, this research answers the call for more understanding into the online learning environment and the characteristics of successful online students (Doe et al., 2017; Kerr et al., 2006; Knight, 2019; Lee & Choi, 2011; Peck et al., 2018). The social change implications include providing better understanding of adult learners who are successful in the online environment as well as guidance in course design, instruction, curriculum development, and training. The findings may also help to improve course completion, retention, and success by providing direction to students in selecting the most appropriate learning environment to best meet their learning needs.

Chapter 2 provides a review of the existing literature on EI, SDL, what is known and not known about the relationship between EI and SDL in the traditional and online learning environments, and their impact on the OS of adult learners. Chapter 3 describes the methodology used in this study to address the research questions, the sample population, statistical and data techniques, and the ethical issues involved. Chapter 4 contains the results of the research followed by Chapter 5, which is a discussion of the results and how they may be integrated into the current literature.

Chapter 2: Literature Review

Introduction

Since the birth of distance education in the 1980s, higher education has been experiencing a paradigm shift in instruction and delivery, where traditional ground courses became just one option among several modalities (Allen & Seaman, 2011, 2017; Bakia et al., 2012; Holmberg, 1988; Keegan, 2002; Seaman et al., 2018). Distance education started as an asynchronous activity outside of class (e.g., visiting a website, watching a video) and has evolved over the last few decades to encompass fully online courses, certifications, and degree programs (Allen & Seaman, 2011, 2017; Bakia et al., 2012; Keegan, 2002; Kruger-Ross & Waters, 2013). Even most traditional courses have some online component to facilitate delivery (Allen & Seaman, 2017; Bakia et al., 2012; Kauffman, 2015). Online learning is now considered a critical long-term strategy for higher education to provide greater access to students and meet market and global demands (Bakia et al., 2012; de los Santos & Zanca, 2018; Peck et al., 2018; Seaman et al., 2018). At the same time, it has become a reliable alternative for populations (e.g., working parents, veterans, individuals with disabilities) who may not otherwise have had the opportunity to earn a degree or the prospect for better qualifications (Doe et al., 2017; Hassan et al., 2014; Peck et al., 2018).

As theorized by Keegan (2002), a learning revolution has begun: Institutions of higher education and professional training have embraced audio and video conferencing, social media, online, and mobile learning. As a result, adult learners across the globe can choose to take traditional courses, online courses, or various combinations of the two, such as hybrid or web-facilitated (Allen & Seaman, 2011, 2017; Bakia et al., 2012; Hassan et al., 2014; Seaman et al., 2018; Vayre & Vonthron, 2017). Modern society is rapidly changing, and to keep up, adult learners must balance work, family, and school, while also learning academic knowledge and professional skills vital for success in their careers as well as for living in a tech-savvy world (Bawa, 2016; de los Santos & Zanca, 2018; Doe et al., 2017; Zhoc et al., 2018).

For over a decade, overall higher education enrollment rates have declined (NCES, 2017; Seaman et al., 2018), while online enrollment rates have continued to increase (Allen & Seaman, 2011, 2017; Choi & Park, 2018). For example, there were 1 million fewer students on campus in 2016 than in previous years (Camera, 2019; NCES, 2017; Seaman et al., 2018). In contrast, the proportion of online students (undergraduate and graduate) has increased each year, with almost half taking only online courses (NCES, 2017; Seaman et al., 2018). In addition, online learning has also become a favorite choice for training and professional development (Bawa, 2016; Majeski et al., 2017; Peck et al., 2018). More recent events (i.e., COVID pandemic) have also made online education a critical component to the long-term success of many institutions (de los Santos & Zanca, 2018). However, despite global market demands for online courses, training, and degree programs, attrition rates for online education remain higher than traditional courses, with 40–80% of online students failing and/or dropping out compared to traditional on-campus students (Bawa, 2016; Choi & Park, 2018; Kauffman, 2015; Peck et al., 2018). There is a need for more research to better understand the reason for the high attrition rates in online learning and the low rates of OS (Choi & Park, 2018; Goodwin, 2016; Kauffman, 2015; Knight, 2019).

Most researchers agree that the online environment is comparable to the traditional classroom environment in terms of learning outcomes, but it is different in design, curriculum, and learning strategies (Allen & Seaman, 2011, 2017; Bakia et al., 2012; Bawa, 2016; Berenson et al., 2008; Broadbent & Poon, 2015; Choi & Park, 2018; Hassan et al., 2014; Kauffman, 2015; Kerr et al., 2006; Knight, 2019; Peck et al., 2018; Vayre & Vonthron, 2017). Both learning environments have advantages and disadvantages. For example, traditional courses offer two-way interaction with instructors and peers, while online courses offer convenience and flexibility (Clayton et al., 2010; de los Santos & Zanca, 2018; Hassan et al., 2014; Knight, 2019).

A search of the literature revealed how learner characteristics play a significant role in whether learners achieve academic success in either the traditional classroom (e.g., Koc, 2019; Thomas, Cassady, & Heller, 2017; Zhoc et al., 2018) or online learning environment (e.g., Kauffman, 2015; Lee & Choi, 2011; Vayre & Vonthron, 2017). It has been suggested that successful learner characteristics in the traditional classroom (e.g., elaboration, rehearsal, self-regulation) may not transfer to the online learning environment (Bakia et al., 2012; Broadbent & Poon, 2015; Kauffman, 2015; Kerr et al., 2006; Lee & Choi, 2011; Peck et al., 2018). Online learners have different needs, and the “one size” approach used in traditional classrooms does not fit well in the online learning environment (Berenson et al., 2008; Goodwin, 2016; Han & Johnson, 2012; Knight, 2019; Van Doorn & Van Doorn, 2014, p.11).

Recently, researchers have found that online learning helps develop metacognition and problem-solving skills, which in turn help to develop motivation and self-efficacy, which then lead to increases in retention, satisfaction, and success (Doe et al., 2017; Goodwin, 2016; Hobson & Puruhito, 2018; Kauffman, 2015; Peck et al., 2018; Song & Bonk, 2016; Vayre & Vonthron, 2017). The attributes, metacognition and problem-solving, are both found in EI and SDL (Bar-On, 2006; Knowles, 1984; Koc, 2019; Zhoc et al., 2018). In this way, the active, process-based, and social aspects of online learning may help support EI (Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016) and SDL (Chan, 2018; Engin, 2017; Lai, 2011; Song & Bonk, 2016). For instance, researchers (i.e., Berenson et al., 2008; Doe et al., 2017; Kauffman, 2015; Kerr et al., 2006; Peck et al., 2018) have found successful online students to be self-motivated, self-directed, and self-regulated. Berenson et al. (2008) and Kauffman (2015) also found them to have above average EI.

Previous research also supports EI and/or SDL as predictors of OS (i.e., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016), but there is little to no research on the indirect effects of EI and/or SDL on academic success in the online learning environment. Recent research findings support a positive correlation between EI and SDL on academic success in the traditional learning environment (e.g., Koc, 2019; Mueller, 2007; Zhoc & Chen, 2016; Zhoc et al., 2018). Zhoc et al. (2018) also discovered that SDL mediated, or influenced, the relationship between EI and academic success (GPA). However, what is not known is whether SDL mediates EI and academic success in the online learning environment.

The purpose of this quantitative study was to explore EI and SDL as predictors of OS and to test whether SDL mediated the relationship between EI and OS. It addressed the future research recommendations of Cazan and Schiopca (2014), Koc (2019), and Zhoc et al. (2018), and filled a gap in the literature, by examining the indirect effects of adult learner characteristics (i.e., EI and SDL) on OS. This study also answered the call for more research to better understand EI and SDL as predictors of academic success in online learning, which in turn, will help to identify student characteristics and learning needs for OS and whether online learning is appropriate (Berenson et al., 2008; Doe et al., 2017; Goodwin, 2016; Kauffman, 2015; Kerr et al., 2006; Knight, 2019; Lee & Choi, 2011; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017). This information could also be used to help create more effective and efficient online courses, training, and programs (Bawa, 2016; Bakia et al., 2012; Doe et al., 2017; Majeski et al., 2017; Peck et al., 2018; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017).

This chapter begins with the scope of the literature review and the search strategies employed to find scholarly, peer-reviewed sources. Next, the theoretical frameworks, seminal works, and relevant literature pertaining to EI and SDL are reviewed. Then, the conceptual model is presented, where the hypothesized relationships among the variables EI, SDL, and OS are discussed.

Literature Search Strategy

Questions concerning the importance of emotions and self-learning in human behavior date back to ancient Greece and the writings of Socrates, Plato, and Aristotle (Bar-On, 2007; Dewey, 1897/2016; Knowles, 1984; Mayer et al., 2008). American psychologists have been searching for a factor outside of intelligence (IQ) to explain human behavior and success since the 1920s (Bar-On, 2006; Mayer et al., 2008; Thorndike, 1920). Distance education, the forerunner to online learning, evolved from the "Electronics Revolution" in the 1980s (Holmberg, 1988; Keegan, 2002, p. 10). For these reasons, no parameters were set on years searched for this review. To better capture the essence of these constructs, the seminal works of Bar-On's (2006) mixed EI model and Knowles' (1975) SDL theory were examined.

Over time, ideas evolve, theories are tested, and models are created and refined. For this reason, most of the literature review was focused on scholarly, peer-reviewed articles from the last 5 years. Articles were retrieved from the following online databases: Academic Search Complete, Business Source Complete, CINAHL Plus with Full Text, Complementary Index, Education Source, ERIC, Gale Academic OneFile Select, MEDLINE, Mental Measurements Yearbook, Open Access Journals, ProQuest Central, ProQuest Dissertations & Theses Global, PsycARTICLES, PsycINFO, PubMed, SAGE Journals, ScienceDirect, Social Sciences Citation Index, SocINDEX, Supplemental Index, and Teacher Reference Center. Keyword searches were conducted on the following search terms: *ability EI model*, *academic achievement*, *academic performance*, *academic success*, *adult education*, *adult learners*, *adult learning*, *andragogy, attrition*, *Bar-On, college*, *course completion*, *distance education*, *distance learning*, *student drop-out*, *e-learning*, *emotion*, *emotional skills*, *emotional intelligence*, *emotional-social intelligence*, *GPA*, *grade point average*, *higher education*, *highest education level*, *Knowles*, *mediation*, *mediation analyses*, *mediation analysis*, *meta-analysis*, *mixed EI* *model, online, online courses, online education, online learning, online success, pedagogy, postsecondary education, predictors, predictors of online success, self-directed learner readiness (SDLR), self-directed learner readiness scale for nursing education (SDLRSNE), self-directed learning (SDL), student success, systematic review, tertiary education, trait EI, trait emotional intelligence questionnaire-short form (TEIQue-SF),* and *university*. Online websites with relevant information were also searched: Consortium for Research on Emotional Intelligence in Organizations (www.eiconsortium.org), International Society for Self-Directed Learning (www.sdlglobal.com), London Psychometric Laboratory (www.psychometriclab.com), National Center for Education Statistics (https://nces.ed.gov), Reuven Bar-On's website on his model of EI (www.reuvenbaron.org), and Science Direct (http://www.sciencedirect.com).

Theoretical Foundation

The theoretical frameworks for this study were Reuven Bar-On's (2006) mixed EI model and Malcolm Knowles' (1975) theory of SDL. These are reviewed in this section along with how they relate to this study and the rationale for why they were selected.

Emotional Intelligence (EI)

Origin. In his *Nicomachean Ethics,* Aristotle (trans. 2011) observed how "it is possible to be confident…[or] to be angry…to a greater or lesser degree than one ought, and in both cases, this is not good," (Book 2, Chapter 6, Para. 3). Then, he went on to note, "[however] to feel them when one ought… at the things one ought, in relation to [the] people…one ought…is best," (Book 2, Chapter 6, Para. 3). Here, Aristotle refers to the gamut of emotions (e.g., confidence, anger) and the need for emotional awareness, regulation, and utilization of emotions in oneself and towards others. This could be argued as the first definition of EI (Goleman, 1995/2005).

Background. Since the time of John Dewey and Edward Thorndike, American psychologists have been searching for a third factor to explain human behavior in life satisfaction, well-being, and work success (Bar-On, 2006; Mayer et al., 2008; MacCann et al., 2019). Like Aristotle, Dewey (1916/2016) postulated on the integration of emotion and cognition in the healthy development and psychological well-being of human beings. Soon after, Thorndike (1920) theorized on a social intelligence, or the "ability to understand and manage…human relations" (p.228). However, their theories were disregarded by the dominant forces in psychology at the time (Mayer et al., 2008; Thorndike & Stein, 1937). The pendulum gradually swung from cognition and emotion being opposite, separate forces to being complementary, interconnected forces (Bar-On, 2006; Goleman, 1995/2005; Imel, 2003; O'Regan, 2003; Rager, 2009; Storbeck & Clore, 2007). It was discovered that emotion, cognition, and behavior are interdependent and interrelated, which continues to be supported in the research literature (e.g., Bar-On, 2006; Han & Johnson, 2012; Mayer et al., 2008; MacCann et al., 2019; O'Regan, 2003; Rager, 2009; Storbeck & Clore, 2007; Schutte et al., 2011).

Just as Aristotle (trans. 2011) and Dewy (1916/2016) posited, researchers found that healthy development and psychological well-being are not possible without controlling and regulating emotions (Bar-On, 2006; Goleman, 1995/2005; Imel, 2003; Mayer et al., 2008; Noor & Hanafi, 2017; O'Regan, 2003; Rager, 2009; Schutte et al., 2011). For instance, researchers (i.e., Bar-On, 2006; Berenson et al., 2008; Imel, 2003; Noor & Hanafi, 2017; O'Regan, 2003; Rager, 2009; Schutte et al., 2011) found that emotions can: activate attention and the processes to learn, enhance or impede learning, and affect cognitive learning in both traditional and online learning environments.

Multiple intelligences. It was in the wake of this paradigm shift that researchers began once again to investigate the possibility of an emotional and/or social intelligence, alongside cognitive intelligence (Bar-On 2006; Gardner, 1983/2011; Mayer et al., 2008; Sternberg & Sternberg, 2017). In the 1980s, Howard Gardner and Robert Sternberg posited their theories on the existence of multiple intelligences. Gardner (1983/2011) proposed a theory of eight distinct intelligences that function independently as well as interactively: Linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal (relating to others), intrapersonal (self-understanding), and naturalist. His personal intelligences, interpersonal (social) and intrapersonal (emotional), were built on Thorndike's conceptualization of a social intelligence and most closely relate to the construct of EI (Bar-On, 2006; Gardner, 1983/2011; Mayer et al., 2008).

Like Thorndike, Sternberg's (1985; as cited in Sternberg & Sternberg, 2017) triarchic theory of human intelligence conceived of intelligence existing in three interrelated parts: analytical, practical, and creative. These intelligences work together to solve problems and implement strategies to improve everyday living (Sternberg & Sternberg, 2017). In this way, theories of cognitive intelligence (e.g., IQ) and the personal intelligences (emotional, social) were being developed in the context of which type made more of an impact on academic and life success (Bar-On, 2006; Gardner, 1983/2011; Mayer et al., 2008; Sternberg & Sternberg, 2017).

IQ versus EI. Both IQ and EI have been shown to predict academic success (e.g., GPA) in traditional learning environments (Bar-On, 2006; Bukhari & Khanam, 2016; Goleman, 1995/2005; Kornilova et al., 2018; Mayer et al., 2008; MacCann et al., 2019; Song, Huang, Peng, Law, Wong, & Chen, 2010; Thomas et al., 2017). Even though both IQ and EI help increase academic performance, retention, and success, the focus in education and training has been on IQ (Ackley, 2016; Bar-On, 2007; Gardner, 1983/2011; Goleman, 1995/2005; Imel, 2003; MacCann et al., 2019; O'Regan, 2003; Rager, 2009; Song et al., 2010; Sternberg & Sternberg, 2017). Some researchers (i.e., Bar-On, 2007; Gardner, 1983/2011; Goleman, 1995/2005; Sternberg & Sternberg, 2017) have posited that IQ is a weak predictor of how individuals manage relationships, perform at work, and cope with daily life.

EI models. Not long after Gardner and Sternberg introduced their models of multiple intelligences, Reuven Bar-On (2006) introduced his model of emotional-social intelligence (ESI) in his doctoral dissertation published in 1988. Inspired by the works of Darwin and Thorndike, he conceptualized ESI as an interrelated set of intrapersonal and interpersonal competencies, skills, and facilitators that combine to determine human behavior (Bar-On, 2006). Like others before him (e.g., Gardner, Thorndike), Bar-On theorized that there must be other factors at work in psychological well-being, satisfaction, and life success besides behavior and IQ (Bar-On, 2006; Gardner, 1983/2011; Goleman, 1995/2005; Mayer et al., 2008; Thorndike, 1920).

In 1990, psychologists Peter Salovey and John Mayer introduced their theory of ability EI (Mayer et al., 2008). They conceptualized EI as “a set of interrelated [cognitive] abilities” that are used to engage and process one’s own and others’ emotions and to use this information as a guide in one’s thinking and behavior (Mayer et al., 2008, p. 503). Their theory builds upon earlier ones in that it includes a social component (e.g., Gardner, Thorndike) as well as cognitive abilities (e.g., Sternberg, Thorndike).

Daniel Goleman (1995/2005), a Harvard-trained psychologist and investigative reporter for *The New York Times*, was inspired by the Salovey and Mayer EI model. In 1995, he wrote a book synthesizing their findings along with the scientific developments of affective neuroscience and the importance of emotions in life success (Goleman, 1995/2005). With the release of Goleman’s book, *Emotional Intelligence: Why It Can Matter More Than IQ* (1995/2005), EI soon became a growing industry of consulting, education, training, and research (Ackley, 2016; Mayer et al., 2008, 2016; MacCann et al., 2019; Sternberg & Sternberg, 2017).

Ten years after Bar-On’s model was introduced, and not long after Goleman’s book was published, Konstantinos Petrides developed a model and measure of EI as part of his doctoral dissertation in 1998 (Petrides, 2009). He conceptualized EI as a personality trait located at lower levels of personality hierarchies (Petrides, 2009). Like Bar-On, he built upon previous research (e.g., Darwin, Gardner, Thorndike) and linked emotion- and EI-related constructs (e.g., emotional expression, empathy) in his model of EI (Petrides, 2009). However, instead of viewing EI as an interrelated set of competencies and skills (i.e., Bar-On, 2006), Petrides viewed EI as a constellation of self-perceptions and traits that reflect the subjective nature of the emotional experience (Cooper & Petrides, 2010; Petrides, 2009).

Modern EI. Even though the different conceptualizations of EI share common elements (i.e. empathy, emotional expression, emotion regulation), they have created confusion, controversy, and ultimately a schism in the best way to approach, define, measure, and name this construct (Ackley, 2016; Bar-On, 2006; Goleman, 1995/2005; Mayer et al., 2008; MacCann et al., 2019; Petrides & Mavroveli, 2018). For example, Bar-On (2006) prefers to name this construct emotional-social intelligence, abbreviated ESI. Yet, he coined the term “EQ” to describe scores on his measurement tool, the Emotional Quotient Inventory (EQ-i), because they are converted into standard scores based on a mean of 100 and standard deviation of 15 like IQ scores (Bar-On, 2006, p. 4). With the global utilization of the EQ-i, the abbreviation EQ is often used in the literature as the abbreviation for the construct emotional intelligence (Ackley, 2016; Goleman, 1995/2005; Petrides & Mavroveli, 2018). At the same time, with ability EI being more closely related to IQ, some researchers refer to ability EI as EQ (i.e. Fei-Zhou, Chen, Xie, & Xie, 2013; Kornilova et al., 2018).

Petrides and Mavroveli (2018) stated that all self-report measures of EI are measures of trait EI, or a mix of “emotion-related perceptions” and personality traits (p. 26). Given the alternative, they prefer the name trait emotional self-efficacy, abbreviated trait EI, to describe their model (Petrides & Mavroveli, 2018). Goleman (1995/2005) and Mayer, Salovey, and Caruso (2008) conceptualized EI differently, but they both prefer to utilize the term emotional intelligence, abbreviated EI. In response, Bar-On refers to his model as both EI and ESI (e.g., Bar-On 2006, 2007); however, he emphasized how ESI is the more accurate term for his model because it is comprised of both interpersonal (social) and intrapersonal (emotional) competencies and skills (Bar-On, 2006, p. 2). On his website (http://www.reuvenbaron.org/wp/), Bar-On refers to his model as the EI model. In following with Bar-On, and for the purposes of the current investigation, the term emotional intelligence, abbreviated EI, is used.

Likewise, the various conceptualizations of EI (ability, mixed, trait) have made it more difficult to understand what EI is and what it is not (Bar-On, 2006; Goleman, 1995/2005; Mayer et al., 2008, 2016; MacCann et al., 2019; Petrides, 2007; Petrides & Mavroveli, 2018; Schutte et al., 2011). The main conceptual terms that describe EI are "ability" (e.g., Mayer et al., 2008), "mixed" (e.g., Bar-On, 2006), and "trait" (e.g., Petrides, 2007). These conceptualizations of modern EI (ability, mixed, and trait) are briefly reviewed in the sections below.

Ability EI. Mayer, Caruso, and Salovey's (2016) ability model of EI, formerly known as the four branch model, remains the only mental [cognitive] ability model of EI (Ackley, 2016; Mayer et al., 2008; MacCann et al., 2019). The four branches are arranged in a hierarchy from distinct psychological functions such as emotional perception to more developmentally complex ones like emotional regulation (Mayer et al., 2008, 2016). The four EI branches are perceiving emotions, using emotions to facilitate thinking, understanding emotions, and managing emotions to attain goals (Mayer et al., 2008, 2016). The first branch, emotion perception, is defined as the ability to identify emotional content in faces, voices, and designs and includes the ability to "accurately express emotions" (Mayer et al., 2016; MacCann et al., 2019, p. 2). Emotion facilitation, the second branch, is described as using emotions and emotional information to make decisions and/or complete tasks (MacCann et al., 2019). There is empirical evidence (i.e., factor analyses) that this branch is a subset of the fourth branch, emotion management, which is conceptualized as the ability to manage emotions in oneself and others (Mayer et al., 2016; MacCann et al., 2019). The third branch, emotion understanding, was not in the original model (MacCann et al., 2019). It is considered the domain-specific knowledge for emotions (i.e., vocabulary of emotion terms, the likely effect of a situation on one's emotions), and it has the strongest links to cognitive [IQ] abilities, with meta-analytic estimates ranging from p = .39 to .42 (MacCann et al., 2019).

Ability EI is conceptualized as a mental [cognitive] ability, and like verbal or quantitative ability (i.e., IQ), it has a specific content domain consisting of emotions, rather than words or numbers (Mayer et al., 2016; MacCann et al., 2019). Emotional abilities support emotional understanding, regulation, and the integration of emotion and cognition (Mayer et al., 2008, 2016; MacCann et al., 2019). In this way, ability EI is considered innate (Mayer et al., 2008, 2016). In this sense, Mayer et al. (2008, 2016) have postulated that ability EI is the emotional equivalent of cognitive intelligence, so it should be operationalized and measured as a mental ability (i.e., IQ). The authors' corresponding measurement tool, the Mayer-Salovey-Caruso-Emotional-Intelligence-Test (MSCEIT) relies on assessing mental [cognitive] abilities (e.g., abstract reasoning and problem-solving skills), and for this reason, it has minimal correlations with mixed or trait models of EI (Mayer et al., 2008, 2016).

Recently, Mayer et al. (2016) revisited their model and reiterated their conceptualization of EI as a mental [cognitive] ability and the four branches of their original model. In addition, they have classified EI as a "hot intelligence," meaning that it involves reasoning with information significant to the individual and how the individual uses this information to manage what matters most to them (Mayer et al., 2016, p.292). They concluded that it is possible EI operates within a broader personal, emotional, and/or social intelligence, or even as a combined socio-emotional-personal intelligence, but it remains distinctive from IQ and personality (Mayer et al., 2016).

Rationale for not using the ability EI model and measure. To date, the leading conceptual models of EI are (a) Bar-On's and Goleman's mixed models; (b) the Mayer et al. ability model; and (c) Petrides and Furnham's trait model (Ackley, 2016; Fernandez-Berrocal & Extremera, 2006; MacCann et al., 2019). For the purposes of the current investigation, only the mixed and trait models of EI were considered because, even though ability EI measures are widely used, they do not consistently correlate with and/or predict academic performance (Mayer et al., 2008, 2016; MacCann et al., 2019; Schutte et al., 2011). Recently, Mayer et al. (2016) speculated the reason for this was because the specific mental [cognitive] abilities of EI have yet to be determined. MacCann et al. (2019) posited that there is a significant correlation between ability EI and academic performance but noted how this relationship has never been investigated in a meta-analysis, which would control for the effects of intelligence and personality. Also, the scoring procedures (i.e., expert consensus on correct emotional answers) for the MSCEIT have been criticized as being psychologically invalid (i.e., MacCann et al., 2019; Petrides

& Mavroveli, 2018). Last, and on a more practical note, the MSCEIT must be purchased for academic research. For these reasons, the Mayer et al. (2008, 2016) ability EI model and measurement were not selected for this study. The remaining mixed and trait models were considered, and they are reviewed below.

Mixed and Trait EI Approaches

Mixed EI. Mayer and colleagues categorized all other (nonability) EI models as mixed EI models (Bar-On, 2006; Mayer et al., 2008, 2016). In reference to the term “mixed,” Bar-On (2006) responded that all EI models are “mixed” because they are by varying degrees a “cross-section of bio-psycho-social predictors and facilitators of human behavior” (p. 11). For the purposes of the current investigation, and in following with Bar-On (2006), Goleman (1995/2005), and Mayer et al. (2008), the models of EI by Bar-On and Goleman are labeled as mixed EI models.

Unlike researchers of ability and trait EI, researchers of mixed EI models (i.e., Bar-On, Goleman) have postulated that EI competencies and skills can be learned, taught, and improved (Ackley, 2016; Bar-On, 2006; Boyatzis, 2016; Goleman, 1995/2005; MacCann et al., 2019). In addition, mixed EI models have been linked with performance success in the school and workplace environment (Ackley, 2016; Bar-On, 2006, 2010; Boyatzis, 2016; Goleman, 1995/2005; MacCann et al., 2019). Both Bar-On and Goleman have developed successful education and professional training programs based on their models (Ackley, 2016; Bar-On, 2007; Boyatzis, 2016; Goleman, 1995/2005; MacCann et al., 2019). For these reasons, the Bar-On and Goleman mixed models of EI, and their corresponding measurements, were considered for this study. They are reviewed in more detail below.

The Bar-On EI model. Bar-On was inspired by his fellow faculty on campus to examine the factors of success outside of IQ (Ackley, 2016; Bar-On, 2006). For instance, he noted how most of his colleagues were highly intelligent, but only some of them were highly successful (Ackley, 2016; Bar-On, 2006). For his theoretical framework, he drew from Darwin's work on emotional expression and adaptation, Thorndike's description of social intelligence, Wechsler's observations related to the impact of noncognitive factors on intelligence and behavior, and Sifneo's description of alexithymia (Bar-On, 2006). After 17 years of research (i.e., 1980 – 1997), Bar-On (2006) conceptualized EI as "a cross-section of interrelated emotional and social competencies, skills, and facilitators" that determine how effectively individuals can understand and express their emotions, understand and relate to the emotions of others, and cope with daily life demands (p. 3).

Bar-On (2006) explained to be emotionally and socially intelligent is to effectively express oneself and relate well to others, understand oneself and others, and successfully cope with daily life. He identified 15 emotional skills that were associated with success beyond what IQ predicted alone (Bar-On, 2006): self-regard, emotional self-awareness, assertiveness, independence, self-actualization, empathy, social responsibility, interpersonal relationships, stress tolerance, impulse control, reality testing, flexibility, problem-solving, optimism, and happiness. These 15 emotional competencies became the sub-scales for Bar-On's (2006) measurement tool, the EQ-i. In this way, Bar-On's model of EI consists of both intrapersonal (e.g., self-awareness) and interpersonal (e.g., empathy) competencies and skills, which he divided into 5 scales: intrapersonal, interpersonal, stress management, adaptability, and general mood (Bar-On, 2006). His model and measurement tool combined emotional, social, personal, and environmental factors that help individuals to effectively manage, cope, adapt, problem-solve, and make decisions (Bar-On, 2006). In this sense, his model encompasses the classic three aspects of human intelligence: cognitive (e.g., problem-solving), behavior (e.g., adaptability), and emotional-social factors (e.g., awareness).

Bar-On (2006) originally developed the EQ-i to guide his research as well as measure and assess his conceptualization of EI. He did this to refine and maintain a theory that is empirically based (Bar-On, 2006). The EQ-i is a self-report measure, but it has a built-in scoring algorithm that incorporates age- and gender-specific norms that automatically adjusts the scale scores and includes four scales designed as validity indices (Bar-On, 2006; Van Rooy & Viswesvaran, 2007). These features help to reduce potentially distorting effects from response bias and increase the accuracy of the results (Bar-On, 2006; Van Rooy & Viswesvaran, 2007). The EQ-i was revised in 2011 and renamed the EQ-i 2.0 (Ackley, 2016). The revisions were minimal and reflect semantic changes and an additional test version - for more information, go to Bar-On's website (http://www.reuvenbaron.org/wp/) or contact Multi-Health Systems (www.mhs.com). The EQ-i 2.0 can be administered as the standard self-report measure or as a multisource (360 degree) measure (Ackley, 2016). The original EQ-i has been decommissioned and is no longer available for research purposes per copyright laws (MHS, personal communication, March 9, 2020). The EQ-i 2.0 is available to purchase for research use, but it must be administered through the MHS website (MHS, personal communication, March 11, 2020). Although this may make it less practical for academic research, the EQ-i 2.0 remains an appealing option for business, education, and training development (Ackley, 2016; Di Fabio, Palazzeschi, & Bar-On, 2012; Nasir & Masrur, 2010; Noor & Hanafi, 2017).

The Goleman EI model. As mentioned earlier, Goleman was inspired by the Salovey-Mayer EI model from 1990, and he used their psychological research, as well as data from the fields of business and education, to guide the development of his EI model of emotional competence (Ackley, 2016; Goleman, 1995/2005; Mayer et al., 2008). His scientific method and model have been criticized as being "weak" because he did not go through the traditional process of theory development and testing that characterizes pragmatic scientific research (Ackley, 2016; Boyatzis, 2016; MacCann et al., 2019). Goleman (1995/2005) conceptualized EI as the capacity for recognizing the feelings of self and others, motivating self and others, and managing emotions well in self and others. He later collaborated with other researchers (i.e., Richard Boyatzis) and divided his conceptualization of EI into four core competencies: (1) self-awareness, (2) self-management, (3) social awareness, and (4) relationship management (Ackley, 2016; Boyatzis, 2016; Goleman, 1995/2005). Like the Mayer et al. (2008, 2016) ability model of EI, these core competencies are hierarchical in nature, starting with emotional awareness and progressing to self- and relationship management (Goleman, 1995/2005; Boyatzis, 2016; MacCann et al., 2019). However, like Bar-On's (2006) model, these four EI competencies also represent learned abilities that can be taught and improved (Ackley, 2016; Bar-On, 2007; Boyatzis, 2016; Goleman, 1995/2005; MacCann et al., 2019). Another distinction to note is that the Mayer et al. (2008) ability model represents the cognitive level of EI (EQ), whereas the Goleman model represents the "behavioral level of EI" (Boyatzis, 2016, p. 288). Each EI competency is associated with specific leadership skills, such as the development of self and others, conflict management, and collaboration (Boyatzis, 2016; Goleman, 1995/2005).

To measure EI, Goleman and colleagues developed a multisource (360 degree) assessment originally known as the Emotional Competency Inventory (ECI; Boyatzis, 2016; Goleman, 1995/2005). It requires both self- and other-reports to assess EI in an individual (Boyatzis, 2016; Goleman, 1995/2005). This design was selected to overcome the potential difficulties found with self-report instruments (Boyatzis, 2016; Goleman, 1995/2005). In 2006, the ECI was renamed the Emotional and Social Competency Inventory (ESCI) to reflect that it measures both the intrapersonal and interpersonal recognition and management of emotions in self and others (Boyatzis, 2016). The four competencies became the four clusters (i.e., 2 for EI, 2 for social intelligence) to match the updated conceptual model (Boyatzis, 2016). There are two versions of the ESCI: The standard version for working adults and managers, and a university version (ESCI-U) for higher education students (undergraduates and graduates), faculty, and staff (Boyatzis, 2016). Both versions (ESCI, ESCI-U) provide feedback about specific behaviors within the four EI clusters that have been shown to improve performance success (Boyatzis, 2016). This lends either version to be used in professional development and training (Boyatzis, 2016).

Rationale for not using Goleman's mixed EI model and measure. Both Bar-On's and Goleman's mixed EI models and scales measure a combination of emotional and social factors that contribute to the prediction of performance and success (Ackley, 2016; Bar-On, 2006; Goleman, 1995/2005). They have postulated that these factors can be learned, taught, and improved (Ackley, 2016; Bar-On, 2006; Goleman, 1995/2005). Also, both measures correlate similarly with IQ (Ackley, 2016; Bar-On, 2006; Goleman, 1995/2005). More specifically related to the current investigation, both EI models include factors of SDL (Bar-On, 2006; Boyatzis, 2002; Koc, 2019).

Despite this, Goleman's mixed model of EI, and his ESCI measurement tool, were not selected for this study because his approach to EI does not align with the focus of this dissertation for the following reasons. First, a key difference between Bar-On's and Goleman's mixed models is that Goleman wanted to bridge the gap between psychology and work, whereas Bar-On wanted to move beyond IQ and find what other factors account for success and well-being in life (Ackley, 2016; Bar-On, 2006; Goleman, 1995/2005). Next, Goleman's model and measurement tool focus on assessing and improving EI in the traditional, face-to-face workplace and/or learning environment utilizing a multisource (360 degree) measurement design; in contrast, the focus of this study was to assess the EI of adult learners in the online learning environment via a self-report measure (i.e. Berenson, et al., 2008; Goodwin, 2016). For these reasons, Goleman's mixed EI model and measure were not selected for the current investigation. However, Bar-On's mixed EI model and measure as well as Petrides' (2009) trait EI model and measure were seriously considered for this study. Petrides' (2009) trait EI model and measure are discussed below.

Trait EI. In response to the various conceptualizations of EI (i.e., ability, mixed, trait), Petrides and Furnham divided EI into two different types of intelligence: personality trait emotional intelligence (trait EI) and information processing (ability) EI (Engin, 2017; Mayer et al., 2008; Petrides & Mavroveli, 2018). They acknowledged EI as an innate cognitive ability, but they also postulated that EI was an innate personality character trait because of the strong relationship findings between EI and personality in the literature (Petrides, Mikolajczak, Mavroveli, Sanchez-Ruiz, Furnham, & Perez-Gonzalez, 2016; Petrides & Mavroveli, 2018). Unlike ability EI, trait EI strongly correlates with personality traits and self-efficacy (Petrides et al., 2016; Petrides & Mavroveli, 2018). Recent research has revealed that the correlations between trait EI and higher-order personality dimensions (e.g. Big Five) can be directly attributed to genetic factors (Petrides et al., 2016; Petrides & Mavroveli, 2018). Petrides and Mavroveli (2018) recently reaffirmed the theory of trait EI as a "constellation" of emotional perceptions and personal character traits, which is why they prefer the name "trait emotional self-efficacy" (Petrides & Mavroveli, 2018, p. 24). Essentially, trait EI concerns people's beliefs and perceptions about their emotions in conjunction with their personal character traits. In this sense, EI conceptualized as trait describes a collection of emotion-related perceptions and personality traits.

Petrides and colleagues (2016, 2018) have expounded on the possibility of trait EI connecting all EI models, and their measures, under one psychological theory. They have posited that all EI models fall under trait EI theory because they consist of emotion-related perceptions and personality traits (Petrides, 2009; Petrides et al., 2016; Petrides & Mavroveli, 2018). Like Bar-On's (2006) mixed model of EI, trait EI, and its corresponding measurement tool, the Trait Emotional Intelligence Questionnaire (TEIQue), were derived from a content analysis of earlier EI models and related constructs, such as Darwin's emotional expression, Gardner's personal intelligences, Roger's empathy, and Thorndike's social intelligence (Petrides, 2009). In trait EI's theoretical framework, Petrides and Furnham included facets found in more than one model and excluded those found only in one model (Petrides, 2009; Petrides & Mavroveli, 2018). As a result, trait EI has been posited as the most comprehensive EI model and currently consists of 15 facets, four factors, and one global trait (MacCann et al., 2019; Petrides & Mavroveli, 2018). The facets are narrower than the factors, which are narrower than the global trait (Petrides, 2009; Petrides & Mavroveli, 2018). Like Bar-On's EQ-i, Petrides (2009) found 15 facets in the research that represent the sampling domain of trait EI: adaptability, assertiveness, emotion expression, emotion management (others), emotion perception (self and others), emotion regulation, impulse control, relationships, self-esteems, self-motivation, social awareness, stress management, trait empathy, trait happiness, and trait optimism. These 15 facets correspond to four factors: emotionality, self-control, sociability, and well-being (Petrides, 2009).

The current version of the TEIQue has 153 items and produces scores on 15 facets, four factors, and one global trait (Petrides, 2009). Due to time constraints of this study, the TEIQue Short Form) was selected to measure EI in the online learning environment (e.g., Engin, 2017). Like the TEIQue, the TEIQue-SF was designed to measure trait EI. However, because it consists of only 30 items (two items for each facet), only the total score is recommended for statistical analysis (Cooper & Petrides, 2010). It does not yield scores for each of the 15 facets (Cooper & Petrides, 2010). The latest version of the TEIQue-SF (version 1.50), along with scoring information, is available, free of charge, for research purposes from the London Psychometric Laboratory (www.psychometriclab.com).

Rationale for using Bar-On's EI model and Petrides' TEIQue-SF. In sum, Bar-On's mixed model of EI was selected as the EI theoretical framework for this study because his focus to identify and improve factors (outside of IQ) that lead to success in life (e.g., home, school, work) aligns with the focus and purpose of this study to identify and improve factors that lead to OS in adult learners. Also, Bar-On (2006) linked EI and SDL in his model and EQ-i measure. In his research, Bar-On (2006) found that the subscale, independence (described as being self-directed), acted more like a facilitator of EI, rather than a direct emotional competency. This was confirmed in a factor analysis he conducted on his normative sample data (Bar-On, 2006). Bar-On (2006) explained that, at the time, the construct independence (self-directedness) was rarely linked with EI. The current investigation aligned with Bar-On's linkage of EI and SDL in that it examined the relationship between EI and SDL and the indirect effects of their relationship on the academic success of adult online learners.

As mentioned previously, Bar-On's original measure, the EQ-i, is no longer available for research due to copyright laws, and the EQ-i 2.0 is not practical for academic research because of its high cost and administration requirements. However, Bar-On (2006) pointed out how all EI models could be labeled “mixed” because they consist of a “cross-section of bio-psycho-social” competencies and traits to explain human behavior (p. 11). In the same way, Petrides and colleagues (2016, 2018) have posited how all EI models fall under the trait model because they essentially describe personality traits. In comparing the EQ-i and TEIQue-SF, their construction and content are similar. Like Bar-On, Petrides developed his measurement based on previous emotion and EI related research (e.g., Darwin, Gardner, Thorndike). In this way, most of the factors and facets in Bar-On’s (2006) mixed model of EI and Petrides’ (2009) TEIQue-SF represent similar constructs in the research literature on emotion and EI-related constructs (e.g., emotional expression, emotional regulation, empathy). For these reasons, Bar-On’s model was the theoretical framework for this study, and Petrides’ TEIQue-SF was selected to measure participants EI in the online learning environment (e.g., Engin, 2017). The next section provides a brief empirical review of EI (ability, mixed, and trait), including studies from both traditional and online learning environments.

Empirical Review of EI

The three approaches to EI (ability, trait, mixed) described above have notable similarities and differences. The common components within most EI models are (a) recognizing and understanding emotions in oneself and others; (b) controlling and managing emotions in oneself and others; and (c) adapting to change and solving interpersonal problems (Bar-On, 2006; Goleman, 1995/2005; Mayer et al., 2008; Petrides & Mavroveli, 2018; Schutte et al., 2011). From a positive psychology perspective, these common EI elements are associated with well-being, quality interpersonal relationships, conflict resolution, overcoming problems, performance, and academic/career success (Bar-On, 2010; Goodwin, 2016; Koc, 2019; Noor & Hanafi, 2017; Petrides & Mavroveli, 2018; Schutte et al., 2011; Thomas et al., 2017; Zhoc et al., 2018). In general, high levels of EI have been found to be associated with adaptability, flexibility, coping, motivation, persistence, satisfaction, well-being, performance, and success in life, school, and work (Ackley, 2016; Bar-On, 2006, 2010; Di Fabio et al., 2012; Fei-Zhou et al., 2013; Goleman, 1995/2005; Mayer et al., 2008, 2016; Petrides et al., 2016; Saklofske, Austin, Mastoras, Beaton, & Osborne, 2012; Schutte et al., 2011).

As noted earlier, Bar-On (2006) conducted some of the earliest studies on EI and academic success in the traditional learning environment, beginning with his doctoral dissertation through the normalization of his measurement tool, the EQ-i, which took 17 years. His studies found significant relationships between EI and physical health, psychological well-being, and life success (i.e., school and work performance) in adults across seven countries (Bar-On, 2006, 2007, 2010). For instance, Bar-On (2010) conducted a study for the United States Air Force (USAF) that directly examined the relationship between EI and occupational performance. The EQ-i scores of USAF recruiters (N = 1,171) were compared to their annual recruitment quotas. The results indicated a moderately high regression coefficient (r =.53) and “threefold” reductions in attrition rates and financial costs when the model was applied to recruitment and training (Bar-On, 2010, p.1).

In an academic success related study, 200 pararescue jumpers (PJ) completed the EQ-i, and their results were compared with their completion rates of the two year PJ academic training program (Bar-On, 2010). The overall regression coefficient (r =.45) demonstrated that EI has a significant impact on PJ performance and that it can predict, with a 75% accuracy level, who will successfully complete the program (Bar-On, 2010). These studies by Bar-On (2010) demonstrate the significant ability of the EQ-i in predicting academic success and completion. Like the USAF, institutions of higher education could benefit from assessing EI in students to identify strengths and weaknesses in related skills (e.g., self-awareness, independent learning) and to better assist students in selecting the appropriate format for their desired courses and programs.

Since then, research on EI has increased substantially and is currently one of the fastest growing areas in psychology (Ackley, 2016; Mayer et al., 2016; Petrides & Mavroveli, 2018). For instance, a recent search of the Academic Search Complete, Education Source, ERIC, PsycARTICLES, and PsycINFO databases using the key words *emotional intelligence* yielded 22,650 peer-reviewed articles since 2010. Due to time constraints and the vastness of EI research, this empirical review was limited to studies that met the following criteria: (a) sampled adult learners (age 18 and over; undergraduate or graduate); (b) set in either a traditional or online learning environment; (c) used EI as either an independent, predictor, and/or mediator variable; (d) included academic success outcomes (e.g., GPA, final exam score); and (e) mentioned or measured possible indirect effects of EI on academic success.

Research on EI and academic success outcomes (e.g., GPA) has demonstrated that EI is critical for understanding and improving adult learning in both traditional ground learning (e.g., Brown et al., 2016; Nasir & Masrur, 2010; Noor & Hanafi, 2017; Perera & DiGiacomo, 2015; Song et al., 2010; Urquijo & Extremera, 2017) and online learning environments (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016; Majeski et al., 2017; Pool & Qualter, 2012). Many researchers agree that EI is a primary predictor of student success in both learning environments (e.g., Berenson et al., 2008; Brown et al., 2016; Buzdar et al., 2016; Engin, 2017; Fei-Zhou et al., 2013; Goodwin, 2016; Kauffman, 2015; MacCann et al., 2019; Nasir & Masrur, 2010; Noor & Hanafi, 2017).

In addition, a growing trend in the literature supports the notion that EI skills can be taught in either learning environment (Ackley, 2016; Berenson et al., 2008; Boyatzis, 2016; Brown et al., 2016; Buzdar et al., 2016; Goodwin, 2016; Kauffman, 2015; Majeski et al., 2017; Noor & Hanafi, 2017; Pool & Qualter, 2012). In this sense, developing and practicing EI skills could be useful to overcome problems, reduce stress, and increase academic- and career-related success (Ackley, 2016; Bar-On, 2006; 2010; Berenson et al., 2008; Boyatzis, 2016; Brown et al., 2016; Buzdar et al., 2016; Di Fabio et al., 2012; Goleman, 1995/2005; Goodwin, 2016; Majeski et al., 2017; Noor & Hanafi, 2017).

Improving student EI could also be valuable for higher education, to not only help students reduce emotional issues, but also help them increase their academic success in either learning environment (Berenson et al., 2008; Brown et al., 2016; Boyatzis, 2016; Buzdar et al., 2016; Kauffman, 2015; Majeski et al., 2017; Noor & Hanafi, 2017). In turn, improving student EI could help to reduce the high attrition rates in online education (Berenson et al., 2008; Goodwin, 2016; Kauffman, 2015; Majeski et al., 2017).

Mixed findings in the literature. Despite this, a search of the literature revealed mixed findings on the relationship between EI and academic success outcomes (e.g., GPA), regardless of which conceptualization of EI (ability, mixed, trait) or learning environment (traditional, online) was assessed. One of the earliest studies to determine this was by O'Connor, Jr. and Little (2003). These authors measured the predictive utility of EI on academic success in traditional college students utilizing the MSCEIT (an ability EI measure) and the EQ-i (a mixed EI measure). They found both measures (ability, mixed) were not predictive of academic success (e.g., GPA). O'Connor, Jr. and Little (2003) concluded that this was because ability EI correlated more with cognitive skills (e.g., IQ) and mixed EI correlated more personality traits.

Since then, some EI studies (ability, mixed, trait) have shown it has correlative and predictive utility to successful academic, career, and/or life outcomes in either the traditional or online learning environment (e.g., Berenson et al., 2008; Brown et al., 2016; Bukhari & Khanam, 2016; Buzdar et al., 2016; Engin, 2017; Fei-Zhou et al., 2013; Goodwin, 2016; Nasir & Masrur, 2010; Song et al., 2010; Zhoc et al., 2018), whereas other EI studies have not (e.g., Barchard, 2003; Ford & Tamir, 2012; Han & Johnson, 2012; Koc, 2019; Kornilova et al., 2018; Rahimi, 2016). There are even a few studies that have demonstrated negative effects of EI on academic, career, and life outcomes (e.g., Chew, Zain, & Hassan, 2015; Thomas et al., 2017). Highlights of the mixed findings regarding EI and academic success are briefly reviewed below.

Positive EI findings. Following Bar-On's (2010) study, Nasir and Masrur (2010) randomly sampled undergraduates (N = 132) and found EI correlated and predicted academic achievement (R = .34; R^2 = .12) in the traditional learning environment using the EQ-i (a mixed EI measure). In a similar study, Bukhari and Khanam (2016), using a convenience sample (N = 313) of traditional university students, found statistically significant results (R = .16; R^2 = .03) using the TEIQue (a trait EI measure). The R values are higher in the study by Nasir and Masrur (2010), which supports previous research findings of mixed EI measures (e.g., EQ-i) having more correlative and predictive utility with academic achievement than ability or trait EI measures (Bar-On, 2006; Goleman, 1995/2005; Mayer et al., 2016; Petrides & Mavroveli, 2018).

In one of the earliest studies of EI and OS, Berenson et al. (2008) explored the effects of mixed EI, resilience, personality, and demographics (i.e., age, gender, GPA, number of semesters completed, number of online courses completed) on a convenient sample (N = 82) of adult online learners (ages 18 – 57 years) attending a local community college. All the variables of the study intercorrelated with GPA except for gender and number of semesters completed. Using stepwise multiple regression, Berenson et al. (2008) found EI was directly related to GPA (R = .33) and accounted for 11% of the variance in GPA (Berenson et al., 2008). The combination of EI and personality accounted for 18% of the variance in GPA (Berenson et al., 2008). Resilience was associated with EI, but it did not predict GPA (Berenson et al., 2008). Berenson et al. (2008) recommended future research should continue to focus on psychological traits (i.e., EI) as predictors of OS, since all learning is a function of cognitive, emotional, and behavioral responses.

These positive findings of EI have been supported in more recent research. For example, since the study by O'Connor, Jr. and Little (2003), mixed and trait EI measures have been found to consistently correlate more with personality measures because they measure a mix of personality traits and other attributes (Brown et al., 2016; Mayer et al., 2016; MacCann et al., 2019; Noor & Hanafi, 2017; Petrides & Mavroveli, 2018). In addition, since the study by Berenson et al. (2008), EI continues to be a stronger predictor of student success (e.g., GPA) than personality in either the traditional or online learning environment (e.g., Brown et al., 2016; Bukhari & Khanam, 2016; Goodwin, 2016; Kauffman, 2015). In building on these positive findings of EI and academic success in the online learning environment, the current investigation examined the relationship between EI and the OS of adult learners.

Negative EI findings. Other researchers have examined the relationship between EI and academic performance (e.g., GPA) among students in a traditional learning environment and found EI was negatively correlated with academic success (i.e., Chew et al., 2015; Thomas et al., 2017). For instance, Chew, Zain, and Hassan (2015) used the MSCEIT to measure the effect of social management (SM), one branch of ability EI, on academic performance (e.g., average of final exam scores) in a sample of undergraduate students (N = 163). They found that the SM score was significantly associated with academic performance (R^2 = .45), but it was a predictor of poor academic performance (Chew et al., 2015). The authors concluded that the low reliability of the MSCEIT taken by itself in statistical analyses was one limitation to their study (Chew et al., 2015). Their future research recommendations included identifying and defining desirable [emotional] social skills needed to improve academic performance.

More recently, Thomas, Cassady, and Heller (2017) explored potential factors that could facilitate and/or debilitate academic performance (e.g., cumulative GPA) in a convenient sample (*N* = 141) of traditional undergraduate students. These authors measured trait EI, coping, and cognitive test anxiety in participants during their 2nd or 3rd year of study at the university and then collected participants' final (cumulative) GPA at the end of their 4th year (Thomas et al., 2017). Thomas et al. (2017) found EI related positively to social-, emotion-, and problem-focused coping strategies and negatively to avoidance coping: social-focused ($R = .34$); emotion-focused ($R = .40$); problem-focused ($R = .34$); and avoidance coping ($R = -.24$). They also found that EI increased the amount of variance explained by the four-year cumulative GPA ($\Delta R^2 = .03$), which indicated that increased levels of EI are associated with increased academic performance at graduation (Thomas et al., 2017). Cognitive test anxiety (CTA) scores also improved the amount of variance in the model ($\Delta R^2 = .10$). However, the inclusion of CTA reduced the predictive utility of EI to a nonsignificant level (Thomas et al., 2017). Thomas et al. (2017) noted that CTA was more impactful to cumulative GPA than levels of EI. Coping strategies were added last to the regression model, and only emotion-focused coping significantly predicted graduating GPA, but it was associated with lower cumulative GPA at graduation (Thomas et al., 2017).

Thomas et al. (2017) explained how their research supports previous findings regarding the negative influence of emotion-focused coping on cumulative GPA (i.e., MacCann, Fogarty, Zeidner, & Roberts, 2011; Saklofske et al., 2012) and previous research that found ability- and/or trait-based measures of EI as poor predictors of academic success in comparison to cognitive and personality measures (e.g., Barchard, 2003; Chew et al., 2015; Ford & Tamir, 2012; O'Connor, Jr. & Little, 2003). They recommended future research should focus on identifying other factors to understanding long-term student performance. In the current investigation, a trait EI measure (the TEIQue-SF) that has similar constructs to a mixed measure (the EQ-i) was used to identify and measure emotional and social characteristics in adult online learners and examine the effects they have on academic achievement (e.g., GPA). In addition, SDL was explored as another factor in understanding and improving student success in the online learning environment.

No EI findings. Some researchers have found that ability- and/or trait-based EI measures do not associate with academic success nor predict life success outcomes in a traditional learning environment (e.g., Barchard, 2003; Ford & Tamir, 2012; Koc, 2019; Kornilova et al., 2018; Rahimi, 2016). In one of the earliest predictive studies of EI, Barchard (2003) compared the predictive validity of EI with traditional cognitive and personality measures in a female only sample (N = 94) of traditional undergraduate students. She used 12 timed IQ tests, 23 scales of the International Personality Item Pool (IPIP), and 31 ability- and/or trait-based EI measures. The participants completed these measures over a period of two months. Barchard (2003) found that only the cognitive (*R*

= .44; R^2 = .19) and personality measures (R = .34; R^2 = .11) significantly correlated and predicted academic achievement (GPA). However, she noted that EI had higher R values (R = .45; R^2 = .21), even though it was not statistically significant.

Since then, researchers have found that ability-based EI measures correlate more with cognitive tests and mixed/trait-based EI measures correlate more with personality tests (MacCann et al., 2019; Mayer et al., 2016; Petrides & Mavroveli, 2018). In retrospect, this could explain the high correlations between the EI, cognitive, and personality measures Barchard (2003) used in her study. The current investigation examined the predictive validity of the TEIQue-SF (a trait EI measure) on academic achievement (GPA) in adult learners taking online courses.

More recently, Han and Johnson (2012) examined the relationships between ability EI (MSCEIT), social bond (Social Bonding Scales), and online interactions (total number, type) in a sample (N = 81) of graduate students in a fully online master's degree program. No statistically significant correlations were found between ability EI and social bond, or between ability EI and type of online interactions, in either the synchronous or asynchronous online learning environment (Han & Johnson, 2012). A negative correlative relationship was found between ability EI and the amount of online interactions in the synchronous environment, but no correlations were found between ability EI and the asynchronous environment (Han & Johnson, 2012). Han and Johnson (2012) concluded that these results indicated the limited function of ability EI in the online learning environment. They also noted how adult learners may have less need for social bond and interactions in the online learning environment (Han & Johnson, 2012).

They recommend future research should continue to explore the impact of EI on student learning using other models in the online environment. In the current investigation, the effects of EI on adult learners using a trait EI measure (TEIQue-SF) were explored.

EI as a mediator. From this review, the relationship between EI and academic success was inconclusive across countries, cultures, and learning environments (e.g., Chew et al., 2015; Han & Johnson, 2012; Koc, 2019; Kornilova et al., 2018; Rahimi, 2016; Zhoc et al., 2018). To better understand the mixed findings of EI on academic success, some researchers (i.e., Noor & Hanafi, 2017; Schutte et al., 2011) have recently examined EI as a mediator variable in the traditional learning environment. For instance, instead of conceptualizing ability and trait EI as mutually exclusive constructs, Schutte, Malouff, and Hine (2011) reconceptualized ability and trait EI as being complementary dimensions of adaptive emotional functioning. In their dimensional model, ability EI may support the development of trait EI, in that higher levels of ability EI may predispose individuals to display more trait EI characteristics (Schutte et al., 2011). Higher levels of EI, measured as either ability EI or trait EI, are associated with greater psychological well-being and persistence (Petrides et al., 2016; Schutte et al., 2011).

In their study regarding the effects of ability and trait EI on alcohol-related problems in adult learners ($N = 100$), Schutte et al. (2011) found that ability and trait EI were significantly associated with each other ($R = .33$). Using path analysis and a product mediation test, they also discovered that trait EI mediated the relationship between ability EI and alcohol-related problems (95% CI [.001, .129], $p < .05$) and between ability EI and heavy episodic (binge) drinking (95% CI [.009, .138], $p < .05$) in adult learners

(Schutte et al., 2011). For future research, Schutte et al. (2011) recommended further exploration of the indirect effects of EI on adult learners.

In a pioneer study of exploring mixed EI as a mediator, Noor and Hanafi (2017) found EI indirectly influenced the relationship between emerging adulthood (EAH) and academic achievement (AA) in a random sample (*N* = 90) of undergraduate students. All measures used in their study were self-report: Bar-On's EQ-i was used to measure EI; EAH was measured by the Inventory of Dimensions of Emerging Adulthood (IDEA); and demographics (e.g., GPA) were collected using the Student Demographic Survey (SDS) questionnaire. Data were analyzed using structural equation modeling (SEM) and path analysis.

Noor and Hanafi (2017) found the direct effect of EAH on AA was insignificant ($p = .60$), and the indirect effect of EI on EAH and AA was significant ($p \leq .001$). This demonstrated a full mediation effect (Baron & Kenny, 1986; Noor & Hanafi, 2017). The effect size ($R^2 = .50$) was large, which also supported the explanatory power of their model (Noor & Hanafi, 2017). Noor and Hanafi (2017) recommended EI should be measured in higher education students and EI training programs should be made available to students to improve their EI, which in turn helps to increase their life (school, work) success. These studies demonstrated that EI (ability, mixed, or trait) can indirectly influence the relationship between learner characteristics (e.g., EAH) and academic success outcomes (e.g., GPA).

EI and indirect findings. Previous research findings have demonstrated that when the indirect effects of a third variable (e.g., coping, SDL) were examined on EI and academic success, the results supported EI as having both correlative and predictive utility with academic success through the third variable (i.e., Fei-Zhou et al., 2013; MacCann et al., 2011; Perera & DiGiacomo, 2015; Saklofske et al., 2012; Urquijo & Extremera, 2017; Zhoc et al., 2018). For instance, some researchers (i.e., MacCann et al., 2011; Perera & DiGiacomo, 2015; Saklofske et al., 2012) found that EI predicted academic success through coping strategies. In a similar study to Noor & Hanafi (2017), Urquijo and Extremera (2017) found that academic engagement indirectly influenced the relationship between EI and academic satisfaction.

However, more closely related to the current investigation are the studies by Fei-Zhou et al. (2013), Koc (2019), and Zhoc et al. (2018). Fei-Zhou et al. (2018) found that learning adaptability, as a third variable, increased the correlative and predictive utility of EI on academic achievement (GPA; $\Delta R^2 = .15$) in a sample ($N = 553$) of undergraduate students. Koc (2019) and Zhoc et al. (2018) found that EI did not directly correlate or predict academic success (e.g., GPA) by itself. Zhoc et al. (2018) examined the indirect effects of SDL on the relationship between EI and academic success in the traditional learning environment and found that EI correlated and predicted academic success through SDL.

Given these positive and significant findings regarding the indirect effects of SDL on EI and academic success discussed above (i.e., Zhoc et al., 2018) in the traditional learning environment, the current investigation explored the indirect effects of SDL on EI and academic success in adult online learners. The SDL theoretical framework by Malcolm Knowles is presented in the next section.

Self-Directed Learning (SDL)

Origin. The origin of SDL can be traced back to ancient Greece and the teachings of Socrates (Dewey, 1897/2016; Knowles, 1975). Socrates, the father of Western philosophy, is best known for his Elenchus method, better known as the Socratic method (King, 2008; "Socrates Quotes," 2013). It is the process of asking and answering questions to teach critical thinking, stimulate ideas, and draw out underlying assumptions (King, 2008; "Socrates Quotes," 2013). Socrates emphasized how "an unexamined life is not worth living" so one must "know thyself," and that "true wisdom is in knowing you know nothing" (King, 2008; "Socrates Quotes," 2013, Para. 24, 40, 44). His teaching focused on self-learning, the forerunner to self-directed learning (King, 2008). Socrates taught Plato, who in turn taught Aristotle, who in turn taught Alexander the Great (Aristotle, trans. 2011).

In his *Nicomachean Ethics*, Aristotle (trans. 2011) took Socrates' self-learning a step further and observed how "For what a person happens to need, he is also intent on, and for the sake of the satisfaction of this need, he will give what he does" (Book 9, Chapter 1, Para. 3). In other words, the intention and focus of an individual is on what the individual needs. Aristotle later noted how "learning engages, by means of thinking, in an activity concerned with the objects of contemplation" and then how with "pleasure [one] completes the activities" (Book 10, Chapter 4, Para. 8). Here, Aristotle refers to the pleasure, or satisfaction, one gains after learning something that one is passionate about, interested in, or has completed to meet a need. These observations (e.g. love of learning and learning to meet one's needs) are at the heart of SDL.

Background. John Dewey (1897/2016), an American philosopher, educator, social reformer, and theorist, echoed the teachings of Socrates, Plato, and Aristotle in his lectures and writings on the need for education reform. Later, Dewey (1916/2016) posited how the institutions of school and society are vital to life success in that they both "foster, nurture, and cultivate growth" (Book 1, Chapter 2, Para. 1). He emphasized the importance of experience, freedom, self-renewal, self-direction, and social activism in learning (Dewey, 1916/2016). Dewey (1938) is considered the most influential of all American philosophers, the father of pragmatism in education, and the most important educational theorist of the twentieth century. He helped to lay the foundation for the progressive movement in education, in which he advocated for active, experiential learning [learn by doing] and self-direction in the classroom.

Eduard Lindeman, another American philosopher, was greatly influenced by Aristotle and Dewey (Knowles, Holton, & Swanson, 1973/2015). In 1926, Lindeman equated the "Greek ideal" – the self-search for the "good life" - to self-directed learning (Knowles, 1975, p. 63). Echoing Aristotle, Lindeman described self-directed learners as those individuals "who seek after things such as intelligence, self-expression … and fellowship" (Knowles, 1975, p.63). Like Socrates and Dewey, he emphasized problem-solving, student-centered learning, and the importance of experience to provide meaning in adult education (Conaway, 2009; Knowles, 1975). Lindeman proposed a new way of thinking about adult learning; he implied individuals of all ages might learn better if their "needs, interests, experiences, self-concepts, and individual differences" were considered in the education process (Knowles et al., 1973/2015, p. 22). Lindeman's key assumptions about adult learners are as follows: (a) Adults are motivated to learn to satisfy needs and interests; (b) Adults' orientation to learning is life-centered; (c) Experience is the richest resource for adult learning; (d) Adults have a deep need to be self-educating; and (e) Individuals differences increase with age (Knowles et al., 1973/2015, p.22).

These assumptions were later supported by research (e.g., Houle, 1961, and Tough, 1971, as cited in Knowles, 1975, 1984) and formed the foundation of adult learning theory (Knowles et al., 1973/2015). Malcolm Knowles, the father of andragogy and one of the leading adult educators in American history, stated that Eduard Lindeman was the "single most influential person" in guiding the development of his andragogical principles of adult learning and his SDL theory (Knowles, 1984, p. 3). Lindeman was Knowles' supervisor at the National Youth Association (NYA) in Massachusetts, and Knowles regarded him as his mentor (Knowles, 1984). Knowles (1984) also acknowledged the influence of three other individuals on the development of his andragogical principles and theory of self-directed learning: Dorothy Hewitt, Carl Rogers, and Cyril Houle. These three individuals, and their influence on Knowles, are briefly discussed below.

Multiple influences. While working at the NYA from 1935 to 1940, Knowles (1984) described how Dorothy Hewitt, the director of the Boston Center for Adult Education and a member of his advisory council, taught him how she planned and managed her adult education program, which provided informal courses to adults in the Boston area. In addition, she co-authored a book with Kirtley Mather in 1937, *Adult Education: A Dynamic for Democracy*, that served as Knowles' "how-to-do-it manual" for the remainder of his career in adult education (Knowles, 1984, p. 3). In 1946, Knowles became the director of adult education at the Central YMCA, and he enrolled in the University of Chicago's graduate program in adult education (Knowles, 1984). There, he was greatly influenced by Carl Rogers' (1961/1995) student-centered approach to education and by the teaching style of his professor and chair, Cyril Houle.

Carl Rogers (1961/1995) was a co-founder of humanistic psychology and one of the most prominent American psychologists of all time. Rogers (1961/1995) emphasized the therapeutic (or personal) relationship as the catalyst for change, and he posited three conditions necessary for human growth: acceptance, empathy, and "unconditional positive regard" (Introduction, Para. 2). Rogers (1980/1995) believed that what is true in a relationship between therapist and client may be true for all relationships. He started with the viewpoint that therapy is a learning process in his conceptualization of client-centered therapy, and then he sought to apply this to education (Rogers, 1961/1995). In this way, he conceptualized student-centered teaching as a parallel to his client-centered approach to psychotherapy (Rogers, 1961/1995). Rogers (1980/1995) preferred the term person-centered to student-centered in his approach to education because it could be applied to all individuals. His person-centered approach to teaching was based on five propositions; these were (a) Significant learning cannot be directly taught; (b) A person learns significantly what is relevant to life; (c) Learning occurs in a climate of acceptance and support; (d) A person learns significantly what is self-directed; and (e) Learning is an internal process controlled by the learner (Knowles et al., 1973/2015; Rogers, 1961/1995). Like others before him (e.g., Socrates, Dewey, and Lindeman), Rogers

(1980/1995) believed that experiential, self-directed learning was a more powerful approach to eliciting personal understanding, growth, and change. He explained, “I am no longer talking simply about psychotherapy, but…an approach to life, a way of being, which fits any situation in which growth…is part of the goal” (Preface, Para. 7).

For decades, Rogers (1980/1995) advocated for affective as well as cognitive learning within education for both children and adults. He emphasized the importance of acceptance, genuineness, and empathic understanding within all learning environments for the psychological well-being and success of all individuals (Rogers, 1980/1995). Rogers (1980/1995) revolutionized psychology and higher education with his focus on teaching counseling skills to future psychotherapists (before clinical psychology existed!) and training future educators on how to be facilitators of learning in a time when didactic teaching was considered the highest academic standard. Knowles (1984) recalled how he experienced the challenge of learning to be a self-directed facilitator in a seminar on student-centered teaching, given by Arthur Shedlin, an associate of Carl Rogers. He found this experience to be “fundamental and terribly difficult” and explained that it required him to “focus on what was happening in the students rather than on what [he] was doing” and to “join students honestly as a continuing co-learner” (pp. 33-34).

Knowles (1984) remarked how his graduate professor and faculty chair, Cyril Houle, helped him to see how Rogers’ propositions (e.g., significant, self-directed learning) could be applied in a traditional university setting. Knowles (1984) described how Houle related to his students as colleagues and as “continuing co-learners” (p. 5). Houle conducted some of the earliest research on the characteristics of adult learners, and in 1961, he published the results in his book, *The Inquiring Mind* (as cited in Knowles, 1984, p. 5). His work ultimately redirected the focus of adult education research, and the work of his graduate students (i.e., Allen Tough and Malcolm Knowles), from student "reactions to teaching" to the "internal dynamics" of how adults learn (Hiemstra, 2003; Knowles, 1984, p. 5). In 1950, and with the help of Houle, Knowles' early collection of ideas on adult learning was published under the title, *Informal Adult Education* (Knowles, 1984; Knowles et al., 1973/2015). This was the forerunner to his andragogical principles and theory on self-directed learning, in which Knowles (1984) drew from the progressive principles of Dewey, the key assumptions of Lindeman, and from Rogers' propositions of student-centeredness and significant learning. Over the next 14 years (i.e., 1960 – 1974), Knowles compiled research by Houle, Tough, and the findings from his own laboratory at Boston University, and developed a framework for adult education. The only thing he was missing was a "label" (Knowles, 1984, p. 5).

In 1967, Dusan Savicevic, a Yugoslavian adult educator, attended one of Knowles' courses on adult learning, and at the end of it, informed Knowles that what he was teaching was called "andragogy" over in Europe (Knowles, 1984, p. 6). Knowles responded with, "Whatagogy?" because he had never heard the term before (1984, p. 6). Savicevic explained to Knowles that andragogy was a term coined by European adult educators as a "parallel to pedagogy" and that it was being defined as "the art and science of helping adults learn" (Knowles, 1984, p. 6). In 1968, Knowles (1984) adopted the term *andragogy* as the label to describe his framework for adult learning, which was published in 1970 with the title, *The Modern Practice of Adult Education: Andragogy versus Pedagogy*.

Andragogy versus pedagogy. In 1926, Eduard Lindeman, along with his colleague Martha Anderson, introduced the term *andragogy* in America (Conaway, 2009). Alexander Kapp, a German teacher, first introduced the term *andragogy* in 1833 (Conaway, 2009; Knowles et al., 1973/2015). Andragogy, or *andragogik* in German, combines the form *andr* of the Greek word *aner* (meaning "man") and *agogos* (meaning "leader of"), so it literally means the "art and science of teaching or leading adults," or mature human beings (Knowles, 1975, p. 19; Knowles, 1984, p. 6). Kapp used it to describe an educational theory by the ancient Greek philosopher Plato, even though Plato never used the word himself (Knowles, et al., 2015). In 1921, Eugen Rosenstock, a German social scientist, used the term *andragogy* to distinguish adult education from *pedagogy,* the traditional education theory, because he believed adult education required a "special philosophy" along with distinct methods (Knowles et al., 1973/2015, p. 38).

The term *pedagogy* combines the Greek words *paid* (meaning "child") and *agogus* (meaning "leader of"), so it literally means "the art and science of teaching or leading children" (Knowles et al., 1973/2015, p. 40). The pedagogical model of education is a set of beliefs, or an ideology, based on assumptions about teaching and learning (Knowles et al., 1973/2015). It emerged from the medieval European monastic and cathedral schools where basic scholastic skills were taught to young boys (Conaway, 2009; Knowles et al., 1973/2015). It began in the 7th century, and by the 19th century, with the rise of public schools, it was still the only existing model of education (Knowles, 1984; Knowles et al., 1973/2015).

The pedagogical model is teacher-centered, meaning the teacher is solely responsible for deciding what is learned, how and when it will be learned, and if it has been learned (Knowles, 1984; Knowles et al., 1973/2015). Knowles (1984) described the methodology of pedagogy (e.g., lectures, assigned readings) as “transmission techniques” because knowledge is being transmitted to learners by the teacher and curriculum (p. 8). In this way, the learner’s self-concept is dependent on the teacher, and their orientation to learning is subject-centered (Knowles, 1984). In the pedagogical model, students must be ready and motivated to learn what they are told to learn by parents and teachers, and follow all directions, if they want to advance to the next level (Knowles, 1984). Psychologically, developmentally, and culturally speaking, these pedagogical assumptions are appropriately applied to individuals when they experience the highest degree of dependency, from infancy to roughly 10 years old (Knowles et al., 1973/2015).

As individuals mature to preadolescence and adolescence, their need and capacity to be self-directing, and to use their own experiences to organize their learning around their own life circumstances, rapidly increases (Knowles et al., 1973/2015). This maturation process can be described as moving from a state of dependency towards increasing independency and self-directedness (Erikson, 1950, as cited by Knowles et al., 1973/2015, p. 251; Rogers, 1961/1995). However, Western culture does not nurture the development of self-direction and other andragogical principles until most individuals can be considered adults (Knowles et al., 1973/2015). Knowles, Holton, and Swanson

(2015) defined “adult” in four facets: (a) biologically when one is old enough to have children; (b) legally when one is old enough to vote and get married; (c) socially when one performs adult roles, such as becoming a spouse and/or parent; and (d) psychologically when one reaches a self-concept of being self-directed in one’s life (p. 43). In this sense, individuals view themselves as adults over time. This process begins in preadolescence, develops through adolescence, and fully formulates in adulthood when one graduates from college, works full-time, marries, and/or starts a family (Knowles et al., 1973/2015). As a result, there is a gap between the teacher-directed pedagogical approach to education and the developmental need for more self-directed, lifelong learning in adolescence and adulthood.

Knowles’ andragogical model. Knowles (1984) acknowledged that the education models of andragogy and pedagogy were not opposing forces, but parallel approaches to education that can be combined in the learning environment based on the needs of the learners. He recognized that the application of only andragogical principles may not suit all adult learners because these develop over time and in response to one’s life experiences and situation (Knowles, 1984). For example, Knowles (1984) explained how pedagogical strategies may be more appropriate in adult learning when new material is being introduced. In addition, Knowles (1984) recognized that the andragogical principles may be applied to children and adolescents as well depending on the situation. Knowles agreed with researchers of the time such as Cross (1981; as cited in Knowles, 1984) and Hartree (1984; as cited in Merriam, 2001) that andragogy was less of a theory and more of a conceptual framework for a continuum of lifelong learning (Knowles, 1984; Merriam, 2001). For these reasons, Knowles (1984) preferred to describe his andragogical framework as a system of concepts, or assumptions, that incorporates aspects of pedagogy (dependent learning) along with self-directed (independent) learning. His andragogical framework is as follows: (a) Adult learners are self-responsible and self-directed; (b) Adult learners are the richest resource for learning; (c) Readiness to learn is dictated by adult learners' experience; (d) Adult learners' orientation to learning is life-centered; (e) Motivation to learn is more internal than external; and (f) Adult learners need to know "the why" before they learn it (Knowles, 1984; Knowles et al., 1973/2015, p. 43). As mentioned earlier, Knowles compiled the works of Lindeman, Rogers, and Houle, alongside his own research, and used this to build the foundation of his framework for adult education. Originally, Knowles (1975) presented the first four assumptions on andragogy and adult learning (Knowles et al., 1973/2015). However, he periodically revised his model to reflect the findings of the growing research literature on adult learning to keep it empirically based. In this way, he added the fifth assumption in 1984, and the sixth assumption in 1989 (Knowles et al., 1973/2015).

Andragogy as a process model. In addition to these assumptions, Knowles (1984) described his andragogical framework as a *process* model, instead of as a *content* model (e.g., pedagogy). The focus of the content model is on transmitting information and skills via the instructor, textbook, and classroom media, whereas the focus of the process model is on providing procedures and resources for helping learners to acquire information and skills (Knowles et al., 1973/2015). Also, the content model is teacher-centered, whereas the process model is learner-centered like Rogers' (1980/1995) person-centered approach

(Knowles et al., 1973/2015). In this way, the instructor's role fluctuates between consultant, facilitator, change agent, and teacher based on learners' needs. Knowles spent two decades experimenting with his andragogical process model and reached two conclusions: (1) The andragogical model is a flexible system of elements that can be adopted or adapted in whole or in part – it is not an ideology like pedagogy; and (2) The appropriate strategies for applying the andragogical model depend on the needs of the learners and the context of the learning situation (Knowles, et al., 2015, pp. 77-78).

Knowles (1975, 1984) originally posited seven elements conducive to producing an andragogical process design within the learning environment. These elements were hierarchical and cyclical, meaning they could repeat with each new topic or course module. They consisted of: (1) climate setting; (2) mutual planning; (3) diagnosing learning needs; (4) formulating learning goals; (5) designing learning plans; (6) carrying out learning plans; and (7) evaluating learning plans (Knowles, 1975, 1984). These elements are briefly described below.

Elements in andragogy. Climate setting included the procedures most likely to create an environment conducive to learning (Knowles, 1975, 1984). Knowles (1984) believed the most important aspect of climate setting was establishing the psychological environment. Echoing Rogers' (1961/1995) client-centered therapy and person-centered teaching, this involved forming an atmosphere of mutual respect, trust, collaborativeness, supportiveness, openness, authenticity, pleasure, and humanness. In another nod to Rogers, *humanness* included providing for learners' physical needs (e.g., frequent breaks) as well as providing a mutual caring, respectful, and helping atmosphere (Knowles, 1984). Next, mutual planning involved creating procedures that allowed learners to provide input into the lesson planning process and share responsibility for this with the instructor (Knowles et al., 1973/2015). For example, Knowles (1975, 1984) described how he would present several options for learning activities (e.g., research paper, oral presentation) and ask groups to discuss them and present their preferences. According to the basic findings of applied behavioral research (e.g. Houle, 1961, and Tough, 1971, as cited in Knowles, 1984), people tend to feel committed to a decision or activity in direct proportion to their participation and influence on its planning and decision making (Knowles et al., 1973/2015). More importantly, it was found that adults tend to feel uncommitted to any decision or activity they feel is being imposed on them because their motivation to learn is more internally driven rather than externally driven (Maslow, 1970, as cited in Knowles, 1984; Knowles et al., 1973/2015).

Along these lines, the andragogical instructor also helps students to diagnose their own learning needs (Knowles, 1975, 1984). Knowles explained this could be problematic for two reasons: (1) The “felt needs” of the learners were often different from the “ascribed needs” of the educational institution (1984, p. 17); and (2) The lack of a research-based tool for learners to self-diagnose their learning needs, abilities, and skills (1975, p. 89). As a remedy, Knowles (1975, 1984) would present a list of competencies to the students which reflected both personal and organizational learning needs. This allowed students to identify gaps in their learning between where they were personally and professionally on a given course or topic. This also helped students in formulating their learning goals and designing their own learning plans. To help facilitate this process, Knowles (1975, 1984) would have students create learning contracts where students would translate their learning needs into learning goals. With the help of Knowles, they would also identify resources and strategies for accomplishing their goals as well as the evidence they would need to produce to demonstrate mastery (Knowles, 1975, 1984). Once the learning contracts were approved, students began to carry out their learning objectives and build their portfolios of evidence. The evaluation of learning plans and portfolios would consist of group activities (e.g., peer review, group presentations), feedback from specialists (including the instructor and others in the organization and/or community), and individual projects (Knowles, 1975, 1984).

Over time, and contrary to his belief, Knowles (1984) observed how many of the adults he worked with were not self-directed learners and/or did not acknowledge their own capacity for self-direction in learning. He cited an example by saying, “usually in a class of thirty [only] about half a dozen” would elect to work independently (Knowles, 1975, p. 52). In other words, he found most adult learners were not independent or self-directed. Knowles (1975, 1984) explained one reason for this could be because pedagogy has been the predominant education model, and it places sole responsibility for content and learning on the teacher. It does not nurture SDL because it is based on teacher-directed learning. This could condition learners to be dependent on teachers and cause “a form of culture shock” when they are introduced to the andragogical model of education which is based on SDL (Knowles et al., 1973/2015, p.52). As a result, Knowles added an eighth element to his andragogical model called “preparing the learner” (Knowles et al., 1973/2015, p.51). He believed this was the most important element of all and that it should precede, or be included with climate setting (Knowles et al., 1973/2015).

In following with Dewey (1938) and Rogers (1980/1995), Knowles et al. (1973/2015) described this element as a brief orientation in self-direction and learning how-to-learn. They suggested this element should consist of three main facets: (a) an explanation of the difference between pedagogy and andragogy (e.g., teacher-directed learning versus self-directed learning); (b) a collaborative activity where learners can identify each other as peer resources (i.e., who is an expert in what, or who has experience doing what); and (c) a brief experiential encounter with the skills and concepts of SDL (Knowles et al., 1973/2015, p. 53). For the latter, Knowles (1975, 1984) presented learners with a list of SDL competencies and asked them to rate themselves in each area. For example, one SDL competency is to understand the differences between teacher-directed learning (pedagogy) and SDL (andragogy) and explain these differences to others (Knowles, 1975, 1984). Students would rate themselves on a scale ranging from having none of this competency to being competent in it (Knowles, 1975). Later, Knowles (1984) added that learners should also identify when either pedagogy or andragogy is more appropriate to use in the learning environment. For instance, the pedagogical model is more appropriate to use when learners have rated themselves low in competency or as having no competency in a topic (Knowles, 1984; Knowles et al., 1973/2015). In contrast, the andragogical model is more appropriate when learners have rated their competency moderate to high (Knowles, 1984; Knowles et al., 1973/2015).

Here, it is important to note that SDL learners must still have access to resources and support, as well as opportunities to ask for help, even if they have rated themselves as competent on a given topic, because adults can be unaware of what they need to know to achieve a task or succeed in a goal (Knowles, 1984; Rogers, 1961/1995). In this way, Knowles' andragogical model emphasized SDL skills, but it also specified how the andragogical principles were to be applied based on the needs of learners and the context of the learning situation (Knowles et al., 1973/2015; Merriam, 2001).

Andragogy versus SDL. In 1926, Lindeman posited that the terms andragogy and SDL were synonymous with adult education (as cited in Knowles, 1984). Knowles (1975, 1984) built his framework and approach to adult education around both, and later, Merriam (2001) would refer to these as the "two pillars" of adult education in her update on adult learning theory. However, Knowles (1975, 1984) and other education researchers (i.e., Houle, 1961 and Tough, 1971, as cited in Merriam, 2001; Rogers, 1980/1995) found that SDL was the most important characteristic of adult learning. According to these researchers, SDL skills and abilities make the andragogical process possible. For instance, as individuals' transition into adulthood, they transform from dependent, teacher-directed learners to independent, self-directed learners (Knowles, 1984; Rogers, 1980/1995). The process happens naturally, over time, and is generally directed by individuals' life experience and situation (Knowles et al., 1973/2015; Rogers, 1980/1995).

In following with others before him (i.e., Lindeman, Rogers), Knowles (1975, 1984) emphasized that when adults experience a need to improve or change their life situation, their motivation drives them towards a task. If their experience (or competence) in an area falls short of successfully completing a task, then they will recognize the need for growth and be ready to learn what they need to know in order to change (Conaway, 2009; Knowles, 1975, 1984). In this way, their orientation to learning switches from subject-centered and teacher-directed to life-centered and self-directed (Knowles, 1984; Knowles et al., 1973/2015). Knowles' (1975, 1984) and others (e.g., Rogers, 1961/1995) saw how SDL could fill in this gap and help adult learners' transition between the two education models.

SDL as a process. Knowles' (1975) defined SDL as a process where learners take initiative, diagnose their own learning needs, formulate goals, identify resources, select and implement appropriate learning strategies, and evaluate their own learning outcomes (p. 18). Here, it is important to note how Knowles' (1975) definition of SDL forms the basis for the elements he described as conducive to producing an andragogical learning environment (e.g., diagnose learning needs, formulate goals, evaluate learning outcomes). In other words, self-directed learners carry out these steps successfully on their own, regardless of the learning environment. However, Knowles (1975, 1984) emphasized how SDL abilities and skills were on a continuum of lifelong learning and not a one-size-fits-all approach since learners will have varying degrees of SDL competencies.

For this reason, Knowles advocated for instructors of adult learners to *facilitate* the SDL process, by helping learners to transition from the pedagogy model to the andragogy model of education based on the learners' needs and the learning situation (Knowles et al., 1973/2015). Like Rogers (1961/1995), Knowles (1975, 1984) preferred the term *facilitator* to instructor or teacher, and he advocated for facilitators to help students self-assess their learning needs and gaps in a profession, course, or topic, and then translate these needs into learning goals and objectives. As noted earlier, individuals vary in their self-concepts, life experience and situations, and in their approaches, strategies, and preferences to learning, all of which can impact their ability to be self-directed and successful inside and outside of the classroom (Knowles et al., 1973/2015; Rogers, 1980/1995). For these reasons, Knowles' (1975, 1984) emphasized self-assessment, awareness, reflection, and evaluation in his approach to SDL as a process.

For the purposes of the current investigation, Knowles' (1975, 1984) theoretical approach to SDL was selected. However, there are other approaches to SDL in the literature that were also considered. These are briefly reviewed below.

SDL Approaches and Measures

Approaches to SDL. SDL is not only the most important element of andragogy, but it is also the most researched and debated (Hiemstra & Brockett, 2012; Knowles et al., 1973/2015; Merriam, 2001). As mentioned previously, one reason for this is how it can be applied to adults as well as children and adolescents (Knowles et al., 1973/2015; Merriam, 2001). Some researchers (e.g., Candy, 2000; Knowles, 1984; Rogers, 1980/1995) have posited that SDL can be applied to individuals of all ages because it is a situational, instructional process that depends on the needs of the learners and the learning situation. These researchers also described SDL as contextual, meaning that learners may have high levels of SDL in some areas and low levels of SDL in other areas (Candy, 1991, and Grow, 1991, as cited in Merriam, 2001; Garrison, 1997; Knowles et al., 1973/2015). Therefore, they postulated SDL as a set of skills on a continuum required for lifelong learning (Candy, 2000; Garrison, 1997; Knowles, 1984; Rogers, 1980/1995).

Other researchers have posited that SDL is a personality trait (e.g., Guglielmino, 1977) or a combination of both instructional process and personality (e.g., Brockett and Hiemstra, 1991, as cited in Hiemstra & Brockett, 2012). In addition, Garrison (1997) expanded on Knowles' (1975, 1984) approach to SDL by adding the psychological (i.e., cognitive, metacognition) dimensions of learning. These SDL approaches, and their corresponding measures (if applicable), are briefly described in this section, followed by the rationale for the approach and measure selected for this study.

Goal, process, or trait? In the literature, SDL has been approached in three ways: (a) As a goal; (b) process; and (c) as a learner characteristic (Hiemstra & Brockett, 2012; Merriam, 2001; Song & Hill, 2007). When SDL is approached as a goal, it is grounded in humanistic philosophy, and it becomes one of the main outcomes of learning (Knowles, 1984; Merriam, 2001; Song & Hill, 2007). For example, Houle, Knowles, and Tough all approached SDL as a goal because their overall focus was on developing and improving SDL abilities and skills in their students to help them become independent, lifelong learners (Hiemstra, 2003; Knowles et al., 1973/2015; Merriam, 2001).

As discussed previously, Houle, Knowles, and Tough also approached SDL as an instructional process. When SDL is approached as a process, it becomes the methodology of instruction, where instructors focus on what they can do to help foster SDL abilities and skills in the classroom (Candy, 2000; Knowles et al., 1973/2015; Merriam, 2001). In their review, Cadorin, Bressan, and Palese (2017) categorized SDL approaches (models) using the terms *linear*, or a series of steps (e.g., Knowles, 1975), *instructional*, or strategies implemented by a facilitator (e.g., Knowles, 1975), and *interactive*, or a combination of learner characteristics and instructional processes (e.g., Brockett & Hiemstra, 1991). The same terms are used below to help distinguish between other SDL approaches.

Other SDL instructional models. Gerald Grow agreed with Knowles and other researchers (e.g., Candy, 2000) that SDL was situational, where learners may be higher in SDL in some areas and lower in others, and that SDL can be taught (as cited in Merriam, 2001). As a result, Grow developed the Staged Self-Directed Learning (SSDL) model which posited four stages of SDL and four corresponding teaching styles (Merriam, 2001; Hiemstra & Brockett, 2012). The SSDL stages reflected Knowles' SDL process (or transition) from pedagogy to andragogy (Knowles et al., 1973/2015). Grow suggested students could evaluate their level of SDL by identifying which stage they feel most comfortable with (i.e., dependent, interested, involved, or self-directed), and then the instructor could match the learner's stage with the appropriate instructional strategies (as cited in Merriam, 2001). For example, a dependent learner would prefer lecture to introduce material, whereas a self-directed learner would prefer independent study (Knowles et al., 1973/2015; Merriam, 2001).

Philip Candy posited a constructivist-oriented model of SDL which emphasized four dimensions: (a) personal autonomy; (b) self-management; (c) independent pursuit of learning; and (d) learner-control of instruction (as cited in Hiemstra & Brockett, 2012, and Song & Hill, 2007). He further divided instructional SDL into two domains: (1) the learning context within an institution, and (2) what he called *autodidaxy*, or the learning context outside of an institution (as cited in Merriam, 2001; Song & Hill, 2007). Candy (2000) agreed with other researchers (e.g., Houle, Knowles, Tough) that SDL was an important goal of higher education, and that it was also an instructional process that could be taught. He emphasized how SDL should be developed inside and outside of the classroom because SDL abilities and skills (e.g., setting goals, evaluating progress) were required for lifelong learning (Candy, 2000; Garrison, 1997; Song & Hill, 2007).

SDL personality model. Not long after Knowles published his book, *Self-Directed Learning: A Guide for Learners and Teachers* (1975), Lucy M. Guglielmino (1977) published her dissertation, *Development of the Self-Directed Learning Readiness Scale*, as a response to Knowles' (1975) need for a research-based tool that educators could give to their students to self-diagnose their learning needs and SDL skills. Before this, researchers and educators (i.e., Houle, Knowles, Tough) would either: (1) Ask learners to report what competencies (related to the course or self-direction) they would like to improve upon; or (2) Provide learners with a list of competencies to evaluate themselves at the beginning of the course or learning project (Knowles, 1975, 1984). As a result, the main goal of Guglielmino's (1977) study was to develop an instrument that could be used by institutions of higher education to screen and/or select suitable learners for their programs requiring SDL as well as determine their strengths and weaknesses in self-direction.

Guglielmino (1977) agreed with researchers (e.g., Candy, Knowles, Rogers) that SDL existed along on a continuum, meaning that it is present in each person to some degree, and that it can occur in a variety of learning situations. However, she believed that “it is the personal characteristics of the learner…which ultimately determine whether self-directed learning will take place” (Guglielmino, 1977, p. 34). Using the Delphi method, including panel SDL experts such as Houle, Knowles, and Tough, Guglielmino (1977) established 41 Likert-type items falling along eight factors of SDL for her Self-Directed Learning Readiness Scale (SDLRS). These were as follows (with sample items included; as cited in Guglielmino, 1977): (1) Openness to learning opportunities (e.g., I’ll be glad when I’m finished learning); (2) Self-concept as an effective learner (e.g., I am capable of learning for myself almost anything I might need to know); (3) Initiative and independence in learning (e.g., I don’t work very well on my own); (4) Informed acceptance of responsibility for one’s own learning (e.g., If I don’t learn, it’s my fault); (5) Love of learning (e.g., I like to learn); (6) Creativity (e.g., I can think of many different ways to learn about a new topic); (7) Positive orientation to the future (e.g., I like to think about the future); and (8) Ability to use basic study skills and problem-solving (e.g., I don’t have any problem with basic study skills).

In 1991, the SDLRS was renamed the Learning Preference Assessment (LPA), and it was revised from 41 to 58 Likert-type items, with higher scores indicating higher SDL abilities (Guglielmino & Guglielmino, 2006). Both versions (SDLRS, LPA) were reported to have an internal reliability of .87 (Guglielmino, 1977; Guglielmino & Guglielmino, 2006). Despite how the SDLRS/LPA is the oldest, most widely used, and the most influential measurement tool in the study of SDL (Cadorin, Bressan, & Palese, 2017; Guglielmino & Guglielmino, 2006; Hiemstra, 2003; Slater & Cusick, 2017), it continues to be criticized for the following issues (as cited in Cadorin et al., 2017; Chan, 2018; Fisher, King, & Tague, 2001; Schulze, 2014): (a) Too many constructs; (b) Constructs measuring positive attitude and not SDL; (c) Problems with validity and reliability; and (5) High cost. Field (1989, as cited in Fisher et al., 2001) found it difficult to replicate the original eight-factor structure and noted how items connected with readiness for SDL correlated less than 5% with total SDLRS scores. Cadorin et al. (2017) also pointed out how the SDLRS/LPA has not been validated by different authors, except for Crook (1985, as cited in Cadorin et al., 2017). For the reasons described above, the SDLRS/LPA was not selected to use in this study.

SDL interactive models. Ralph Brockett and Roger Hiemstra were influenced by Knowles' (1975) development and definition of SDL as a goal and instructional process (Hiemstra, 2003; Stockdale & Brockett, 2011) and the distinction between process and personality made by Oddi (1986; as cited in Hiemstra & Brockett, 2012). They took SDL to the "next level" and explored it as an "interactive" combination of instructional process and personality (Cadorin et al., 2017; Merriam, 2001, p. 10). In 1991, Brockett and Hiemstra proposed the personal responsibility orientation (PRO) model of SDL (Hiemstra, 2003). They defined "personal responsibility" as when learners assumed "ownership for their thoughts and actions," and described it as "the starting point" to SDL (Hiemstra & Brockett, 2012, p. 156; Stockdale & Brockett, 2011, p. 163).

Brockett and Hiemstra conceptualized SDL as the integration of the external characteristics of the instructional process and the internal characteristics of learners (as cited in Stockdale & Brockett, 2011). They explained that both sets of characteristics operated within a learner's social context, so they both contributed to a learner's SDL (Stockdale & Brockett, 2011). In 2012, these authors reconfigured their model and renamed it the person process context (PPC) model (Hiemstra & Brockett, 2012). The basic elements are the same as the PRO model, but they are renamed "person, process, and context," and they are treated as dynamically interrelated and with equal importance in their influence on SDL (Hiemstra & Brockett, 2012). The PRO/PPC model of SDL was presented as an conceptual framework for understanding the similarities and differences in SDL as a "teaching and learning transaction" external to the individual (instructional process) and the individual's internal personal orientation to SDL (Hiemstra & Brockett, 2012; Stockdale & Brockett, 2011, p. 163). All that was missing was a measurement tool.

In response to this need, Susan Stockdale developed the PRO-SDLS, a measure of SDL based on the PRO model that uses a 5-point Likert-type format to assess SDL in higher education students (Hiemstra, 2003; Stockdale & Brockett, 2011). From the 35 items retained after pilot testing in 2003, a panel of experts familiar with the PRO model selected 25 items as representative of the scale's four factors: Initiative, control, self-efficacy, and motivation (Stockdale & Brockett, 2011). The 25 items were further tested using a confirmatory factor analysis, and Cronbach's alpha (α) was .91, which supports the scale as conforming to the PRO/PPC model (Hiemstra & Brockett, 2012; Stockdale & Brockett, 2011). Despite these findings, and how the PRO-SDLS was designed specifically for use in higher education, it was not selected for this study because the PRO-SDLS was based on Brockett and Hiemstra's PRO/PPC interactive model of SDL.

Another reason was because it was not one of the SDL measurements reviewed by Cadorin et al. (2017) or Slater and Cusick (2017).

Randy Garrison (1997) pointed out how previous SDL models focused on the external management of learning with little attention to the cognitive and motivational dimensions of learning. He posited this was because the bulk of research in SDL (i.e., Houle, Knowles, Tough) was from an educational perspective (Garrison, 1997; Pilling-Cormick & Garrison, 2007). Garrison (1997) pointed out how the psychological dimension of SDL (e.g., Rogers' significant learning) had been generally ignored. He agreed with Knowles (1975) that SDL was an instructional process and with others (i.e., Brockett & Hiemstra, 1991, as cited in Garrison, 1997) that personal responsibility was at the heart of it. However, in echoing Rogers (1961/1995), Garrison (1997) felt more attention should be paid to the learning process itself. For instance, Garrison (1997) supported that SDL as a process must include external management (e.g., task control), but he emphasized that it should also include the following: (a) The acceptance of personal responsibility to construct meaning; (b) Cognitive self-monitoring of the learning process (e.g., metacognitive awareness); and (c) Motivational states (e.g., task value) given their "mediating effect on task management" and "monitoring" (Garrison, 1997, Para. 14).

As a remedy, Garrison (1997) proposed a comprehensive SDL model in which he integrated the "intimately interconnected constructs" of external management (i.e., task control), internal (cognitive) monitoring, and motivation (i.e., value task issues) associated with learning in an educational context (Para. 15). He defined SDL as "an approach where learners are motivated to assume personal responsibility and collaborative control of the cognitive and contextual processes in constructing and confirming meaningful and worthwhile learning outcomes" (Garrison, 1997, Para. 51). Garrison (1997) operationalized "collaborative control" as the individual taking personal responsibility for constructing meaning while including others in the construction and confirming of knowledge. In this way, he acknowledged how meaning and knowledge are constructed both personally and socially (Garrison, 1997; Vygotsky, 1978). In the development of his model, Garrison (1997) recognized Dewey (1938) as being the first to integrate cognitive and social dimensions within the educational experience, and Rogers' (1969, as cited in Garrison, 1997) for defining self-direction as including "taking responsibility for the internal cognitive and motivational aspects of learning" (Para. 8). In the presentation of his comprehensive model, Garrison (1997) acknowledged how more research was still needed on understanding the interrelations and interconnections between the constructs at the heart of it: external management, internal monitoring, and motivation (Garrison, 1997; Pilling-Cormick & Garrison, 2007).

Like Dewey, Knowles and Rogers, Garrison (1997) also acknowledged the challenge ahead for educators and administrators was "to create educational conditions that will facilitate self-direction" (Para. 46). In following with others before him (i.e., Dewey, Knowles, Rogers), Garrison (1997) emphasized how the learning situation (i.e., context and environment) influences the growth and development of the SDL process. His recommendation for future research was to explore in greater detail the cognitive and motivational dimensions of SDL (Garrison, 1997). Garrison (1997) concluded how opportunities for SDL enhance cognition and metacognition, which in turn, help to create those educational conditions (or elements) conducive to developing lifelong learners.

The current investigation can be considered a response to Garrison (1997) in that it explored the indirect relationships between SDL and EI, two constructs with established links to cognition, metacognition, and motivation in educational settings, and the impact their relationship has on academic success (Bar-On, 2006; Engin, 2017; Koc, 2019; Zhoc et al., 2018).

Rationale for using Knowles' SDL theory. Knowles' (1975, 1984) approach to SDL as a process was selected as the SDL theoretical framework for this study. Not only does it align organically within an individual's lifespan development (Erikson, 1950, and Rogers, 1969, as cited in Knowles et al., 1973/2015), but it has also gained support from other fields such as education, psychology, and neuroscience (Garrison, 1997; Hiemstra, 2003; Knowles et al., 1973/2015; Rager, 2009; Song & Hill, 2007). Knowles' (1975, 1984) and others (e.g., Candy, 2000; Garrison, 1997; Merriam, 2001; Song & Hill, 2007; Zhoc et al., 2018) acknowledged SDL as a critical goal for higher education, as an instructional process, and as being dependent on the needs of the learner and context of the learning situation.

In addition, Knowles' definition of SDL is the most cited in the literature (Cadorin et al., 2017; Chan, 2018; Koc, 2019; Merriam, 2001; Song & Bonk, 2016). In this way, the argument could also be made for how Knowles' SDL theory forms the foundation for all other SDL models because their central focus remains on SDL and the factors influencing the SDL process, such as instruction, learner attributes, and SDL readiness assessment (Cadorin et al., 2017; Chan, 2018; Schulze, 2014; Song & Hill, 2007; Stockdale & Brockett, 2011). From the work of Knowles (1975, 1984) and other researchers (e.g., Cadorin et al., 2017; Candy, 2000; Hsu & Shiue, 2005; Lai, 2011; Song & Hill, 2007; Sumner, 2018), the literature supports that SDL can be taught and improved in either the traditional or online learning environment. For these reasons, Knowles' (1975, 1984) SDL theory was selected for the current investigation.

SDL measurement. As mentioned previously, Knowles (1975, 1984) did not develop a measurement tool to correspond with his SDL approach. Instead, he emphasized the need for a research-based measurement tool to assess learner needs, abilities, and characteristics associated with SDL (Guglielmino, 1977; Fisher et al., 2001; Knowles, 1975). This is more commonly referred to as the learner's readiness for SDL, or self-directed learning readiness (SDLR; Fisher et al., 2001; Guglielmino, 1977; Hsu & Shiue, 2005). Knowles (1975, 1984) and other researchers (e.g., Fisher et al., 2001; Hsu & Shiue, 2005; Song & Hill, 2007) found that matching a learner's SDLR with the appropriate educational delivery method (e.g., context or learning environment) can lead to optimal learning outcomes.

As mentioned previously, Lucy Guglielmino (1977) answered Knowle's (1975) call for an SDL measurement and developed the SDLRS as her dissertation study. The SDLRS was considered for this study, along with Susan Stockdale's PRO-SDLS (2003, as cited in Stockdale & Brockett, 2011). However, as previously explained, these measurements were not selected. Instead, an alternative measure to Guglielmino's (1977) SDLRS was selected for the current investigation. This measurement is discussed below.

Fisher et al. (2001) SDLRSNE. Like Knowles (1975, 1984), Fisher, King, and Tague (2001) approached SDL as a process and as existing on a continuum of lifelong learning, where the amount present in each individual varies but it can be developed and improved with awareness and practice (Fisher et al., 2001). In following with others before them (i.e., Candy, Guglielmino, Knowles), Fisher et al. (2001) emphasized that SDL, measured as self-directed learning readiness (SDLR), can vary within an individual depending on the context or learning situation. For example, an individual may possess high levels of SDLR in a familiar subject but demonstrate low levels of SDLR in a new topic (context) or learning situation (Candy, 2000; Guglielmino, 1977; Fisher et al., 2001; Knowles, 1975, 1984; Schulze, 2014; Song & Hill, 2007; Sumuer, 2018).

In this way, Fisher et al. (2001) set out to develop an SDLR measure that could be used within a specific context or learning environment (i.e., nursing education), which resulted in the measure being named the Self-Directed Learning Readiness Scale for Nursing Education (SDLRSNE). The measure development process was conducted in two stages: (1) A modified Reactive Delphi technique was used to develop the measure items and to determine content validity; and (2) A pilot study was conducted on a convenience sample (N=201) of undergraduate nursing students to determine the measure's construct validity and internal consistency (Fisher et al., 2001). A principal components analysis was performed, and two of the 42 Likert-type items were dropped because they did not load on any of the components at the 0.30 cutoff (Fisher et al., 2001). The resulting measurement included 40 items factoring onto three components: self-management (13 items), desire for learning (12 items), and self-control (15 items;

Fisher et al., 2001). Similar components of SDLR are also found in Guglielmino's (1997) and the PRO-SDLS (Stockdale & Brockett, 2011). Sample items for each component are as follows (as cited in Fisher & King, 2010): self-management (e.g., I have good management skills); desire for learning (e.g., I enjoy learning new information); and self-control (e.g., I am responsible).

Internal consistency for the 40 items was estimated using Cronbach's coefficient (α) and reported as .92 (Fisher et al., 2001). Fisher and King (2010) re-examined the factor structure of the SDLRSNE and its validity. A cross-sectional survey of first year undergraduate nursing students (N = 227) was used to examine the factor structure, and the reported Cronbach's coefficient alpha (α) was .87 (Fisher & King, 2010). The original factor structure held true, except for 11 items (Fisher & King, 2010). As a result, a revised 29 item SDLRSNE could be considered for future research (Fisher & King, 2010; Nasir, Nopiah, Osman, & Zaharim, 2014). However, the authors recommended using all 40 items of the SDLRSNE until further research examines the relationships between variables across factors in different samples (Fisher & King, 2010).

In addition, even though it is named the SDLRSNE, the scale does not contain items specifically related to nursing education (Fisher & King, 2010). In this way, it can be used in other student populations (Fisher & King, 2010). For instance, the SDLRSNE has been used to assess SDLR in higher education settings (e.g., Alotaibi, 2016; Nasir et al., 2014). More specifically related to this study, the SDLRSNE (adapted as the SDLRS) has been used to assess SDLR in online education (e.g., Chan, 2018; Schulze, 2014; Sumuer, 2018). It is the second most used measure of SDLR on a global scale, with

Guglielmino's (1977) SDLRS being the most used (Cadorin et al., 2017; Slater & Cusick, 2017). In the review by Cadorin et al. (2017), the SDLRSNE was one of the SDL measurements found to be based on Knowles' (1975) andragogical model and SDL theory, which means it aligned with the SDL theoretical framework selected for this study. In their review, Slater and Cusick (2017) found the need for more SDL research utilizing the SDLRSNE (SDLRS) in student populations besides medicine and nursing education. In the current investigation, the SDLRSNE (SDLRS) was selected to measure SDL in adult learners taking online courses as part of their degree programs.

The next section includes a discussion of the constructs often confused with SDL, early SDL research, and then a brief empirical review of SDL studies from both traditional and online learning environments.

SDL Empirical Review

Modern SDL. SDL is often confused as being synonymous with other constructs, such as self-education, self-learning, self-managed learning, autonomous learning, and independent learning, because their meanings are closely related and intertwined with SDL (Chou & Chen, 2008; Knowles et al., 1973/2015; Macaskill & Denovan, 2013; Meyer, 2010; Schulze, 2014). These constructs indicate learning is taking place without an instructor (Macaskill & Denovan, 2013; Meyer, 2010; Schulze, 2014). For example, self-education is self-learning without an instructor (Schulze, 2014). Socrates considered himself a self-learner, but he also emphasized the need for a guide or mentor to carry out *elenchus*, his method of questioning to draw out the truth, develop critical thinking, and gain knowledge (King, 2008). Macaskill and Denovan (2013) equated SDL with self-managed learning and autonomous learning, while Meyer (2010) equated SDL with independent learning. Like self-education and self-learning, autonomous learning and independent learning have also been described as identifying one's own learning needs and formulating a learning plan (Brockett & Hiemstra, 1991, as cited in Schulze, 2014; Jossberger, Brand-Gruwel, Boshuizen, & van de Wiel, 2010; Macaskill & Denovan, 2013; Meyer, 2010).

The constructs above align with SDL in that they posit the learner as having sole responsibility in assessing needs, formulating plans, and making decisions about what and how to learn (Francom, 2010; Jossberger et al., 2010; Macaskill & Denovan, 2013; Meyer, 2010). However, a key difference between these constructs and SDL is that SDL does not equate to the learner carrying out these processes alone (Alotaibi, 2016; Francom, 2010; Knowles et al., 1973/2015; Meyer, 2010; Sumuer, 2018). Like others before him (i.e., Dewey, Rogers), Knowles (1975, 1984) emphasized the presence of a facilitator who could assist in identifying learning needs and resources, consult on learning projects, as well as offer the learner encouragement and support. As explained by Meyer (2010), independent learning does not have to equate to students working alone. Meyer (2010) further clarified the confusion between these similar constructs (i.e., autonomous learning, independent learning) by noting how they both refer to the process of transitioning learners from dependent (teacher-directed) to independent (self-directed) learning.

SDL versus SRL. The term most often confused with SDL is self-regulated learning (SRL; Francom, 2010; Garrison, 1997; Koc, 2019; Zhoc et al., 2018). They are both related to motivation and academic achievement (Francom, 2010; Garrison, 1997; Koc, 2019). These two terms are difficult to distinguish because their definitions are very similar, and they are often used interchangeably in the literature (Francom, 2010; Jossberger et al., 2010; Pilling-Cormick & Garrison, 2007). Traditionally, SDL and SRL have both been defined as students taking primary responsibility and control of their learning process (e.g., setting goals, evaluating outcomes), but with SRL specifically focused on the internal (i.e., constructive, cognitive) processes of learning (Pilling-Cormick & Garrison, 2007). Pilling-Cormick and Garrison (2007) posited that both SDL and SRL deal with the same concepts: external management practices and internal monitoring processes. However, they explained that the "essential difference" between the two constructs is their "starting point" (Pilling-Cormick & Garrison, 2007, p. 14). In other words, SDL starts with the external management of a task and SRL starts with internal monitoring (Pilling-Cormick & Garrison, 2007).

Along these lines, Jossberger, Brand-Gruwel, Boshuizen, and van de Wiel (2010) suggested that SDL operates at the macro level, while SRL operates at the micro level. SDL is a macro process because it is where learners must direct their own learning, and SRL is a micro process because it is where learners must direct cognitions, emotions, and behaviors within a given task (Jossberger et al., 2010; Zhoc & Chen, 2016; Zhoc et al., 2018). In other words, SDL encompasses "the learning trajectory as a whole," while SRL entails the "execution of a task" (Jossberger et al., 2010, pp. 417-419). Like Pilling-Cormick and Garrison (2007), Francom (2010) and Jossberger et al. (2010) proposed that SDL includes SRL, meaning that self-directed learners can also self-regulate their learning. In this sense, learners need SDL skills, which include SRL, to be successful lifelong learners (Francom, 2010; Jossberger et al., 2010; Pilling-Cormick & Garrison, 2007; Zhoc & Chen, 2016; Zhoc et al., 2018).

Here, it should be noted that some researchers (e.g., Broadbent & Poon, 2015; Kruger-Ross & Waters, 2013; Peck et al., 2018) have found that SDL aligns more with the online learning environment whereas SRL aligns more with the traditional on campus learning environment. One reason for this is that a learner's ability to manage and control the learning process has been found to be critical in online learning and OS (Hsu & Shiue, 2005; Lai, 2011; Schulze, 2014; Song & Hill, 2007; Sumuer, 2018). In their conceptual model, Song and Hill (2007) explained how online learning contributes to the development of SDL in that learners need to be able to plan, monitor, and evaluate their own learning processes and progress to be successful in the online environment. These are cognitive and metacognitive skills that are not typically developed in the traditional learning environment (Chan, 2018; Chou & Chen, 2008; Hsu & Shiue, 2005; Lai, 2011; Schulze, 2014; Song & Hill, 2007; Sumuer, 2018).

Early SDL research. As noted earlier, Houle (1961, as cited in Knowles, 1975, 1984) conducted some of the earliest studies on SDL and academic success in adult learners at the University of Chicago. Houle sought to discover why adults engaged in continuing education and how they learn (Knowles et al., 1973/2015). In his seminal study, he interviewed 22 adult learners and identified three categories: goal-oriented, activity-oriented, and learning-oriented. Goal-oriented learners have a life need or interest to meet (e.g., job training, planning a trip), whereas activity-oriented learners join for social and professional networking purposes (Knowles et al., 1973/2015). Houle did not use the term self-directed learning, but it can be implied from his definition of the learning-oriented category: “learn for the sake of learning” (Schulze, 2014, p. 37).

From his pioneering research, Houle (1964, as cited in Knowles, 1975) developed and published seven guiding principles for adult learners in his book, *Continuing Your Education*: (a) Act [be prepared] to learn; (b) Set realistic goals; (c) Remember [be aware of] your own point of view during the learning process; (d) Actively fit new ideas and facts into the context of experience; (e) Seek help and support; (f) Learn beyond the point of recall [deeper learning]; and (g) Use a combination of psychological and logical strategies (as cited in Knowles, 1975, pp. 68-69).

In following with Houle, his faculty mentor, Allen Tough not only investigated why and how adults learn, but he wanted to know what help they seek. He also did not use the term self-directed learning; instead, he referred to it as self-initiated learning or adult projects (Knowles et al., 1973/2015). In one seminal study, Tough interviewed 66 adults and discovered that adult learners, even those who were self-initiated, turn to others for help who may or may not be educators or experts on the subject (Schulze, 2014). Like Knowles (1975), Tough found that adult learners become more self-initiated [self-directed], and learn more deeply, when they are learning something self-initiated versus being directly taught by someone else (Knowles et al., 1973/2015).

He also observed that many adults do not realize the number of learning projects, or the amount of self-initiated learning, they undertake in a year (Davis, Bailey, Nypaver, Rees, & Brockett, 2010). Tough agreed with Knowles (1975) that adults become aware of this only through a facilitated process of self-awareness and reflection (Davis et al., 2010). In following with Aristotle and others (e.g., Bandura, Dewey), Tough also found that pleasure and self-esteem were critical elements in an adult learner's motivation and success (Knowles et al., 1973/2015). In 1971, Tough published his findings in *The Adult's Learning Projects* (Davis et al., 2010). It was from Tough's research that Knowles added the last assumption, "adults need to know the why," to his andragogy model (Knowles et al., 1973/2015, p.43).

Tough's most influential finding was that informal learning practices (e.g., self-planning, collaboration) were a larger component of adults' lives than formal education (Davis et al., 2010; Hiemstra, 2003; Knowles, 1984). Numerous replications of Tough's research have supported his findings (Davis et al., 2010). For instance, Davis, Bailey, Nypaver, Rees, and Brockett (2010) replicated Tough's study on a convenient sample of 40 graduate students, and like Tough, found 70% of participants' self-initiated learning took place outside of formal education. In addition, they discovered 40% of participants relied on technology (e.g., Internet, web videos, webinars) as a major source for their self-initiated projects (Davis et al., 2010). These findings support the need for more understanding of self-initiated (self-directed) learning in adult learners.

Like Davis et al. (2010), most of the research on SDL after Houle, Knowles, and Tough builds on, reinforces, and refines their work (Knowles et al., 1973/2015; Merriam, 2001; Meyer, 2010; Song & Hill, 2007). Much of this research has used case studies and observations, with the focus on matching instructional approach to the traditional learning environment (Candy, 2000; Koc, 2019; Meyer, 2010; Song & Hill, 2007). Meyer (2010) noted how the findings of this research may not be applicable in different contexts of learning. As previously mentioned, the SDL process is dependent upon the context of learning and the needs of the learner (Candy, 2000; Garrison, 1997; Knowles, 1975, 1984; Meyer, 2010; Song & Hill, 2007). In this sense, both context and learner needs should be considered in the factors that influence academic success, such as course design, instructional methods, and peer engagement (Bawa, 2016; Doe et al., 2017; Kerr et al., 2006; Koc, 2019; Lee & Choi, 2011; Song & Hill, 2007; Zhoc et al., 2018).

SDL continues to be a popular topic in educational and psychological research (Chan, 2018; Knowles et al., 1973/2015; Lounsbury, Levy, Park, Gibson, & Smith, 2009; Slater et al., 2017). For instance, a recent search of the Academic Search Complete, Education Source, ERIC, PsycARTICLES, and PsycINFO databases using the key words *self-directed learning* and *SDL* yielded 13,646 peer-reviewed articles since 2010. The context of this study is focused on adult learners actively attending online courses as part of their degree program. However, research on both the traditional and online learning environments was considered in this literature review to gain insights and understanding into what has, and has not, been studied in terms of learning context and learner needs in SDL and academic success. For these reasons, and due to time constraints, this empirical review was limited to studies that met the following criteria: (a) sampled adult learners (age 18 and over; undergraduate and/or graduate); (b) set in either a traditional or online learning environment; (c) used SDL as either an independent, predictor, and/or mediator variable; (d) included academic success outcomes (e.g., GPA, course grade, final exam score); and (e) mentioned or measured possible indirect effects of SDL on academic success.

Findings in SDL research. In general, SDL has been found to increase self-efficacy, motivation, persistence, and academic performance (e.g., GPA) in adult learners in traditional (e.g., Macaskill & Denovan, 2013; Meyer, 2010; Zhoc et al., 2018) and online learning environments (e.g., Hsu & Shiue, 2005; Lai, 2011; Sumuer, 2018). In support of Knowles (1975, 1984), researchers have also found that SDL abilities and skills can be taught and improved with awareness and practice in both traditional (e.g., Macaskill & Denovan, 2013; Nasir et al., 2014; Zhoc et al., 2018) and online (e.g., Chan, 2018; Lai, 2011; Sumuer, 2018) educational settings.

SDL skills include a range of cognitive (e.g., attention, problem-solving), metacognitive (e.g., planning, evaluating progress), and affective (e.g., related to emotions) attributes (Chan, 2018; Francom, 2010; Garrison, 1997; Koc, 2019; Meyer, 2010; Rager, 2009; Song & Hill, 2007; Zhoc et al., 2018). These skills are also often interrelated and positively correlated in the literature (Bar-On, 2006; Chan, 2018; Garrison, 1997; Koc, 2019; Meyer, 2010; Rager, 2009; Zhoc & Chen, 2016; Zhoc et al., 2018). For example, learners with higher levels of SDL are often independent, active, and can self-regulate their own learning (Chan, 2018; Doe et al., 2017; Kauffman, 2015; Kerr et al., 2006; Koc, 2019; Meyer, 2010; Peck et al., 2018; Zhoc et al., 2018). More specifically related to the present study, adult learners with higher levels of SDL often have higher levels of EI (Kauffman, 2015; Koc, 2019; Zhoc et al., 2018).

Knowles et al. (1973/2015) and other researchers (e.g., Candy, 2000; Garrison, 1997; Meyer, 2010; Song & Hill, 2007; Sumuer, 2018; Zhoc et al., 2018) have found that SDL abilities and skills are not only vital to carrying out the andragogical process model and SDL, but they are also essential for success in higher education, professional development, and lifelong learning. In this sense, SDL has been described as the basis of all learning (Cazan & Schiopca, 2014; Chan, 2018; Song & Bonk, 2016; Williamson, 2007; Zhoc et al., 2018). In support of this, researchers have found that SDL enables, and improves, continuous lifelong learning (e.g., Candy, 2000; Fisher et al., 2001; Knowles et al., 1973/2015; Lai, 2011; Meyer, 2010; Song & Bonk, 2016; Sumuer, 2018; Williamson, 2007; Zhoc et al., 2018). For this reason, SDL skills are necessary for success in higher education and professional development (Candy, 2000; Cazan & Schiopca, 2014; Garrison, 1997; Knowles et al., 1973/2015; Song & Bonk, 2016; Sumuer, 2018; Williamson, 2007; Zhoc et al., 2018).

As previously explained, SDL is contextual and exists along a continuum, where individuals have varying degrees of SDL skills depending on the learning context and their needs (Fisher et al., 2001; Guglielmino, 1977; Knowles, 1975; Meyer, 2010; Song & Hill, 2007; Stockdale & Brockett, 2011). In this way, and as advocated by Knowles (1975, 1984) and others (e.g., Candy, 2000; Doe et al., 2017; Fisher et al., 2001; Francom, 2010; Kerr et al., 2006; Meyer, 2010; Zhoc & Chen, 2016), it would be necessary for students to learn how to assess their level of SDL in each learning context, or to use a measure of SDL readiness (SDLR). This reiterates research findings that have identified the need in higher education to assess learner characteristics (e.g., SDL) and then match students with the most appropriate learning environment and instructional strategies (Alotaibi, 2016; Bawa, 2016; Kauffman, 2015; Kerr et al., 2006; Lee & Choi, 2011; Meyer, 2010; Peck et al., 2018; Slater & Cusick, 2017; Zhoc & Chen, 2016). This practice could not only help to improve student course satisfaction and academic success, but it could also decrease attrition rates in higher education (Bawa, 2016; Doe et al., 2017; Kauffman, 2015; Lee & Choi, 2011; Peck et al., 2018; Schulze, 2014).

In addition, researchers have found that SDL skills can be taught, especially with adult learners (Boyatzis, 2002; Candy, 2000; Garrison, 1997; Knowles et al., 1973/2015). In turn, teaching SDL strategies to adult learners can increase motivation, self-efficacy, self-management, emotional regulation, persistence, and satisfaction in either the traditional or online learning environments (Boyatzis, 2002; Knowles et al., 1973/2015; Lai, 2011; Macaskill & Denovan, 2013; Meyer, 2010; Song & Bonk, 2016; Song & Hill, 2007; Sumuer, 2018; Zhoc et al., 2018). In this way, SDL is related to academic success and lifelong learning outcomes in adult education (Candy, 2000; Cazan & Schiopca, 2014; Chan, 2018; Garrison, 1997; Hsu & Shiue, 2005; Knowles et al., 1973/2015; Meyer, 2010; Nikitenko, 2009; Schulze, 2014; Song & Bonk, 2016; Song & Hill, 2007; Sumuer, 2018; Zhoc et al., 2018).

The positive association between SDL and academic achievement (e.g., GPA) within traditional and online learning environments has been extensively researched and supported in the literature (Alotaibi, 2016; Fisher et al., 2001; Hiemstra, 2003; Hsu & Shiue, 2005; Knowles et al., 1973/2015; Lai, 2011; Lounsbury et al., 2009; Macaskill & Denovan, 2013; Meyer, 2010; Song & Hill, 2007; Stockdale & Brockett, 2011; Sumuer, 2018; Zhoc et al., 2018). The literature also supports the notion that SDL is a primary predictor of academic success outcomes (e.g., GPA, course completion) in both learning environments (Alotaibi, 2016; Cazan & Schiopca, 2014; Chan, 2018; Knowles et al., 1973/2015; Lai, 2011; Macaskill & Denovan, 2013; Nikitenko, 2009; Schulze, 2014; Song & Hill, 2007; Sumuer, 2018; Zhoc & Chen, 2016; Zhoc et al., 2018).

For instance, Alotaibi (2016) investigated the relationship between SDL and academic performance (e.g., GPA) in a convenience sample (N = 142) of final-year nursing and medical service undergraduate students attending a university in Saudi Arabia. The author used the SDLRSNE by Fisher et al. (2001) to measure SDLR and found that all three SDLR variables significantly ($p < .001$) related to GPA: self-management (r = .45), desire to learn (r = .52), and self-control (r = .46). Alotaibi (2016) concluded that SDLR is an important factor in enhancing academic performance in adult learners and recommended higher education institutions promote SDL development through individual assessments (e.g., SDLRS) and qualitative methods (e.g., interviews) to match students with the appropriate learning environment and instructional strategies.

Macaskill and Denovan (2013) examined how the psychological strengths that first year undergraduate students bring with them into the traditional university learning environment (e.g., autonomous learning skills) related to their academic achievement before and after an educational intervention (i.e., three seminars on their strengths and study skills). In a convenience sample (N = 139), these authors found that before the intervention, hope (defined as the belief in one's success) was the strongest predictor of self-esteem and autonomous [self-directed] learning, with the model accounting for 24%

of the variance (Macaskill & Denovan, 2013). After the intervention, entry [prior] grades were the strongest predictor of first year academic achievement (β = .31, p <.001) followed by levels of autonomous (that is, self-directed) learning (β = .21, p <.01), with the model accounting for 14% of the variance in academic achievement (Macaskill & Denovan, 2013). In other words, students who had higher levels of self-efficacy and self-esteem entering the university also had higher levels of autonomous learning (Macaskill & Denovan, 2013). In this sense, autonomous learning is not only an important predictor of academic achievement, but it is a psychological strength associated with confidence, as measured by self-efficacy and self-esteem, that can be assessed, taught, and encouraged to increase university and life success (Macaskill & Denovan, 2013). The current study examined whether SDL influences the academic achievement of adult learners in the online learning environment.

Some researchers (e.g., Cazan & Schiopca, 2014; Lounsbury et al., 2009) have found that SDL is a better indicator of academic success than personality. For instance, Lounsbury, Levy, Park, Gibson, and Smith (2009) investigated the relationships between SDL and academic achievement (cumulative GPA), personality traits (i.e., Big Five), life satisfaction, and other factors in an archived data set that consisted of data collected from students in middle school (age 12), high school, and college. The data source for the middle and high school students (N = 966) was from Lounsbury and Gibson (2001; as cited in Lounsbury et al., 2009). The data sources for the college students were from students participating in a First Year Studies Program and/or taking undergraduate psychology courses at a large, southeastern university (n = 1218) and from

Monster.Com's Making College Count 2009 program (n = 4125; as cited in Lounsbury et al., 2009). The SDL and personality measures for adults in the data set included (as cited by Lounsbury et al., 2009): The Resource Associates Self-Directed Learning Scale developed by Lounsbury and Gibson (2006), the Myers-Briggs Type Indicator, the NEO-PI-R Big Five Inventory, and the 16 PF fifth edition. The authors collected the students' cumulative GPAs from their school records.

Regarding the relationship between SDL and academic achievement, Lounsbury et al. (2009) found SDL significantly correlated (p < .01) with cumulative GPA for all grade levels (middle school, high school, and college). The strongest correlations were between SDL and higher grade levels. For example, in the high school sample for both 9th and 10th grades, r = .26, but for 12th grade, r = .37 (Lounsbury et al., 2009). In the college sample, the correlations between SDL and cumulative GPA were as follows: freshmen (r = .20), sophomores (r = .28), and juniors (r = .42). The authors concluded these results may reflect increased opportunities for students to practice SDL in higher grade levels. Lounsbury et al. (2009) also noted that there was a modest correlation range (r = .16 to r = .20) between SDL and age; however, the correlations did not increase chronologically or across all grade levels (Lounsbury et al., 2009). In this case, higher levels of SDL positively correlated with higher grade levels, higher GPAs, and even with higher levels of life satisfaction (r = .28, p < .01) and college satisfaction (r = .35, p < .01).

In terms of their investigation of the relationship between SDL and personality (i.e., Big Five, 16 PF 5th ed.), Lounsbury et al. (2009) found that SDL significantly correlated with three of the Big Five traits (Openness, Conscientiousness, and

Neuroticism). The strongest association was with Openness on both the Big Five ($r = .30$, $p < .01$) and the 16 PF ($r = .44$, $p < .01$) inventories. They concluded that the personality trait most characteristic of SDL was Openness (Lounsbury et al., 2009). The authors explained individuals higher in SDL would be expected to be higher in Openness, especially since one of the main expressions of Openness is learning new material (Lounsbury et al., 2009). In this sense, they also posited that SDL appears to be connected to a wide range of personality traits, so it does not seem to occur in isolation (Lounsbury et al., 2009). In other words, SDL may consist of a group of traits instead of just being a single personality trait (Lounsbury et al., 2009).

Lounsbury et al. (2009) further speculated that perhaps some personality traits (i.e., openness, emotional stability) are prerequisites for SDL, and they recommended this as an important topic for future research. The current investigation is a response to this recommendation in that it examined the relationship between SDL and EI, which is another learner characteristic positively associated with personality and academic success (discussed previously in this chapter), and the impact their relationship has on academic success in the online learning environment.

As a response to Lounsbury et al. (2009), Cazan and Schiopca (2014) analyzed the relationships between SDL, personality traits, and academic achievement (GPA) in a convenience sample of first and third year Romanian undergraduate students ($N = 121$) in a traditional learning environment. The Self-Rating Scale of Self-Directed Learning (SRSSDL) developed by Williamson (2007) was used to measure SDL, and the IPIP-50 developed by the International Personality Item Pool (IPIP) project was used to measure the Big Five dimensions of personality (Openness, Extraversion, Emotional Stability, Conscientiousness, and Agreeableness). The authors stated that academic achievement was measured by the academic results collected for all participants at the end of the academic year (Cazan & Schiopca, 2014).

Like Lounsbury et al. (2009), they found that SDL and the Big Five personality traits were correlated, with the highest positive correlation between SDL and Openness ($r = .243$, $p < .001$). Also, like Lounsbury et al. (2009), Cazan and Schiopca (2014) found that all areas of SDL significantly and positively correlated with academic achievement, with the associations ranging from $r = .21$ to $r = .23$ ($p < .05$). The authors further tested these associations using multiple regression analysis and found SDL significantly predicted academic achievement ($R^2 = .069$, $p = .004$). However, even though the model was significant ($F(5,120) = 2.33$, $p = .04$), personality traits were not significant predictors of academic achievement (Cazan & Schiopca, 2014). Together, SDL and year of study explained 14% of the variance in academic achievement (Cazan & Schiopca, 2014). Cazan and Schiopca (2014) agreed with Lounsbury et al. (2009) in that SDL cannot be readily categorized as a single personality trait. They also suggested that there may be a possible mediation, or indirect effect, between SDL and other psychometric properties (i.e., social interactions) in the prediction of academic success.

The current investigation is a response to Cazan and Schiopca's (2014) future research recommendation to further explore SDL as a predictor of academic achievement, as well as the indirect effects of SDL on the relationship between another psychometric property (in this case, EI) and academic success in the online learning environment.

SDL and online learning. Some researchers have posited that online learning is more conducive for the SDL process than the traditional learning environment (e.g., Bawa, 2016; Chan, 2018; Hsu & Shiue, 2005; Lai, 2011; Nikitenko, 2009; Schulze, 2014; Song & Bonk, 2016; Song & Hill, 2007; Sumuer, 2018). One of the earliest studies to determine this was by Hsu and Shiue (2005). These authors examined the effects of SDLR on academic achievement (i.e., final course grade) and compared the differences between traditional (on campus) and distance (teleconferenced) learning environments in a convenience sample (N = 126) of Taiwanese undergraduates. Participants were randomly assigned to either the traditional classroom or the distance course.

Like other SDL researchers before them (i.e., Fisher et al., 2001; Guglielmino, 1977; Knowles, 1984), Hsu and Shiue (2005) defined SDL as a "level of readiness," or capacity for SDLR. In this sense, SDLR indicates an individual has the capacity to develop SDL skills, which exist along a continuum and are present in each person to some degree (Fisher et al., 2001; Guglielmino, 1977; Hsu & Shiue, 2005; Knowles et al., 2015). Hsu and Shiue (2005) used Guglielmino's SDLRS/LPA to assess SDLR, while the university provided participants' prior GPAs, and the instructor provided participants' final grades (i.e., achievement scores).

As they expected, Hsu and Shiue (2005) found a statistically significant relationship between teaching method (traditional, distance) and achievement scores (t = 2.68, $p < .01$) as well as between achievement scores and prior GPAs (t = 2.13, $p < .05$). These findings supported previous research on prior GPA as one of the most important predictors of academic success in both traditional and distance learning environments (i.e., Anderson, 1993, and Long, 1991, as cited in Hsu & Shiue, 2005). The findings likewise reinforced previous research that supported distance learners producing equivalent academic achievement to their on-campus counterparts (i.e., Anderson, 1993, Payne, 1997, and Russell, 1994, as cited in Hsu & Shiue, 2005).

Hsu and Shiue (2005) also made an unexpected discovery: They found that SDLR moderated the relationship between the distance teaching method and academic achievement (Hsu & Shiue, 2005). Hsu and Shiue (2005) reported that by itself, SDLR did not have a statistically significant effect on academic achievement. However, they found that SDLR had a statistically significant interaction effect on the relationship between distance education and academic achievement (t = 2.04, p< .05). In other words, when combined with the distance teaching method, SDLR strengthened the relationship between distance education and academic achievement (Hsu & Shiue, 2005). In this case, the value of R^2 went from .30 to .48 (Hsu & Shiue, 2005). These findings supported SDLR as an important predictor in OS.

Hsu and Shiue (2005) concluded that students with stronger educational backgrounds (i.e., higher prior GPAs) and higher levels of SDLR will have a greater advantage in taking distance learning courses. In this way, the authors concluded that assessing students' SDLR may serve as a key factor in appropriate placement in classes and learning environments (traditional, online) that better align with the instructional and support needs of higher education students (Hsu & Shiue, 2005).

In her dissertation, Chan (2018) explored SDL skills and video use within a convenience sample of Malaysian undergraduates (N = 309) taking courses in digital animation (DA) in an online, video-based learning environment. She used the SDLRSNE developed by Fisher et al. (2001) to measure participants' SDLR, and she constructed a survey to question them on their self-concept as independent learners and on their use of online videos (VidUse) to learn DA course concepts (Chan, 2018). Chan (2018) found no significant differences between SDLR and gender, age, or year of study. However, she did find significant differences between SDLR and self-concept as an independent learner (r = .332, p < .001) and between SDLR and use of independent learning time (r = .247, p < .001). More specifically, students who had higher SDLR scores (≥ 150) identified more as independent learners and used more independent learning time (ILT; Chan, 2018).

To further explore the relationships between SDLR and VidUse, Chan (2018) used linear and multiple regression analysis. A significant linear regression demonstrated that higher levels of VidUse led to higher levels of SDLR (F(1,307) = 92.3, p < .01, R^2 = .231). Next, a significant multiple regression (F(2, 306) = 26.861, p < .001, R^2 = .144) showed that both total SDLR (β = .033, p < .005, 95% CI [.012, .055]) and VidUse (β = .063, p < .001, 95% CI [.035, .092]) scores were significant predictors of DA skills. A second significant multiple regression (F(7, 301) = 8.949, p < .001, R^2 = .153) of the subscales supported SDLR (β = .081, p < .001, 95% CI [.012, .055]) as being a stronger predictor of DA skills than VidUse (β = .072, p < .05, 95% CI [.015, .129]). In this case, Chan (2018) found SDLR to be a stronger predictor of online learning than the use of videos (e.g. YouTube).

Chan's (2018) findings support the use of the SDLRSNE (adapted for online education as the SDLRS) developed by Fisher et al. (2001) to measure SDLR in adult online learners. Her findings also support SDL as an important predictor of academic success for adult learners in the online learning environment. In the current investigation, the SDLRS will be used to measure SDL in a sample of adult learners taking online courses as part of their degree programs.

In another dissertation study, Nikitenko (2009) investigated the relationships between SDL and course learning outcomes in the affective domain (i.e., perceived learning, course satisfaction), age, and prior e-learning experience within hybrid and online learning environments. The author surveyed a convenience sample (N = 240, 59% female) of adult learners (153 undergraduates, 87 graduate) who had completed online and/or hybrid courses, and who were in the second year of their degree programs at a private nonprofit university on the west coast of the U.S. It should be noted here that all graduate student participants (n = 87) had only completed hybrid courses, while the undergraduate students represented a more even mix of taking online (n = 88) or hybrid (n = 65) classes (Nikitenko, 2009).

Nikitenko (2009) measured SDLR with the SDLRS (Fisher et al., 2001). Even though the SDLRS was reduced from 52 items to 40 items (Fisher et al., 2001), he used the original 52 item instrument, except for two items not related to the study, to retest the expanded scales (Nikitenko, 2009). Following the same guidelines established by Fisher et al. (2001), higher scores of SDLR (≥ 150) would indicate readiness for SDL. Nikitenko (2009) used the Online Learning Environment (OLE) instrument to measure online learning outcomes in the affective domain (i.e., perceived learning, course satisfaction). He added two qualitative items to measure engagement: (1) “How often did you login to the course site per week?” and (2) “What is your level of enjoyment participating in online discussion forums?” (Nikitenko, 2009, p. 90). However, due to a low reliability finding using Cronbach’s coefficient alpha (α = .37), engagement was excluded from further statistical analysis (Nikitenko, 2009). The two scales measuring age and prior e-learning experience were also excluded from further statistical analysis because of having either a very weak correlation (i.e., age, r = .01) or a nonsignificant finding (Nikitenko, 2009).

Nikitenko (2009) found no statistically significant differences between undergraduate and graduate participants, so he combined both for the regression analyses in his comparison between online and hybrid groups. In both groups, he found that the total SDLR score was the strongest predictor of OLE (Nikitenko, 2009). Nikitenko (2009) reported that the total SDLR score accounted for 19% (R^2 = .19) of the variance in course learning outcomes in the online learning format.

In their review of the literature, Lee and Choi (2011) examined 69 factors influencing students to drop out of online courses and found student factors (i.e., psychological attributes, relevant skills) consisted of more than half (55%) of them. Psychological attributes (i.e., motivation, self-efficacy) made up the largest percentage of student factors (20%), followed closely by relevant computer, technology, and study skills (16%; Lee & Choi, 2011). The authors also found a positive relationship between online course completion and OS (i.e., GPA) and persistence. In other words, the more online courses students completed, the longer they persisted in online education, which in turn correlated with higher academic achievement and course satisfaction (Lee & Choi, 2011).

For future research, Lee and Choi (2011) recommended that the interrelationships of learner characteristics (specifically, psychological attributes) be examined, such as their direct and indirect effects on academic success in online education. The current investigation can be considered a response to this call of research because it examined the interrelationships between two psychological attributes (EI and SDL) and their direct and indirect effects on the OS of adult learners.

Other researchers have found that SDLR is more of a reliable indicator of online course completion than having technical competence (e.g., Lai, 2011; Schulze, 2014). For instance, Lai (2011) explored the relationships between SDLR, network literacy, and OLE, as well as the predictive ability of SDLR and network literacy on OLE in a sample (N = 283, 51.2% male) of Taiwanese civil servants. He used Guglielmino’s (1977) SDLRS/LPA to measure participants’ SDLR, where SDLR was operationalized as quantifying participants’ attitudes, values, and abilities to be self-directed (Lai, 2011). Of the original eight subscales of the SDLRS/LPA, Lai (2011) used only four to measure SDLR in participants: active learning, independent learning, love of learning, and creative learning. He explained that these four were selected based on the research settings and the suggestions from the online faculty (Lai, 2011). The measurements used to measure network literacy and OLE were modified from existing instruments (Lai, 2011).

Lai (2011) found that all four subscales of the SDLRS significantly correlated ($p < .001$) with total OLE scores: active learning had the strongest correlation with OLE ($r = .51$) followed by love of learning ($r = .48$), creative learning ($r = .46$), and independent learning ($r = .40$), respectively. He also found that network literacy significantly correlated ($p < .01$) with OLE: information evaluation had a stronger correlation with OLE ($r = .54$) then Internet skill ($r = .48$). Lai (2011) then used multiple regression analysis to determine how well SDLR and network literacy could predict OLE. He found SDLR significantly predicted ($F = 32.13$, $p < .001$) participants' OLE (Lai, 2011). Next, a significant stepwise regression ($F = 98.20$, $p < .001$) revealed that three of the SDLRS subscales, active learning (.27), love of learning (.20), and independent learning (.19), accounted for 32% of the variance in the total scores of OLE (Lai, 2011). Then, another significant stepwise regression ($F = 61.25$, $p < .001$) showed that both dimensions of network literacy, information evaluation (.39) and Internet skill (.20), also significantly predicted OLE and accounted for 30% of the variance in OLE total scores (Lai, 2011).

Lai's (2011) findings support SDL (operationalized as SDLR) as an important component of online learning and how it significantly relates to online learners' attitudes and achievements (Lai, 2011). They also support SDL as a predictor of OLE, which in turn relates to OS (Lai, 20ll). Last, the findings support the notion that SDL is more important in OS than network literacy because SDLR was the strongest predictor of OLE. In this sense, SDL skills can help adult learners to develop their network literacy and facilitate positive online learning experiences (Hsu & Shiue, 2005; Lai, 2011; Song &

Hill, 2007). Lai (2011) recommended future researchers should continue to focus on the impact of adult learners' SDL in online learning success.

In her dissertation study, Schulze (2014) explored the relationship between SDL and course completion in adult learners (*N* = 583, 53% female) enrolled in a massive open online course (MOOC). She used the SDLRS (Fisher et al., 2001) to measure SDLR, where scores 150 and greater indicated the learner is ready for SDL. In this case, 81% of participants were categorized as ready for SDL (Schulze, 2014). Course completion was measured by a self-report survey with four open-ended questions (Schulze, 2014). From this, she found 61.2% of the participants reported they completed all the MOOC requirements (Schulze, 2014). However, Schulze (2014) noted this rate was inflated because of the 21,912 registrants for the MOOC, only 1,475 (7%) completed all the MOOC requirements. One reason for this could be from the self-report nature of the measure and self-selection bias (Schulze, 2014). Another explanation could be that the 583 participants who participated in the study were also part of the 1,475 learners who officially completed all the MOOC requirements for course credit (Schulze, 2014).

Schulze (2014) used correlational, Chi-square, ANOVA, and MANCOVA analyses to explore the relationship between SDLRS and MOOC completion. Like Lai (2011) and Nikitenko (2009), she found a significant correlation between total SDLRS scores and MOOC completion ($r = .175$, $p < .01$). Schulze (2014) noted that even though the Pearson correlation indicated a weak relationship between SDLRS and MOOC completion, with a small effect size ($R^2 = .013$), higher SDLRS scores were associated with higher MOOC online course completion rates. Using Pearson's Chi-squared test, Schulze (2014) did not find significant differences in gender, age, education level, or previous MOOC experience between adult learners who completed the MOOC and those who did not complete the MOOC. However, she did find statistically significant differences ($p < .05$) in the English speaking ability of adult learners ($p = .046$), and the reason for enrolling in the MOOC ($p = .024$), between those participants who completed the MOOC compared to those who did not complete the MOOC.

To further explore the relationships between these variables (i.e., English speaking ability, reason for enrolling in the MOOC, and SDLR), Schulze (2014) conducted a MANCOVA because there were two dependent variables: SDLRS and MOOC completion. She found English speaking ability was the only variable to have a mediating effect on SDLRS scores (partial $ETA^2 = .032$, $p < .001$) and MOOC completion (partial $ETA^2 = .017$, $p = .020$). One possible explanation was that participants were required to have some English ability, so those who were not fluent in English did not participate in the study (Schulze, 2014). Schulze (2014) also conducted an ANOVA to test whether adult learners who scored high in SDLR were more likely to complete the MOOC. She found the means were statistically significant ($p < .001$) with a moderate effect size ($d = .40$). In other words, adults with higher levels of SDLR completed more of the MOOC (Schulze, 2014).

Schulze's (2014) findings support how online courses (e.g., MOOCs) may not be appropriate for all types of learners, such as those with limited English-speaking ability or those with lower SDLR. However, the generalizability of her results was limited to registrants of a single MOOC offered in English (Schulze, 2014). Schulze (2014) recommended future research should examine the relationships between SDLR and online course completion among registrants in other MOOCs or in different learning platforms (i.e., asynchronous online courses in higher education) to help generalize findings to other populations.

From this review (i.e., Chan, 2018; Hsu & Shiue, 2005; Lai, 2011; Nikitenko, 2009; Schulze, 2014), there is evidence that supports positive correlational links between SDL and OS (i.e., GPA) in adult learners. The current investigation explored whether SDL predicted the OS of adult learners and mediated the relationship between EI and academic success outcomes (i.e., GPA) within the online learning environment.

Mixed findings in the literature. As reviewed above, most research findings were in support of the positive correlational link between SDL and academic success (e.g., GPA) in both traditional and online learning environments (e.g., Alotaibi, 2016; Cazan & Schiopca, 2014; Chan, 2018; Schulze, 2014). However, there were a few studies from this review that found no association between SDL and academic success in either the traditional (i.e., Koc, 2019) or online learning environment (i.e., Chou & Chen, 2008). For instance, Chou and Chen (2008) investigated whether SDL was a key factor leading to academic success in the online learning environment. The authors examined six empirical studies: three from Asia and three from the United States (Chou & Chen, 2008). Here, it is important to note that five of the six studies used Guglielmino's (1977) SDLRS/LPA to measure SDL. Of the six studies Chou and Chen (2008) reviewed, only one (Corbeil, 2003, as cited in Chou & Chen, 2008) demonstrated a strong positive relationship ($r = .51$, $p < .01$) between SDL and academic success (i.e., course final grade) in online graduate students (*N* = 98) and indicated that SDL was a significant predictor in OS ($R^2 = .55$, $p < .01$). However, this was the only study to not use the SDLRS/LPA to measure SDL, so no further comparisons could be made between findings (Chou & Chen, 2008).

Chou and Chen (2008) concluded that theoretically there is a positive relationship between SDL and academic success, but that the empirical results are not consistent. They recommended future studies were needed to support SDL as key factor in OS as well as to explore other factors that could affect adult learners' academic performance. In a follow-up experimental study, Chou (2013) explored the effect of SDL (using the SDLRS/LPA) on the online academic performance (i.e., test scores) of undergraduate students (*N* = 126) attending a public university in the United States. Chou (2013) did not find a statistically significant relationship between SDL and OS and concluded that other learner characteristics should be explored.

In a more recent study, Koc (2019) explored the possible relationships between two learner characteristics, EI and SDL, and academic success (GPA) in a convenience sample (*n* = 221) of traditional undergraduate students attending a private university in Turkey. He used a subscale of the Emotional Intelligence Scale (EIS) – the Assessing Emotions Scale (AES) - developed by Schutte et al., 1998 (as cited in Koc, 2019) to measure EI, and Guglielmino's SDLRS/LPA to measure SDL. Koc (2019) found that both EI ($r = .036$, $p = .599$) and SDL ($r = .069$, $p = .309$) did not significantly correlate with GPA. However, he did find a significant and strong correlation between EI and SDL ($r = .629$, $p < .01$), which supported previous findings (i.e., Bar-On, 2006; Muller, 2007;

Zhoc & Chen, 2016; Zhoc et al., 2018). Koc (2019) recommended future research should focus more on the relationship between EI and SDL and their impact on academic success. The current investigation can be considered a response to this call because it examined the relationship between EI and SDL and its impact on the academic success of adult learners in the online learning environment.

SDL and other learner characteristics. Most of the mixed findings in SDL research were related to the relationships between SDL and learner demographics (i.e., age, gender, educational level) in both the traditional and online learning environments. For instance, some researchers (e.g., Cazan & Schiopca, 2014; Lounsbury et al., 2009; Slater, Cusick, & Louie, 2017) found that age, gender, and/or education level were significantly correlated with levels of SDL. Other researchers found no statistically significant differences between these factors (e.g., Chan, 2018; Nasir et al., 2014; Schulze, 2014).

Recently, Slater and Cusick (2017) conducted a pioneer review of SDL and learner characteristics in health professional precertification programs (e.g., medicine, nursing). They examined 49 studies and found the two most used measurements were Guglielmino’s (1977) SDLRS/LPA and the Fisher et al. (2001) SDLRSNE, 49% and 43% respectively (Slater & Cusick, 2017). Slater and Cusick (2017) found that the most common learner characteristics measured were age (32.7%), gender (34.7%), educational level (34.7%), and program delivery (32.7%). However, the findings in the literature on the relationship between these learner characteristics and SDL were mixed, and the authors could not determine a trend (Slater & Cusick, 2017). They noted that few studies

(n = 2) found significant differences related to gender (Slater & Cusick, 2017). Slater and Cusick (2017) pointed out two common themes between age and education level were “the passage of time” and “accumulation of life experience” (p. 31). The authors concluded that further research is needed on these characteristics and their (independent or combined) effects on SDL in adult learners (Slater & Cusick, 2017).

In a follow-up study, Slater, Cusick, and Louie (2017) investigated the relationships between SDL and the learner characteristics previously associated with high levels of SDLR (i.e., age, gender, discipline, previous education, and personality traits) in a convenience sample (n = 407) of first year undergraduates. The authors used Guglielmino’s (1977) SDLRS/LPA to measure SDL and the Big Five personality trait inventory from the IPIP (Slater et al., 2017). All other participant data (i.e., age, gender, discipline, and previous education) were collected with participant permission from the enrollment records at the university, de-identified, and then matched with participants’ surveys by an independent administrative officer prior to researcher access (Slater et al., 2017).

Slater et al. (2017) found females had higher SDLR scores than males ($t(405) = 2.62$, $p = .009$, $d = .264$), and that older students had higher SDLR than younger students; however, the authors noted there was a weak correlation ($r = .266$, $p < .001$) between SDLR and age (Slater et al., 2017). Slater et al. (2017) also found SDLR scores differed significantly depending on participant discipline of study ($F(4402) = 5.267$, $p < .001$, $\eta^2 = .05$) and highest level of previous education ($F(6400) = 4.720$, $p < .001$, $\eta^2 = .066$). The authors noted how the effect sizes for each of these demonstrated only small effects when using Cohen's guidelines (Slater et al., 2017). They concluded how this highlights the need for age, gender, discipline, and previous education to be included in research studies as potential influencing factors or confounders on SDL (Slater et al., 2017).

In addition, Slater et al. (2017) found SDLR was significantly associated ($p < .001$) with increased scores on each of the Big Five personality traits (agreeableness, $r = .44$; conscientiousness, $r = .48$; emotional stability, $r = .17$; extroversion, $r = .22$ and intellect/imagination, $r = .541$). The authors noted how these effects ranged from small (i.e., emotional stability, extroversion) to large (i.e., intellect/imagination). Given this, they further explored the relationships in regression analyses and found that four of the Big Five personality traits (i.e., intellect/imagination, conscientiousness, agreeableness, and emotional stability), previous education, and discipline accounted for 52.9% of the variance in SDLR (Slater et al., 2017). Slater et al. (2017) recommended that future research should explore how other personality traits, and other learner characteristics not explored in their study, impact SDL.

The current investigation examined the impact of SDL and EI on the academic success of adult learners in the online learning environment. From the mixed findings reviewed above, the effects of age, gender, and education level were controlled for by inputting them into the mediation model as covariates (Field, 2018; Hayes, 2018; Slater et al., 2017).

Indirect findings for SDL. From this review, the relationships between SDL, learner characteristics, and academic success remain inconclusive (e.g., Koc, 2019; Slater & Cusick, 2017; Zhoc et al., 2018). To better understand these mixed findings, some researchers (e.g., Schulze, 2014; Sumuer, 2018) have recently examined the indirect effects of other learner characteristics (i.e., English speaking ability, use of technology) on the relationship between SDL and online learning outcomes. As mentioned previously, Schulze (2014) found a statistically significant relationship between SDL and online course completion ($d = .40$, $p < .001$) in adult learners ($N = 583$) enrolled in a MOOC. She further discovered that English speaking ability mediated, or influenced, this effect (Schulze, 2014). In other words, the higher participants rated their English speaking ability, the more they persisted in completing the MOOC (Schulze, 2014). Schulze (2014) noted that this effect could be explained by how participants were required to have some English speaking ability, and she recommended that future research examine the direct and indirect effects of SDL and learner characteristics on academic success in other online learning platforms (e.g., asynchronous higher education courses). The current study was a response to Schulze (2014) because it examined the impact of SDL and EI on the OS (i.e., GPA) of adult learners.

In a more recent study, Sumuer (2018) investigated factors (i.e., SDLR, use of Web 2.0 tools, self-efficacy) as possible predictors of students' SDL with technology in an online learning environment with a convenience sample ($N = 153$, 79.1% female) of undergraduate students at a public university in Turkey. He used the following measurements (as cited by Sumuer, 2018): The SDLRS (Fisher et al., 2001); the Self-Directed Learning with Technology Scale for Young Students; the online communication self-efficacy subscale from the Online Learning Readiness Scale; the Computer Self-Efficacy Belief Scale; and an adapted scale to measure use of Web 2.0 tools. Sumuer

(2018) also included questions related to demographics, students' computer knowledge level, computer experience, computer use, and their comfort level in using a computer.

After conducting correlational and regression analyses, Sumuer (2018) found a significant correlation between SDLR and SDL with technology (SDLt; $r = .37$, $p < .001$) and smaller significant correlations between SDLt and use of Web 2.0 tools (UWTL; $r = .29$, $p < .001$), online communication self-efficacy (OCSE; $r = .26$, $p < .001$), and computer self-efficacy (CSE; $r = .22$, $p < .001$). In Sumuer's (2018) regression model (Step 1), SDLR accounted for 14% of the variance in SDLt ($F(1, 151) = 23.99$, $p < .01$) and SDLR combined with use of UWTL (Step 2) accounted for 19% of the variance in SDLt ($F(2, 150) = 17.08$, $p < .01$, $\Delta R^2 = .05$). The variance in the model remained at 19% with the addition of OCSE (Step 3) and CSE (Step 4), $p = .30$ and $p = .90$ respectively (Sumuer, 2018). In other words, SDLR ($\beta = .31$, $p < .01$) and UWTL ($\beta = .20$, $p < .05$) were found to be the only significant predictors, with SDLR being the most important predictor of SDLt (Sumuer, 2018). This supports previous research where SDL (operationalized as SDLR) was found to be the most important predictor of learning outcomes with adult learners in either the traditional learning (e.g., Cazan & Schiopca, 2014; Macaskill & Denovan, 2013; Zhoc & Chen, 2016) or online learning (e.g., Chan, 2018; Lai, 2011; Schulze, 2014) environments.

To further explore these relationships, Sumuer (2018) investigated for possible indirect effects of these variables by conducting mediation analysis using a bootstrap confidence interval method. In this method, the bootstrap confidence intervals were calculated by "repeatedly random resampling from the original sample" and then estimating the indirect effect in each sample (Sumuer, 2018, p. 35). Sumuer (2018) conducted this method using the PROCESS macro for SPSS (http://www.processmacro.org) developed by Hayes (2018). If the upper and lower bounds of the 95% bootstrap confidence interval do not contain a zero, then with 95% confidence the indirect effect can be claimed as statistically significant (Sumuer, 2018).

In this way, Sumuer (2018) discovered that when controlling for SDLR, UWTL mediated (influenced) the relationships between OCSE, CSE, and SDLt ($F(3, 149) = 14.46$, $p < .001$, $R^2 = .23$). He noted how the 95% bootstrap confidence intervals for OCSE (95% CI [.002, .099]) and CSE (95% CI [.013, .121]) were above zero and concluded that there were significant indirect effects on the relationships between CSE, OCSE, and SDLt through the influence of UWTL (Sumuer, 2018). Sumuer (2018) emphasized how the findings of this study not only supported SDL as an important predictor in online learning, but how UWTL can indirectly influence students' OCSE and CSE in the online learning environment. In this sense, Sumuer (2018) suggested adult learners be taught SDL skills and provided guidance in the use of Web 2.0 tools in the online learning environment to improve their success.

These findings also support previous researchers (e.g., Candy, 2000; Cazan & Schiopca, 2014; Knowles et al., 1973/2015; Macaskill & Denovan, 2013; Meyer, 2010; Zhoc et al., 2018) who have recommended that improving SDL in adult learners could be valuable for institutions of higher education and professional development, to not only help students increase their academic success in either the traditional or online learning environment, but also help them to become lifelong learners and better self-manage their daily lives. In turn, improving student SDL could also help to reduce the high attrition rates in online education (Doe et al., 2017; Kaufman, 2015; Peck et al., 2018). Like Sumuer (2018), the SDLRS (Fisher et al., 2001) will be used in the current study to explore the impact of SDL in the online learning environment.

SDL as a mediator. Some researchers (e.g., Hsu & Shiue, 2005; Zhoc et al., 2018) have investigated the indirect effects of SDL on academic success in both traditional and online learning environments. As mentioned previously, Hsu and Shiue (2005) found that SDL (operationalized as SDLR) moderated, or strengthened, the relationship between distance education and academic achievement ($p < .05$, $\Delta R^2 = .18$), but not for the relationship between on campus education and academic achievement ($p = .07$). In other words, when combined with the distance teaching method, SDL strengthened the relationship between distance education and academic achievement (Hsu & Shiue, 2005).

More specifically related to the purpose of the current study, Zhoc, Chung, and King (2018) examined the relationships between EI, SDL, and higher education learning outcomes (i.e., GPA, generic learning outcomes) in a convenience sample ($N = 560$, 61.8% female) of traditional undergraduate students at a university in Hong Kong. The authors used the following measures (as cited by Zhoc et al., 2018): The EIS (Schutte et al., 1998) to measure EI; the Self-Directed Learning Scale (SDLS; Lounsbury & Gibson, 2006) to measure SDL; and a student learning outcomes scale (SLOS) designed by the authors to measure students' GPA, student satisfaction with the university, and generic (cognitive, social, and self-growth) learning outcomes. In a correlational analysis, Zhoc et al. (2018) found that EI was significantly correlated with SDL (r = .46, p < .01), but not with GPA. However, the authors expected EI and SDL to be significantly correlated from previous research findings (e.g., Muller, 2007; Zhoc & Chen, 2016). Zhoc et al. (2018) noted that SDL significantly correlated with GPA (r = .12, p < .01) and generic learning outcomes (r = .26, p < .01). Using SEM, the authors found that EI had a strong association with SDL (β = .62, p < .005), with EI accounting for 38% (R^2 = .38) of the variance in SDL scores. EI was also significantly associated with generic learning outcomes (β = .20, p < .005), but not with GPA (Zhoc et al., 2018).

Zhoc et al. (2018) noted how the EIS subscale, emotional regulation of self (ERS), was the most influential (adj. R^2 = .21, F(3, 556) = 65.55, p < .001) because it accounted for the largest proportion of variance in SDL (Zhoc et al., 2018). They further surmised that ERS accounted for the most variance in SDL because emotional regulation is a crucial factor in fostering SDL (Zhoc et al., 2018). Also, from a previous study (i.e., Zhoc & Chen, 2016), Zhoc et al. (2018) expected to find SDL significantly associated with both GPA (β = .15, p < .005) and generic learning outcomes (β = .14, p < .005). These findings support previous researchers (e.g., Francom, 2010; Jossberger et al., 2010; Pilling-McCormick & Garrison, 2007) who found that SRL is part of SDL and that adults need both SDL and SRL to be successful lifelong learners.

To further explore the relationships between EI, SDL, and GPA, Zhoc et al. (2018) analyzed the indirect effects of SDL and discovered that it mediated, or influenced, the effects of EI on GPA (β = .14, p < .05). In other words, EI had no impact on GPA by itself, but the authors found it had a significant impact on GPA through the influence of SDL (Zhoc et al., 2018). The authors concluded how their study supports a strong correlation between EI and SDL, as found in Muller (2007) and Zhoc and Chen (2016; Zhoc et al., 2018). As mentioned previously, Koc (2019) also found a strong correlation between EI and SDL and no significant correlation between EI and GPA. However, unlike previous studies (i.e., Zhoc & Chen, 2016; Zhoc et al., 2018), Koc (2019) did not find a significant correlation between SDL and GPA. Zhoc et al. (2018) recommended their study should be replicated in other institutions of higher education.

The current investigation was a response to Koc (2019) and Zhoc et al. (2018) in the sense that it examined the relationships between EI, SDL, and academic success (i.e., GPA), and the indirect (mediated) effects of SDL on EI and academic success in adult learners. However, in contrast to Koc (2019) and Zhoc et al. (2018), the present study focused on participants in the online learning environment, used different measurements to assess EI (TEIQue-SF) and SDL (SDLRS), and different statistical software applications (i.e., PROCESS) to conduct data analyses.

EI, SDL, and online readiness. In the online environment, researchers (i.e., Buzdar et al., 2016; Engin, 2017) found positive links between EI and/or SDL and OLR. In a response to Berenson et al. (2008), Buzdar et al. (2016) examined EI as a predictor of online readiness in a random sample (N = 432) of graduate students in their third or fourth semester of their Master degree programs at a university in Pakistan. The authors used an ability EI scale developed by Wong and Law (2002; as cited by Buzdar et al., 2016) to measure EI, and to measure online readiness, they used the OLRS developed by Hung et al. (2010; as cited by Buzdar et al., 2016). They noted how all aspects of EI and

OLRS were significantly and positively correlated (Buzdar et al., 2016). Buzdar et al. (2016) found strong correlations between EI and OLR (r = .521, p < .01) as well as between EI and a subscale of the OLRS, SDL (r = .603, p < .01). They noted participants had higher scores in EI on the subscale self-emotions appraisal (SEA; M = 3.18, SD = .561) and higher scores in OLR on the subscales motivation for learning (MFL; M = 3.31, SD = .557) and SDL (M = 3.24, SD = .621). In their regression model (F(4, 427) = 46.658, p < .001), the authors found a large effect (adj. R^2 = .298) and that all four subscales of the EI scale (i.e., self-emotions appraisal, others-emotions appraisal, use of emotion, and regulation of emotion) collectively accounted for 29.8% of the variance in OLRS (Buzdar et al., 2016). They concluded that student readiness and performance in online learning can be strengthened through EI awareness and practice (Buzdar et al., 2016).

In following Buzdar et al. (2016), Engin (2017) also investigated the relationship between EI and OLR and whether EI was a predictor of OLR. Participants (N = 95, 51.6% male) were sophomore undergraduates who took the Computer II online course at a university in Turkey during the 2014 – 2015 school year. The author used the OLRS (Hung et al., 2010; as cited by Engin, 2017) and the Trait Emotional Intelligence Scale – Short Form (TEIS) developed by Petrides and Furnham (2001; as cited by Engin, 2017). Engin (2017) noted how participants scored medium levels of OLR, with the highest mean scores in online communication self-efficacy (OCSE; M = 3.667, SD = .888) and SDL (M = 3.640, SD = .674). The author also noted that participants scored above-medium levels in EI, with the highest mean scores in self-control (*M* = 5.058, *SD* = 1.197) and social skills (*M* = 5.034, *SD* = .640).

Using correlational analysis, Engin (2017) found a strong correlation between self-control (EI) and learner control (OLR; $r = .97$, $p < .01$) as well as moderate correlations between social skills (EI) and four subscales of OLR ($p < .01$): learner control ($r = .57$), motivation to learn ($r = .73$), online communication self-efficacy ($r = .68$), and SDL ($r = .65$), respectively. In other words, as levels of EI (i.e., self-control, social skills) increased, the levels of OLR increased (Engin, 2017). Next, Engin (2017) conducted regression analysis to assess the predictive power of EI on OLR. The author found social skills (EI) was a significant predictor ($p < .01$) of all five subscales of OLR: computer/Internet self-efficacy ($\beta = .67$, $R^2 = .47$), learner control ($\beta = .93$, $R^2 = .95$), motivation to learn ($\beta = .71$, $R^2 = .55$), online communication self-efficacy ($\beta = .76$, $R^2 = .51$), and SDL ($\beta = .60$, $R^2 = .43$), respectively (Engin, 2017). Engin (2017) concluded that learners with higher levels of EI (i.e., self-control, social skills) could be more at an advantage in successfully implementing OLR behavior (i.e., motivation to learn, SDL) in the online learning environment.

In relation to the current investigation, these researchers (i.e., Buzdar et al., 2016; Engin, 2017) have found a positive correlation between EI and SDL (as a subscale of OLR) in the online environment. In building on these positive findings of EI, SDL, and online readiness, the present study examined the indirect effects of SDL on EI and the OS of adult learners.

EI, SDL, and OS. From this review, previous researchers have identified correlational links between adult learner characteristics such as self-efficacy, self-regulated learning, motivation, engagement, online learner readiness, SDL, and EI with online learning outcomes and student success (Berenson et al., 2008; Broadbent & Poon, 2015; Buzdar et al., 2016; Chan, 2018; Clayton et al., 2010; Doe et al., 2017; Engin, 2017; Goodwin, 2016; Hobson & Puruhito, 2018; Kauffman, 2015; Kerr et al., 2006; Kruger-Ross & Waters, 2013; Lai, 2011; Lee & Choi, 2011; Peck et al., 2018; Schulze, 2014; Song & Bonk, 2016; Sumuer, 2018; Vayre & Vonthron, 2017).

The current investigation examined the relationships between EI, SDL, and OS and the indirect effects of SDL on the relationship between EI and the OS of adult learners taking online courses for their degree program. The conceptual model for the study is presented below.

The conceptual model. The conceptual model (refer to Figure 1 in Chapter 1) demonstrates relationships between the following: EI and OS, SDL and OS, and the proposed mediation (indirect effect) of SDL on the relationship between EI and OS. This section briefly presents a discussion on how these three constructs (EI, SDL, and OS) have been linked together, applied in previous research, and in what ways this conceptual model adds to the literature.

As mentioned earlier, EI has been established as a primary predictor of student success in the online learning environment (Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Goodwin, 2016). Other researchers have linked SDL with online learning outcomes (Chan, 2018; Lai, 2011; Schulze, 2014; Song & Bonk, 2016; Sumuer, 2018). In alignment with the theoretical frameworks of this dissertation (Bar-On, 2006; Knowles, 1975, 1984), both EI and SDL include cognitive, metacognitive, and affective skills that can be taught and improved with increased self-awareness and practice (Bar-On, 2007, 2010; Berenson et al., 2008; Buzdar et al., 2016; Cazan & Schiopca, 2014; Goodwin, 2016; Knowles, 1975, 1984; Lai, 2011; Schulze, 2014; Song & Bonk, 2016; Sumuer, 2018; Zhoc et al., 2018).

A search of the research literature to date has yielded little research on the relationship between EI and SDL as predictors of online learner readiness (e.g., Buzdar et al., 2016; Engin, 2017) and nothing on the indirect role their relationship plays in the OS (e.g., GPA) of adult learners. The current investigation examined EI and SDL as predictors of OS, which was operationalized as GPA (e.g., Berenson et al., 2008; Goodwin, 2016; Zhoc et al., 2018). The findings may help to strengthen EI as a primary predictor of online student success and support SDL as a predictor of student success in the online environment. Mediation analyses are explored if EI and SDL are found to be significant predictors of OS and positively correlated with each other and OS.

A mediation refers to when a relationship between a predictor variable and an outcome variable can be explained by their relationship to a third variable known as the mediator (Field, 2018; Hayes, 2018). The proposed mediation model for this study (refer to Figure 1) is based on Baron and Kenny's (1986) classic (or triangle) mediation model and Hayes (2018) simple mediation model (No.4) in PROCESS. The mediation model (represented in Figure 1) demonstrates the relationships between the variables in this study: EI and SDL as the predictor variables; SDL as also the mediator variable; age, gender, and level of education as the covariate variables (see C in Figure 1); and OS as the outcome variable, operationalized as GPA.

As demonstrated in Figure 1, EI and SDL were hypothesized to each predict OS as supported by previous research on online learner readiness and success (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017). EI and SDL were also postulated to be positively and significantly correlated, just as previous researchers found them to be correlated in the traditional learning (e.g., Koc, 2019; Muller, 2007; Zhoc et al., 2018) and online learning (e.g., Buzdar et al., 2016; Engin, 2017) environments. Last, SDL was hypothesized to mediate, or influence, the relationship between EI and OS, while age, gender, and education level were controlled for as covariates. In other words, SDL would significantly influence the relationship between EI and OS, just as Zhoc et al. (2018) found in the traditional learning environment.

Summary and Conclusions

Online learning is now considered a critical long-term strategy for higher education to provide greater access to students and meet market demands (Bakia et al., 2012; de los Santos & Zanca, 2018; Peck et al., 2018; Seaman et al., 2018). At the same time, it has become a reliable alternative for populations (e.g., working parents, veterans, individuals with disabilities) who may not otherwise have had the opportunity to earn a degree or the prospect for better qualifications (Doe et al., 2017; Hassan et al., 2014; Peck et al., 2018). Modern society is rapidly changing, and to keep up, adult learners must balance work, family, and school, while also learning academic knowledge and professional skills vital for success in their careers as well as for living in a tech-savvy world (Bawa, 2016; de los Santos & Zanca, 2018; Doe et al., 2017; Zhoc et al., 2018).

However, despite the market demand for online courses, training, and degree programs, attrition rates for online education remain higher than traditional courses, with 40% to 80% of online students failing and/or dropping out compared to on campus students (Bawa, 2016; Choi & Park, 2018; Kauffman, 2015; Peck et al., 2018). There is a need for more research to better understand the reason for the high attrition rates in online learning and the low rates of OS (Bawa, 2016; Choi & Park, 2018; Goodwin, 2016; Kauffman, 2015; Knight, 2019).

A search of the literature revealed how learner characteristics play a significant role in whether learners achieve academic success in either the traditional classroom (e.g., Thomas et al., 2017; Zhoc et al., 2018) or online learning environment (e.g., Lee & Choi, 2011; Vayre & Vonthron, 2017). It has been suggested that successful learner characteristics in the traditional classroom (e.g., elaboration, rehearsal, self-regulation) may not transfer to the online learning environment (Bakia et al., 2012; Broadbent & Poon, 2015; Kauffman, 2015; Kerr et al., 2006; Lee & Choi, 2011; Peck et al., 2018). Online learners have different needs, and the “one size” approach used in traditional classrooms does not fit well in the online learning environment (Berenson et al., 2008; Han & Johnson, 2012; Knight, 2019; Van Doorn & Van Doorn, 2014, p.11).

Recently, researchers have found that online learning helps develop metacognition and problem-solving skills, which in turn help to develop motivation and self-efficacy, which then lead to increases in retention, satisfaction, and success (Doe et al., 2017; Hobson & Puruhito, 2018; Kauffman, 2015; Peck et al., 2018; Song & Bonk, 2016; Vayre & Vonthron, 2017). The attributes, metacognition and problem-solving, are both found in EI and SDL (Bar-On, 2006; Knowles, 1984; Koc, 2019; Zhoc et al., 2018). In this way, the active, process-based, and social aspects of online learning may help support EI (Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017) and SDL (Chan, 2018; Lai, 2011; Song & Bonk, 2016). Researchers (i.e., Berenson et al., 2008; Kauffman, 2015; Doe et al., 2017) have found successful online students to be self-motivated, self-directed, and self-regulated. Berenson et al. (2008) and Kauffman (2015) have also found them to have above average EI.

In this sense, previous research also supports EI and/or SDL as predictors of OS (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017), but there is little to no research involving both EI and SDL as predictors of academic success (i.e., GPA) in the online learning environment. Recent research findings support a positive correlation between EI and SDL on academic success in the traditional learning environment (e.g., Koc, 2019; Mueller, 2007; Zhoc et al., 2018). Zhoc et al. (2018) also discovered that SDL mediated, or influenced, the relationship between EI and academic success (i.e., GPA). However, what is not known is whether SDL mediated, or influenced, the relationship between EI and academic success in the online learning environment.

In addition, this study answered the call for more research to better understand EI and SDL as predictors of academic success in online learning, which in turn, could help to identify student characteristics and learning needs for OS (Berenson et al., 2008; Doe et al., 2017; Goodwin, 2016; Kauffman, 2015; Kerr et al., 2006; Knight, 2019; Lee &

Choi, 2011; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017). This information could also be used to help create more effective and efficient online courses, training, and degree programs (Bawa, 2016; Bakia et al., 2012; Doe et al., 2017; Kauffman, 2015; Majeski et al., 2017; Peck et al., 2018; Van Doorn & Van Doorn, 2014; Vayre & Vonthron, 2017).

Chapter 3 is a discussion of the methodology used to address the research questions and includes a description of the sample population, statistical and data techniques, and the ethical issues involved.

Chapter 3: Research Method

Introduction

This quantitative study used a convenience sample, recruited from either a fully online university's research participant pool or from social media websites, to examine EI and SDL as predictors of OS and to test for any indirect effects of SDL on the relationship between EI and OS. The research questions were as follows:

1. Does emotional intelligence (EI) relate positively and significantly to OS?

   Ho_1: EI does not positively nor significantly relate to OS.

   Ha_1: EI does positively and significantly relate to OS.

2. Does self-directed learning (SDL) relate positively and significantly to EI?

   Ho_2: SDL does not positively nor significantly relate to EI.

   Ha_2: SDL does positively and significantly relate to EI.

3. Does EI and/or SDL predict OS?

   Ho_3: EI and/or SDL does not significantly predict OS.

   Ha_3: EI and/or SDL does significantly predict OS.

4. If EI and SDL are predictors of OS, then does SDL have a mediating effect on the relationship between EI and OS?

   Ho_4: The relationship between EI and OS is not mediated by SDL.

   Ha_4: The relationship between EI and OS is mediated by SDL.

In this chapter, I describe the research design and approach, sample and sampling techniques, data collection, survey instruments used, and statistical analysis procedures.

Research Design and Rationale

A postpositivism worldview represents the traditional form of research, where the "lens of the researcher" is based on careful observation and measurement (Creswell & Creswell, 2018, p. 6). Quantitative research approaches align best with a postpositivism worldview because they test theories using instruments that carefully measure each variable of interest (Creswell & Creswell, 2018). The two most common quantitative approaches to research are surveys and experiments (Creswell & Creswell, 2018). A nonexperimental, survey design was chosen for this study because an experimental design requires manipulation of the variables, which in this case would be unethical, since the variables are psychological traits (e.g., EI) of human beings (Fisher, 2017). Therefore, a survey design was used to collect data, and regression and mediation analyses were conducted to analyze the data, which provided a better picture of the relationships between variables and allowed the proposed mediation model to be tested. This research design also allowed for predictions that could guide future online course and curriculum development, particularly with adult learners. Survey research can include cross-sectional or longitudinal studies using questionnaires and/or structured interviews for data collection (Cox, 2016; Creswell & Creswell, 2018). For this study, a cross-sectional survey design was chosen because data were collected at one point in time using an online questionnaire. For the sample of adult learners, an online questionnaire was the optimal choice for data collection because it allowed me to carry out the research process more efficiently and be less costly than an onsite questionnaire (Cox, 2016). It also provided participants with a greater sense of privacy, which could have helped to improve the response rate (Cox, 2016).

The quantitative nature of this study revolved around explanation, in the sense that surveys were used to explain the relationship between two or more variables (Cox, 2016). Multiple regression and mediation analyses were conducted to investigate the direct and indirect effects of EI and SDL on student success in the online learning environment. The predictor variables were EI and SDL. EI was operationalized using Bar-On's (2006) mixed EI model, where he defined EI as "a cross-section of interrelated emotional and social competencies, skills, and facilitators" that determine how effectively individuals can understand and express their emotions, understand and relate to the emotions of others, and cope with the daily demands of life (p. 3). SDL was operationalized using Knowles' (1975) SDL theory, where he defined it as a process where learners take initiative, diagnose their own learning needs, formulate goals, identify resources, select and implement appropriate learning strategies, and evaluate their own learning outcomes (p. 18). SDL was also the mediator variable – the intervening variable that may influence the relationship between the predictor and outcome variables (Field, 2018; Hayes, 2018). The outcome variable was OS, which was operationalized as GPA.

Methodology

Population

The target sample for this study was recruited from either a fully online university's participant research pool or from social media websites (i.e., Facebook, LinkedIn). All the recruitment sources consisted of adult learners (undergraduates and graduates), ages 18 or older, who were taking online courses as part of their degree programs. This convenience sample was chosen due to the online learning environment and OS components of the study. An online survey platform (i.e., freeonlinesurveys.com) hosted the online questionnaire and all data were self-reported by individuals who volunteered for the study.

Sample and Sampling Procedures

A convenient, nonprobability sampling technique was used to generate the sample, and as explained above, the sample was recruited from either a fully online university's participant pool or from social media websites. Research participants were adult learners (undergraduate or graduate students) taking online courses as part of their degree program. Eligible participants were 18 years or older, have taken at least one online course in their degree program, and have completed one quarter/semester towards their degree program. The study invitation (Appendix A) included a brief description of the study, the eligibility requirements, and provided interested participants with a link to click which would direct them to the online survey platform service (i.e., freeonlinesurveys.com) that was hosting the study. Interested participants were then asked to read through the consent form, and click the "Yes" button, and then "Next," if they gave their consent to participate in the study. This directed them to the online questionnaire. They could also click "No" on the consent form, to indicate they did not give their consent to participate in the study, and this would direct them to an exit page. After clicking on the link and providing their consent, participants completed an online questionnaire that consisted of a brief demographic survey (Appendix B) and two psychometric surveys: SDLRS and TEIQue-SF.

Sample Size

Multiple regression analysis uses multiple linear ordinary least squares (OLS) regressions with a fixed model R^2 increase (Field, 2018). The square of the multiple correlation coefficient (R^2) quantifies the distance the best fitting linear regression model has traveled between the reference model and the perfectly fitting model, which is interpreted as the proportion of variance in the outcome variable explained by the model (Field, 2018). To achieve a balance in detecting effects that do and do not exist using OLS regression, a standard approach is to select a medium effect size, .05 probability of Type I error, and .80 probability of Type II error (Field, 2018). Because mediation analysis would also be conducted, I followed Hayes' (2018) recommendation and used the mediation sample size table developed by Fritz and MacKinnon (2007). For a medium effect size of 0.15, alpha error probability of 0.05, and statistical power (1-β error probability) of 0.80, the minimum sample size required for this study was 71 participants. Multiple regression analysis assumes random sampling, interval-ratio level of measurement, and normal distribution of the target population (Field, 2018; Frankfort-Nachmias & Leon-Guerrero, 2015). However, the mediation analysis method I selected for this study, bootstrap resampling with replacement, does not require assumptions about the shape of the distribution (Hayes, 2018). Based on the central limit theorem, the sampling distribution will approximate a normal distribution, if the sample size is greater than 50 (Frankfort-Nachmias & Leon-Guerrero, 2015). To better meet the assumptions for multiple regression, the sample goal for this study was 142 (71 x 2).

Procedures for Recruitment, Participation, and Data Collection

Participants for the study were recruited from either a fully online university's research pool website or from social media websites (i.e., Facebook, LinkedIn). After receiving IRB approval for this study (No. 06-23-20-0543596), and approval from the group administrators of the social media websites on Facebook and LinkedIn, study invitations were posted online for each recruitment source. The study invitation (Appendix A) included a brief description of the study, the eligibility requirements, and a link that would direct individuals to the online survey platform service (i.e., freeonlinesurveys.com) that hosted the study. Volunteer members of the recruitment sources who were interested in participating could click on the link provided in the recruitment post, which then directed them to an informed consent page. If they agreed to participate in the study, they gave their consent, and acknowledged how they may exit the questionnaire at any time without consequences, by clicking the "Yes" button and then "Next," which then directed them to the online questionnaire. The online questionnaire consisted of three surveys (in this order): Demographics, Fisher et al. (2001) SDLRS, and Petrides' (2009) TEIQue-SF. The demographics survey (see Appendix B) consisted of five questions asking for the participant's age, gender, degree level of education they are seeking (undergraduate or graduate), total number of online courses taken for the degree program, and GPA. The other two surveys (SDLRS, TEIQue-SF) are discussed in more detail in the next section. The entire online questionnaire (Demographics, SDLRS, TEIQue-SF) took approximately 20 to 25 minutes to complete. Afterwards, participants were thanked and debriefed via an exit page on the survey platform service (i.e., freeonlinesurveys.com) website. The survey link would remain operational for one quarter (approximately three months) or until the sample goal (N = 142) was met.

Data were collected by the online survey platform service (i.e., freeonlinesurveys.com) and then downloaded by me through my account with the online survey platform service onto my home computer. Both the home computer and account with the online survey platform service are password protected. Only I had access to the home computer and to the data. No personal identifying information was collected. The data were imported into IBM SPSS 25, reviewed by me, and any incomplete questionnaires were eliminated from this study. After the data were cleaned, the SDLRS and TEIQue-SF were scored by me in Excel, and the total scores, along with age, gender, educational level, and GPA, were imported into SPSS. Next, preliminary data screening (e.g., histograms, scatterplots) was completed. Then, multiple regression and mediation were used to analyze the data.

Instrumentation and Operationalization of Constructs

Petrides’ (2009) TEIQue-SF was used to measure participants’ EI, and Fisher et al. (2001) SDLRS was used to measure participants’ SDL. These measurements are described in more detail below.

Trait Emotional Intelligence Questionnaire – Short Form (TEIQue-SF)

As a response to the label mixed EI model by earlier EI researchers (e.g., Goleman; Mayer and Salovey), Petrides and Furnham (as cited in Petrides, 2009) proposed the label trait emotional intelligence (trait EI). They chose the label trait EI to reflect the longstanding research on emotions and personality and how most of EI research, like personality, is based on self-reports (Petrides et al., 2016). Trait EI (or trait emotional self-efficacy) essentially involves people's perceptions and beliefs about their emotions (Petrides et al., 2016; Petrides & Mavroveli, 2018).

To measure trait EI, Petrides (2009) developed the TEIQue (full form) in 1998 as part of his doctoral dissertation using a content analysis of earlier emotion and EI research (e.g., Darwin, Gardner, Thorndike). It is a self-report measure, which has been translated into 20 languages (Petrides & Mavroveli, 2018). The TEIQue was normed on 1721 adults (912 female, 764 male, 61 unreported) in the UK (Petrides, 2009). The most current version consists of 153 items and provides scores on the 15 facets, four factors, and global trait EI (Petrides & Mavroveli, 2018). The 15 facets are narrower than the four factors (Petrides, 2009). The 15 facets that represent the sampling domain of trait EI are as follows: adaptability, assertiveness, emotion expression, emotion management (others), emotion perception (self and others), emotion regulation, impulse control, relationships, self-esteems, self-motivation, social awareness, stress management, trait empathy, trait happiness, and trait optimism (Petrides, 2009). The four factors of trait EI are well-being, self-control, emotional skills, and social skills (Petrides, 2009; Petrides & Mavroveli, 2018). Most of these facets and factors resemble what Bar-On (2006) found in his earlier EI research. In this way, Bar-On's (2006) model of EI and the TEIQue both represent similar constructs in the research literature on emotion and EI. Due to time constraints and the mediation model proposed for this study, the latest version of the

TEIQue (short form) was selected to measure EI in the online learning environment (e.g., Engin, 2017). This measure is described in more detail below.

The original TEIQue-SF (version 1.00) was normed on 1119 adults (653 females, 455 males, 11 unreported) in the UK (Cooper & Petrides, 2010; Petrides, 2009). The TEIQue-SF was later revised (four items were reworded) to align the short form with the current full form of the TEIQue (Cooper & Petrides, 2010). This latest version of the TEIQue-SF (version 1.50) was re-normed on 866 adults (416 females, 432 males, 18 unreported) in the UK (Cooper & Petrides, 2010). Like the TEIQue, the TEIQue-SF was designed to measure trait EI. However, because it consists of only 30 items (two items for each facet), only the total score is recommended for statistical analysis (Cooper & Petrides, 2010). It does not yield scores for each of the 15 facets (Cooper & Petrides, 2010). It is possible to derive scores on the four factors, but this is not recommended because the internal consistency of each factor averages .69 (Cooper & Petrides, 2010).

The TEIQue-SF (version 1.50) has 30 items in a 7-point response format (e.g., 1 = completely disagree to 7 = completely agree). Sample items on the TEIQue-SF are "I usually find it difficult to regulate my emotions," and "I'm usually able to influence the way other people feel" (Cooper & Petrides, 2010). Items on the TEIQue-SF were taken directly from the full form of the TEIQue and were selected based on their correlations with total facet scores (Cooper & Petrides, 2010; Petrides, 2009). A global trait (total) EI score is calculated by summing up the item scores and dividing by the total number of items (Cooper & Petrides, 2010; Petrides, 2009). Total TEIQue-SF scores range from 30 to 210, with scores over 120 indicating higher levels of EI. The overall internal validity of the TEIQue-SF averages .88, with each factor averaging .69 (Cooper & Petrides, 2010). It is not possible to calculate Cronbach's alpha coefficients for the 15 facets (Cooper & Petrides, 2010; Petrides, 2009). The latest version of the TEIQue-SF (version 1.50), along with scoring information, is available, free of charge, for research purposes from the London Psychometric Laboratory (www.psychometriclab.com).

The TEIQue-SF (version 1.50) was used to measure EI in this study because it aligned with Bar-On's model, which was the EI theoretical framework. The other theoretical framework in the study, Knowles' (1975, 1984) theory of SDL, was measured by Fisher et al. (2001) Self-Directed Learning Readiness Scale for Nursing Education, adapted for online education as the SDLRS (Chan, 2018; Fisher & King, 2010; Schulze, 2014) which is discussed below.

Self-Directed Learner Readiness Scale (SDLRS)

Self-directed learner readiness (SDLR) can be defined as the degree to which an individual possesses the abilities and attitudes associated with SDL (Chan, 2018; Fisher et al., 2001; Fisher & King, 2010). Over the years, SDLR assessment tools have been developed to monitor SDL in adult learners (Chan, 2018; Fisher & King, 2010). Fisher et al. (2001) revised and adapted Guglielmino's (1977) Self-Directed Learner Readiness Scale to focus on SDLR in nursing education (SDLRSNE). Fisher et al.'s (2001) SDLRSNE was the first to measure SDL in a specific context on specific learners. This scale has also been modified (i.e., items removed, or the wording changed) for use in other contexts of higher education (e.g., Nasir et al., 2014). In recent years, it has been adapted for online general education as the Self-Directed Learning Readiness Scale

(SDLRS; Chan, 2018; Fisher & King, 2010; Schulze, 2014). As recommended by Fisher and King (2010), all 40 items from the original SDLRSNE were used, since they apply to learning in general and were designed not to be specific to nursing education.

The 40 items measure the three subscales of SDL: self-management, desire for learning, and self-control (Fisher et al., 2001; Fisher & King, 2010). Item responses are on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) (Fisher & King, 2010). Sample items from the SDLRS include “I prefer to set my own learning goals” and “I am confident in my ability to search out new information” (Fisher & King, 2010). Total scores range from 40 to 200, with scores 150 and over indicating readiness for SDL (SDLR; Fisher et al., 2001; Fisher & King, 2010). The scale was re-examined, and its validity and reliability were re-confirmed (Fisher & King, 2010). The Cronbach’s coefficient alpha for the three subscales range from .85 to .92, and the overall internal consistency of the scale was .87 (Fisher et al., 2001; Fisher & King, 2010).

Data Analysis Plan

Data were downloaded from the online survey platform service (freeonlinesurveys.com) onto my home computer and imported into IBM SPSS 25. Next, data were reviewed by me, and any incomplete questionnaires were eliminated. After the data were cleaned in this way, the SDLRS and TEIQue-SF were scored separately by me in Excel, and only the total scores were inputted into SPSS, along with age, gender, educational level, and GPA. After data collection and input were completed, descriptive analyses were run on the predictor and outcome variables to determine their means, standard deviations, and range of scores (Field, 2018). Next, preliminary data screening was conducted. Scatterplots and histograms were run to determine if the data met the assumptions for multiple regression analysis (Field, 2018). Bivariate correlations and multiple regression analyses were conducted to determine if the variables (EI, SDL, and OS) were correlated and if EI and/or SDL predicted OS. Previous research relating to EI and/or SDL and OS used a quantitative, cross-sectional approach (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017; Lai, 2011; Schulze, 2014).

Hierarchical regression was used to enter the predictor variables into SPSS, where the order variables are entered is based on previous research (Field, 2018). In this study, EI was entered first, since it has been established as a primary predictor of OS (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017). SDL was entered as the second step, since less research has been conducted on the relationship between SDL and OS (e.g., Lai, 2011; Schulze, 2014). Age, gender, and education level were controlled for as covariates (see C in Figure 1) because there were mixed findings in the literature on whether these predicted student success (e.g., Knight, 2019; Rahafar, Randler, Vollmer, & Kasaeian, 2017), EI (e.g., Nasir & Musar, 2010; Noor & Hanafi, 2017), and/or SDL (e.g., Schulze, 2014; Slater et al., 2017).

The indirect (mediated) effects of SDL on the relationship between EI and OS were tested using Hayes' (2018) PROCESS 3.5 (a SPSS macro). EI was entered as the *X* variable and SDL was entered as the *M* variable. OS was entered as the *Y* variable. Age, gender, and level of education were entered as the covariate variables (denoted as C). The macro, PROCESS, is a bootstrap resampling mediation method that estimates the direct, indirect, and total effects of *X* on *Y* through *M* (Hayes, 2018). It also generates percentile bootstrap confidence intervals, where the default is 95% (Hayes, 2018). Bootstrap confidence intervals yield inferences about the indirect effects that are “more accurate,” and test with a “higher power,” than Sobel’s test (Fritz & MacKinnon, 2007; Hayes, 2018, p. 98). Estimating the indirect effects with percentile confidence intervals allows the researcher to focus on the degree of mediation observed in the data (Field, 2018; Hayes, 2018).

Threats to Validity

Regarding internal validity, the nonexperimental, cross-sectional survey design of this study precluded any cause-and-effect conclusions from being drawn on the data. Also, there was a possibility for both self-presentation bias and response bias to occur because the survey instruments that were used in this study to evaluate the constructs of interest are self-report measures (Cox, 2016). Even with the added privacy of an online questionnaire, and the confidentiality and anonymity of no personal identifying information being collected, participants could still answer questions in such a way that will present themselves in as positive a light as possible. They could also respond arbitrarily to each question, such as answering “A” to every question (Cox, 2016). In either case, the results would not be a true representation of their attitudes and beliefs. Threats to construct validity were minimal because only validated, published measures were used in the study.

Threats to the external validity reside in the convenient sample being recruited from online sources (i.e., a fully online university’s research participant pool and social media websites). For instance, it is possible that the results of the study will not generalize to all adult learners who are actively pursuing degrees from universities. Also, because the sample consisted of adult learners who are taking online courses as part of their degree program, the results may not generalize to undergraduate and graduate students who are in traditional degree programs (i.e., taking only on campus courses). In addition, because the sample was recruited from a fully online university's research participant pool and from adult learner groups on social media, those who chose to participant may have more traits in common and interests in EI, SDL, and/or OS than the general public.

Statistical conclusion validity for the regression analysis was minimized by ensuring that there was a power level of at least .80 (N = 71) and 95% confidence intervals (this is the default setting in PROCESS 3.5). A threat to statistical conclusion validity for the mediation analysis may result because with any three variables there are six different mediation models possible (Hayes, 2018). For this reason, any conclusions drawn from this study must be qualified with the statement that other mediators and mediation models are possible.

Ethical Procedures

All participants were adult learners (18 years or older) taking online courses as part of their degree program. They were recruited anonymously from either a fully online university's research participant pool or from social media websites (i.e., Facebook, LinkedIn). Confidentiality was ensured throughout this research process. At no time was identifying information available to me as the researcher, and no personal identifying information was collected. The study involved no more than minimal risk – no more than daily life (Fisher, 2017). Individuals interested in volunteering to participate were first asked to click on the link in the recruitment post (see Appendix A) that directed them to an informed consent page. Participants gave their consent to participate in the study by clicking the “Yes” button and then “Next,” which directed them to the online questionnaire. Participants could exit the study at any time without any consequences. Once they completed the online questionnaire and clicked on “Finish Survey,” they were directed to the final page of the study where they were thanked and debriefed.

The data were received raw and anonymously when I downloaded it from my account with the online survey platform service (i.e., freeonlinesurveys.com) to my home computer. Both the home computer and online survey platform service account are password protected. The data for this study were downloaded and stored on an encrypted, external drive using Microsoft BitLocker that can only be accessed by me. Following data analysis, the external drive was locked in a fire-safe lock box for extended storage; at the end of five years, the data will be deleted from the drive.

Summary

This chapter presented the research design, rationale, and methodology chosen to examine the relationships (correlative, predictive) between EI, SDL, and OS, and if so, then whether SDL mediates the relationship between EI and OS. I hypothesized that EI, SDL, and OS are correlated and that EI and SDL both predict OS. In this way, I also hypothesized that SDL would mediate, or indirectly influence, the relationship between EI and OS. The research sample were drawn from a fully online university’s participant pool and from social media websites (i.e., Facebook, LinkedIn). Data were collected using an online questionnaire with three surveys (Demographics, SDLRS, and TEIQue-SF) that was hosted by an online survey platform service (i.e., freeonlinesurveys.com). Multiple regression and mediation analyses were conducted using SPSS and Hayes' (2018) PROCESS macro.

The results of the study are revealed in Chapter 4.

Chapter 4: Results

Introduction

The purpose of this quantitative study was to explore EI and SDL as predictors of OS and to test whether SDL mediated the relationship between EI and OS. The predictor variables were EI and SDL (Koc, 2019; Zhoc et al., 2018). SDL was also the mediator variable (Zhoc et al., 2018). Age, gender, and education level (undergraduate, graduate) were controlled as the covariates (Slater, Cusick, & Louie, 2017). OS was operationalized as GPA and was self-reported (e.g., Berenson et al., 2008; Zhoc et al., 2018). EI was measured using an online version of Petrides (2009) TEIQue-SF (e.g., Engin, 2017). SDL was measured using Fisher et al. (2001) Self-Directed Learning Readiness Scale for Nursing Education, adapted for online general education as the Self-Directed Learning Readiness Scale (SDLRS; Chan, 2018; Schulze, 2014).

Participants in the study were adult learners (18 years and older; undergraduate and graduate) recruited from a fully online university's participant pool or from social media websites. They were surveyed on their demographic characteristics (age, gender), current level of education (undergraduate or graduate), total number of online courses taken for their degree program, and GPA. Informed consent was obtained electronically. The demographic survey and two questionnaires (SDLRS, TEIQue-SF) were administered online through freeonlinesurveys.com.

The research questions and hypotheses for this study were based on Baron and Kenny's (1986) causal steps approach to mediation analysis and were as follows:

RQ1: Does emotional intelligence (EI) relate positively and significantly to OS, operationalized as GPA?

Ho_1: EI does not positively nor significantly relate to OS.

Ha_1: EI does positively and significantly relate to OS.

RQ2: Does self-directed learning (SDL) relate positively and significantly to EI?

Ho_2: SDL does not positively nor significantly relate to EI.

Ha_2: SDL does positively and significantly relate to EI.

RQ3: Using regression analysis, does EI and/ or SDL predict OS?

Ho_3: EI and/or SDL does not significantly predict OS.

Ha_3: EI and/or SDL does significantly predict OS.

RQ4: If EI and SDL are both predictors of OS, then does SDL mediate the relationship between EI and OS? In other words, does SDL significantly influence the relationship between EI and OS.

Ho_4: The relationship between EI and OS is not mediated by SDL.

Ha_4: The relationship between EI and OS is mediated by SDL.

This chapter provides a description of data collection, descriptive characteristics of the sample, and the results of the data analysis used to test the proposed mediation model (Figure 1) presented in Chapter 1.

Data Collection

Data were collected using an online survey platform (freeonlinesurveys.com) that hosted the online questionnaire for this study. Participants were recruited through a fully online university's participant pool as well as from social media sites (Facebook, LinkedIn). After receiving IRB approval (No. 06-23-20-0543596), a study announcement was posted on the fully online university's participant pool bulletin board by the site administrator. Next, I posted a study invitation to my LinkedIn network, and after receiving approval from the group administrators, I posted a study invitation to one group on LinkedIn and to four groups on Facebook. The study invitation posted on my LinkedIn network and the five social media sites encouraged sharing the study invitation with others who were eligible and who could be interested in participating in the study.

Interested participants clicked on the link provided in the study invitation, which then directed them to an informed consent page. If they agreed to participate in the study, they gave their consent, and acknowledged how they may exit the questionnaire at any time without consequences, by clicking the "Yes" button and then "Next," which then directed them to the online questionnaire. The online questionnaire consisted of three surveys (in this order): Demographics, Fisher et al. (2001) SDLRS, and Petrides' (2009) TEIQue-SF. The demographics survey consisted of five questions asking for the participant's age, gender, degree level of education they are seeking (undergraduate or graduate), total number of online courses taken for the degree program, and GPA. As discussed in Chapter 3, the plan was to leave the survey link operational for three months or until the sample goal (N = 142) was met. The survey link became operational on June 24, 2020, and after 2 weeks, the sample consisted of 345 participants. Therefore, the link to the survey was closed.

Sample demographics. All 345 participants who clicked on the survey link gave their consent. However, 63 of them did not complete the online questionnaire, so the total sample for statistical analysis was 282. For the purposes of this study, participants were asked to report their age, gender, level of education (undergraduate or graduate), the number of online courses they have completed for their degree, and their GPA. From the final sample (n = 282), the age range was 22 to 72 (M = 42.30, SD = 9.565). Most respondents were female (90.1%) graduate (96.1%) students. One reason for this could be that three of the five social media groups used for recruitment were geared towards graduate students. Also, two of these graduate social media groups were female-only. The average number of online courses completed by participants was 11 (M = 11.85, SD = 8.161) with a range from 1 to 48, and the average GPA was 3.76 (M = 3.755, SD = 0.365).

This sample was generally representative of the population because similar studies in the literature have shown more female participants for studies within both traditional and online learning environments (e.g., Hobson & Puruhito, 2018; Koc, 2019; MacCann et al., 2019; Noor & Hanafi, 2017; Sumuer, 2018). However, due to these factors, caution should be used in generalizing findings to male adult learners and to undergraduate students. In following with the recommendation of Slater et al. (2017), and to minimize their statistical influence, age, gender, and educational level were controlled for in the model as covariates (see C in Figure 1).

Statistical Analysis

As described in previous chapters, this study answered a call for more research into the online learning environment, and filled a gap in the literature, by examining both EI and SDL as predictors of OS. It was also a response to the research recommendations of Cazan and Schiopca (2014), Koc (2019), and Zhoc et al. (2018), in exploring the possibility of SDL having an indirect effect on the relationship between psychological traits (e.g., EI) and online learning success. For these reasons, multiple regression and mediation were chosen as the statistical analyses for this study. As mentioned earlier, Baron and Kenny's (1986) causal steps to mediation analysis were used as the research questions for this study: (a) The first two steps are answered with bivariate correlations between variables; (b) the third with multiple regression; and (c) the last step with mediation analysis.

Baron and Kenny (1986) Classic Method

Baron and Kenny's (1986) causal step approach to mediation has been the prominent method for several decades (Field, 2018; Hayes, 2018, 2020). However, this approach is not recommended by mediation experts (e.g., Fritz & MacKinnon, 2007; Hayes, 2018, 2020) for mediation analysis for several reasons. First, it requires a total effect (an effect on *Y* by *X*) before mediation analysis can even be tested (Hayes, 2018). Hayes (2018) noted that most methodologists agree that this total effect should not be a requirement for mediation analysis because the size of the total effect (*X* on *Y*) does not determine the size of the indirect effect (*X* on *Y* through *M*). Second, the causal approach to mediation is a "set of steps" that focus on hypothesis testing and claims no mediation is possible if *X* does not affect *M*, the mediator, or if *M* does not affect *Y* (Hayes, 2020). Hypothesis testing (i.e., *p*-value) is based on sample distribution assumptions that may or may not be met, which means that the more hypothesis tests there are in a study, the more chance for errors (Hayes, 2018, 2020). Third, for mediation to occur using this approach, the direct effect (the effect of *X* on *Y* controlling for *M*) must be closer to zero and statistically nonsignificant – for a complete mediation – or statistically significant – for a partial mediation (Baron & Kenny, 1986). One way to achieve this is to have a low statistical power (i.e., a small sample size), especially if one wants to find a complete mediation (Fritz & MacKinnon, 2007; Hayes, 2020).

Given that the mathematical computation is the same in regression and path analysis using ordinary least squares (OLS; Hayes, 2020), Baron and Kenny's (1986) causal steps were used as the research questions for this study, but a different approach was selected to conduct the last step (research question 4) to determine if there was a mediation (an indirect effect). The method I selected to test for mediation was bootstrap resampling with replacement using Hayes' (2018) PROCESS macro for SPSS.

Bootstrap resampling method and Hayes' (2018) PROCESS

Hayes (2018) defined mediation analysis as a process to evaluate evidence from studies designed to "test hypotheses about how some causal antecedent variable *X* transmits effect on consequent variable *Y*…[through] a mechanism…by which *X* influences *Y*" (p. 78). He defined a mediator as an influencing variable and conceptualized it as "the mechanism through which *X* influences *Y*" (2018, p. 7). The change in *Y* is due to a change in *X* through *M*–also known as the indirect effect–which is really what determines a mediation (Hayes, 2020). The indirect effect is quantified by multiplying path *a* (regression coefficient for the effect of *X* on *M*) by path *b* (regression coefficient for the effect of *M* on *Y*), thus *ab*. Because *ab* is the "proper estimation" of the indirect effect, statistical inference should be based on *ab* and not on hypothesis testing of the direct effect (Hayes, 2018, p. 116).

There are two approaches to statistical inference of the indirect effect: the Sobel test or bootstrap confidence intervals (Hayes, 2018). The Sobel test, also known as the normal theory test, assumes a normal distribution and estimates a *p*-value for the indirect effect to further analyze a mediation (Hayes, 2018). However, the assumption of normal distribution for the indirect effect is a mathematical violation (distribution *a* x distribution *b* ≠ normal *ab* distribution), and as explained earlier, the hypothesis test is lower in statistical power (Hayes, 2020). The bootstrap resampling method for mediation analysis is a higher power test and a "work around" to the non-normal distribution of *ab* because it does not require assumptions for shape and size of a distribution (Fritz & MacKinnon, 2007; Hayes, 2020).

Bootstrap resampling method with replacement empirically simulates a sample distribution of the indirect effect (*ab*) using the data available (Hayes, 2020). In other words, a random sample is "drawn" *k* times from the total sample (in this case, $N = 282$) and the indirect effect is estimated each time. For the current study, this process was repeated 5000 times (the default setting in Hayes' PROCESS 3.5) and then 95% percentile confidence intervals (2.5^{th}, 97.5^{th}) were calculated using the distribution of the indirect effect from the bootstrap samples (Hayes, 2020). If the bootstrap confidence intervals do not include a zero, then a researcher can claim an indirect effect different from zero with 95% confidence (Hayes, 2020). Hayes (2020) noted in his online course how he programed PROCESS to use the percentile method for constructing confidence intervals because it is a “nice compromise between power and validity.” The bias-corrected method, which is also often found in the literature, slightly improves statistical power, but it can come at the cost of accelerated Type I error (Fritz & MacKinnon, 2007; Hayes, 2020).

Preliminary data screening. Multiple regression and OLS-based mediation analyses assume random sampling, interval-ratio level of measurement, independence, linearity, homoscedasticity, and normal distribution of the target population (Field, 2018; Frankfort-Nachmias & Leon-Guerrero, 2015). However, the bootstrap resampling method for mediation analysis does not make assumptions about the shape or size of a distribution (Hayes, 2018). Therefore, preliminary data screening (e.g., histograms, scatterplots) was conducted to test for the statistical assumptions of multiple regression. The results of the statistical assumptions are reported in the next section.

Results

Statistical Assumptions

Data were interval/ratio (age, total number of online courses taken for the degree program, GPA, TEIQue-SF total score, and SDLRS total score), with two dichotomous variables (gender, education level) and assumed to be independent. The Kolmogorov-Smirnova normality test indicated that the distributions for two variables (EI and SDL) met the assumption of normality, but the distribution for GPA did not (alpha level set to .05). This was also visually confirmed with histograms of each variable distribution. Next, scatterplots revealed linear relations between variables, and a tolerance and variance inflation factor test indicated no collinearity, so homoscedasticity was assumed.

Univariate outliers were identified using boxplots and standardized (*z*) scores. There were no univariate outliers identified for EI; however, one was identified for SDL, and five for GPA: all below the mean. Two multivariate outliers were identified using Mahalanobis distances. The EI and SDL scores for these cases (univariate, multivariate) were examined, and most fell within the average range of the distributions. Because more data is generally thought to be better, and to demonstrate the existence of lower values in this population on these dimensions, none of the outliers were removed. Correlations between variables were examined next, and the results are presented below.

Bivariate Correlations

The bivariate correlations among the continuous variables in the study (EI, SDL, GPA, AGE) are presented in Table 1. As demonstrated, there were positive and statistically significant relationships between the predictor (EI), mediator (SDL), and outcome (GPA) variables in the study: EI and SDL (r = .546, $p \leq .01$), SDL and GPA (r = .175, $p \leq .01$), and EI and GPA (r = .122, $p \leq .05$). The size of the *r* also indicated that the relationship between EI and SDL is strong, with a moderate relationship between SDL and GPA, and a weaker relationship between EI and GPA. The covariate variables (age, gender, and educational level) were included in the correlational analysis, but only AGE was included in Table 1 because it was a continuous variable. As noted, AGE had a positive and statistically significant relationship with EI (r = .148, $p \leq .05$), but did not significantly relate to SDL (p = .134) or GPA (p = .189).

Table 1

Means, Standard Deviations, and Intercorrelations for Continuous Variables

			Pearson r			
Measure	*M*	*SD*	1	2	3	4
1. EI	160.87	20.27	-	.546**	.122*	.148*
2. SDL	167.17	16.08	.546**	-	.175**	.089
3. GPA	3.76	.37	.122*	.175**	-	.078
4. AGE	42.30	9.57	.148*	.089	.078	-

Note. $N = 282$.
$^{**}p <. 01$, $^{*}p <. 05$ (two-tailed).

The two categorical variables, gender (male, female) and educational level (graduate, undergraduate), were also covariate variables in the study. They were transformed to dichotomous variables in SPSS: gender to Sex (Female = 0, Male = 1) and educational level to EduLev (Graduate = 0, Undergraduate = 1). These two covariates were not statistically significant with EI (Sex, $p = .655$; EduLev, $p = .360$), SDL (Sex, $p = .449$; EduLev, $p = .777$), or GPA (Sex, $p = .155$; EduLev, $p = .406$). AGE was found to have a positive and statistically significant relationship with Sex ($r = .168$, $p \leq .01$) but a negative and statistically significant relationship with EduLev ($r = -.131$, $p \leq .05$). Sex and EduLev were not significantly related ($p = .352$).

Research Questions 1 and 2

The first two research questions were tested with bivariate correlations (Pearson's *r*) using SPSS 25. These are reported in Table 1 above. The first research question hypothesized that a positive and significant relationship would exist between EI (*X*) and OS (*Y*; operationalized as GPA). The simple bivariate correlation coefficients indicate that the relationship between EI and OS, is positive, statistically significant, and represented a small effect size (r (282) = .122, r^2 = .015, $p \leq .05$). Therefore, the null hypothesis was rejected because EI positively and significantly related to OS. Next, question two was tested.

The second research question hypothesized that a positive and significant relationship would exist between SDL (*M*) and EI (*X*). The simple bivariate correlation coefficients indicate that the relationship between SDL and EI is positive, statistically significant, and represented a large effect size (r (282) = .546, r^2 = .298, $p \leq .01$). Therefore, the null hypothesis was rejected because SDL positively and significantly related to EI. Then, question three was tested.

Research Question 3

Because there were statistically significant bivariate correlations among EI, SDL, and OS, multiple regression analysis was performed to test the third research question. The third research question hypothesized that EI and SDL would be significant predictors of OS, controlling for age, gender, and educational level. In the model, OS (operationalized as GPA) was the outcome variable, EI and SDL were the predictor variables, and the covariates were age (AGE), gender (Sex), and education level (EduLev). To examine the direct impact of EI and SDL on OS, while controlling for age, gender, and educational level, hierarchical regression was implemented and two regressions were conducted: The first regressed GPA on EI while holding age, gender, and educational level constant, and the second regressed GPA on both EI and SDL while controlling for age, gender, and educational level. The first regression model was not significant (p = .075), and EI was not a significant predictor of OS (p = .055). The results of the second regression are displayed in Tables 2 and 3.

Table 2

ANOVA Table for the Regression Model

	SS	*df*	*MS*	*F*	R^2	*p*
Regression	1.77	5	.353	2.728	.047	.020*
Residual	35.76	276	.130			
Total	37.53	281				

*p < .05.

The second regression model was significant (F (5, 282) = 2.728, p < .05), as shown in Table 2. The multiple correlation (R = .217) was small but significantly different from zero. The R^2 equaled .047, which represents a small effect size and indicates that when controlling for age, gender, and education level, EI and SDL are not strong predictors of OS because they only account for approximately 5% of the variance in GPA.

Table 3

Summary of Regression Analysis for Variables Predicting OS

Measure	*B*	*SE*	β	sr^2	*t*	*p*

EI	.001	.001	.030		.424	.672
SDL	.004	.002	.156	.017	2.22	.027*
Constant	2.97	2.43			12.26	

*$p < .05$.

An examination of the regression coefficients in Table 3 indicated that only SDL was a significant predictor of OS. The regression coefficient for SDL ($B = .004$) is positive and statistically significant ($p < .05$). The squared semi-partial correlation for SDL ($sr^2 = .017$) represents a small effect size and accounts for approximately only 2% of the variance in OS. From the findings, only part of the null was rejected (SDL does not predict GPA). Last, the fourth question was tested.

Research Question 4

The fourth research question hypothesized that SDL would mediate, or influence, the relationship between EI and GPA holding age, gender, and education level constant (see Figure 1). As mentioned previously, the bootstrap resampling method with replacement using Hayes' PROCESS (a macro for SPSS) was selected as the mediation analysis method. This method provides a higher statistical power and does not require assumptions about the shape and size of the distribution because it calculates confidence intervals using bootstrap estimates on the indirect effect (Fritz & MacKinnon, 2007; Hayes, 2018). Hayes' (2018) PROCESS macro allows the researcher to estimate path analysis using OLS regression as well as the total, direct, and indirect effects for mediation analysis. The mediation path analysis model for PROCESS is represented in Figure 2 below.

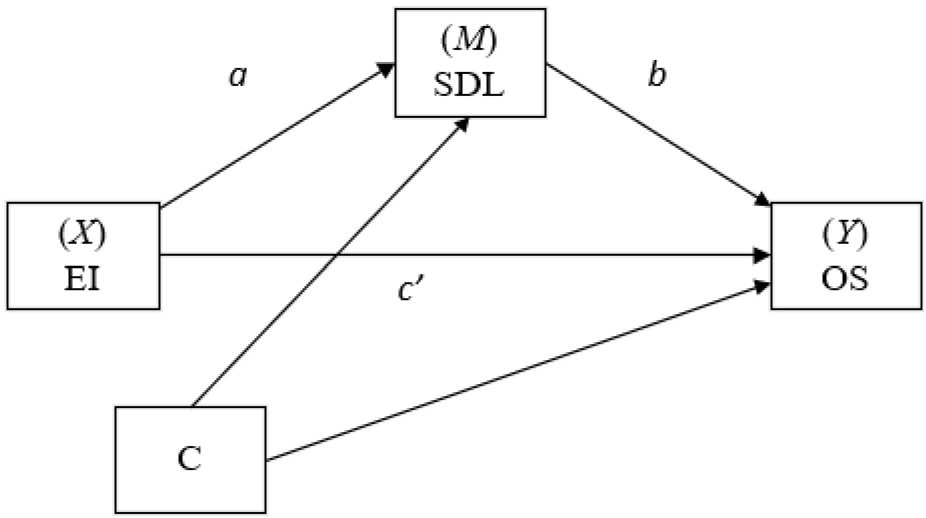

Figure 2. Path analysis model for PROCESS.

As shown in Figure 2, the mediation model for this study proposed that an adult learner's EI influences their level of SDL (path *a*), which in turn influences their OS (path *b*). As shown in Figure 2, the following information was entered into PROCESS: The outcome variable was OS (operationalized as GPA) and entered as *Y*; the predictor variable was EI and entered as *X*; the mediator variable was SDL and entered as *M*; and the covariates (entered as cov=) were age (AGE), gender (Sex), and educational level (EduLev). The number of bootstrap sample estimates was 5000 (default setting), and the partially standardized indirect effect (*ab*) coefficients were requested for effect size (entered as effsize=1). The results of the mediation analysis are presented in Tables 4 and 5 and Figure 3.

As depicted in Figure 3, paths *a* and path *b* are quantified as the unstandardized regression coefficient (*B*) in Tables 4 and 5. In addition, PROCESS generates the direct effect, or the effect of *X* on *Y* while controlling for *M* (path *c'*), which is also quantified as the unstandardized regression coefficient (*B*) in Table 5 and depicted in Figure 3.

Table 4

Regression Coefficients for Path a

	Regression coefficients			
	B	*SE*	*t*	*p*
EI (path *a*)	.435	.040	10.769	≤ .001

Note. DV = SDL. $R = .549$, $R^2 = .301$.
$p < .05$.

As presented in Table 4 and Figure 3, when SDL is regressed on EI (path *a*), the resulting unstandardized regression coefficient (*B*) is positive and statistically significant ($B = .435$, $SE = .040$, $p \leq .001$).

Table 5

Regression Coefficients for Paths b and c'

	Regression coefficients			
	B	*SE*	*t*	*p*
SDL (path *b*)	.004	.002	2.220	.027
EI (path *c'*)	.001	.001	.424	.672

Note. DV = GPA. $R = .217$, $R^2 = .047$.
$p < .05$.

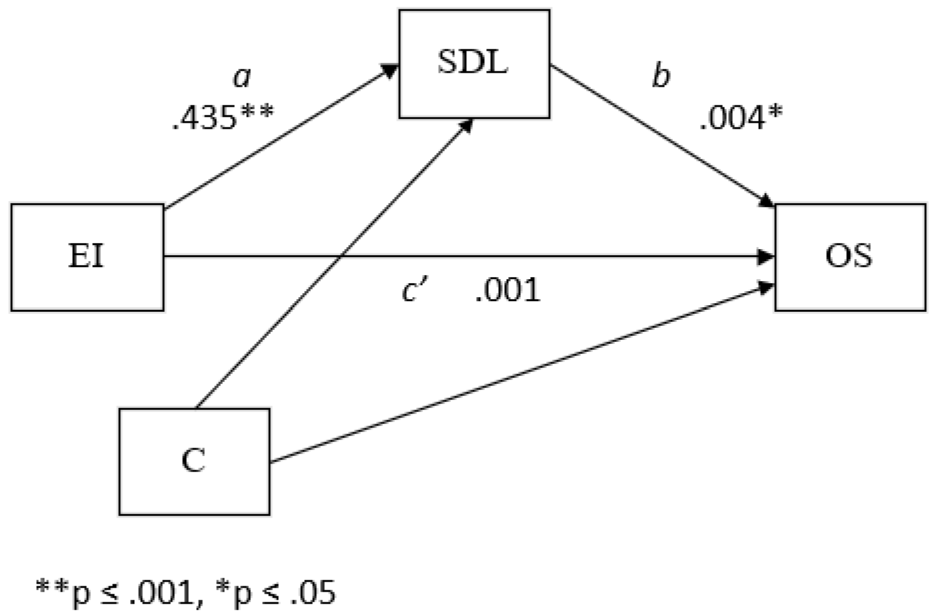

Figure 3. Results of path analysis for mediation model.

As presented in Table 5 and Figure 3, when GPA is regressed on SDL (path *b*), the resulting unstandardized regression coefficient (*B*) is positive and statistically significant ($B = .004$, $SE = .002$, $p \leq .001$). When GPA is regressed on EI while controlling for SDL (path *c'*), as shown in Table 5 and Figure 3, then the resulting unstandardized coefficient ($B = .001$) is the direct effect. Here, it is not statistically significant ($p = .672$).

Indirect Effect

As mentioned earlier, it is the indirect effect, or the effect of *X* on *Y* through *M*, that is what matters most in determining a mediation (Hayes, 2018, 2020). The indirect effect is quantified as the product of paths *a* and *b* (*ab*). This was calculated in PROCESS, and for this present study, path *a* (.435) x path *b* (.004) equaled a very small, positive indirect effect (*ab*) of .002. Because the bootstrap confidence intervals do not pass through zero (95% CIs [.000, .003]), the significance of the indirect effect (*ab*) was further tested by examining the partially standardized indirect effect (ab_{ps}). When this is requested, PROCESS transforms the metric scale of *Y* (in this case GPA) to the *SD* of *Y* (Hayes, 2018). For this study, the partially standardized indirect effect was .004, and the bootstrap confidence intervals do not contain a zero (95% CIs [.001, .008]). From these findings, a mediated (indirect) effect of SDL on the relationship between EI and OS was supported, and even though the effect was very small, the null was rejected.

In sum, EI and GPA (research question 1), as well as EI and SDL (research question 2), were positively and significantly related. Age was the only covariate to relate to EI positively and significantly, whereas SDL did not statistically relate to any of the covariates. Despite this, age, gender, and educational level were controlled for in the model based on the recommendation of Slater et al. (2017) and to minimize their statistical influence (Hayes, 2018). EI did not predict OS (operationalized as GPA) by itself; and when combined with SDL in the model, only SDL was found to be a significant predictor of OS (research question 3). In addition, SDL was found to mediate (or influence) the relationship between EI and OS, but the indirect effect was very small (research question 4).

Chapter 5 presents a summary of the study, interpretation of the findings, and conclusions drawn from the survey results. In addition, the limitations of the study, future recommendations for continued research, and social implications of the current findings are further detailed.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

With the demand for online education remaining steady, but attrition rates for online courses remaining higher than traditional ground courses, more research is needed into online student success (Bawa, 2016; Knight, 2019; Peck et al., 2018). Most researchers have found learner characteristics to be the main factors in predicting student persistence, dropout, and OS (e.g., Choi & Park, 2018; Kauffman, 2015; Vayre & Vonthron, 2017). For instance, online learning researchers (e.g., Berenson et al., 2008; Kerr et al., 2006; Lai, 2011; Peck et al., 2018; Vayre & Vonthron, 2017) have explored self-efficacy, motivation, OLR, SDL, and EI as predictors of OS. Previous research supports EI and/or SDL as predictors of OLR (e.g., Engin, 2017; Lai, 2011) and OS (e.g., Berenson et al., 2008; Lai, 2011). However, research including both EI and SDL in the literature is scarce (Koc, 2019).

In the current study, I proposed and tested a mediation model (see Figure 1) to explore both EI and SDL as predictors of OS as well as the indirect nature of SDL on the relationship between EI and OS. The target population consisted of adult learners (ages 18 and older) taking online courses as part of a degree program (undergraduate or graduate). The predictor variables were EI and SDL (Koc, 2019; Zhoc et al., 2018). SDL was also the mediator variable (Sumner, 2018; Zhoc et al., 2018). OS was the outcome variable, operationalized as GPA (Berenson et al., 2008; Zhoc et al., 2018). Age, gender, and education level (undergraduate, graduate) were controlled as covariates in the mediation model (Knight, 2019; Slater & Cusick, 2017).

This chapter presents an interpretation of the findings presented in Chapter 4, a discussion of the limitations, recommendations for future research, and highlights practical applications and implications for positive social change.

Interpretation of the Findings

Bivariate Correlations

As hypothesized, and consistent with prior research (e.g., Engin, 2017; Koc, 2019; Zhoc et al., 2018), EI positively and significantly correlated with both SDL and OS (operationalized as GPA). In other words, as levels of EI increased in adult learners, so did their levels of SDL and GPA. As supported in the literature, higher levels of EI correspond to more effective skills in communication, rapport-building, and coping with life's daily demands, such as academic and work performance (Brown et al., 2016; Koc, 2019; Noor & Hanafi, 2017; Zhoc et al., 2018). Like EI, higher levels of SDL have been found to improve motivation, self-awareness, and academic performance in both traditional and online learning environments (e.g., Cazan & Schiopca, 2014; Lai, 2011; Song & Bonk, 2016; Zhoc et al., 2018).

In the present study, and in support of previous research (Bar-On, 2006; Engin, 2017; Koc, 2019; Zhoc et al., 2018), EI and SDL were strongly and positively correlated. Recently, some researchers (i.e., Engin, 2017; Koc, 2019; Zhoc et al., 2018) have found that EI and SDL were strongly correlated, regardless of learning environment (traditional, online). This strong association between EI and SDL may result from both EI and SDL consisting of cognitive, metacognitive, and affective traits and skills (Engin, 2017; Koc, 2019; Zhoc et al., 2018).

In the current study, SDL also positively and significantly correlated with OS, but not with any of the covariates (age, gender, and education level). The positive association between SDL and academic achievement (e.g., GPA) within traditional and online learning environments has been extensively researched and supported in the literature (e.g., Knowles et al., 1973/2015; Lai, 2011; Meyer, 2010). Knowles (1975, 1984) observed that adult learners varied in their levels of SDL, which seemed to be dependent on their level of experience/knowledge of the content or topic and not their demographic characteristics (e.g., age, gender). These observations could explain why SDL did not correlate with any of the covariates in the present study.

Among the covariates (age, gender, and education level), age positively and significantly correlated with EI, but not with SDL or GPA. This means that as age increased in participants, so did their level of EI, but not necessarily their SDL and/or GPA. One reason why is because most participants had higher levels of SDL and above average GPAs, regardless of their age, gender, and education level. In addition, some researchers (e.g., Chan, 2018; Lai, 2011; Sumuer, 2018) have posited that online learning is more conducive for the SDL process than the traditional learning environment. In the present study, most participants were graduate students who have completed 11 or more online courses towards their degree program. In other words, participants had already demonstrated previous academic success (e.g., GPA, course completion) in the online learning environment, which could explain their high levels of SDL and OS.

It should be noted here that none of the variables in the present study (EI, SDL, OS) correlated with gender or education level. This lack of correlation could result from how most of the participants were female graduate students (90%, 96% respectively). However, in support of the mixed findings in the present study and in the literature (e.g., Lounsbury et al., 2009; Nasir et al., 2014; Slater et al., 2017), demographic characteristics (age, gender, and education level) were included as covariates in the mediation model.

In following with recommendations from Bar-On (2006), Koc (2019) and Zhoc et al. (2018), future research should focus more on the relationship between EI and SDL and their impact on academic success (e.g., GPA). The current study examined EI and SDL as predictors of OS as well as the indirect effects of SDL on the relationship between EI and OS. The results of the multiple regression and mediation analysis from the current study are discussed below.

Multiple Regression Analysis

In the current study, SDL predicted OS, but EI did not, even though EI and OS were positively and significantly correlated. Instead, EI strongly correlated and predicted SDL, as demonstrated in the literature (e.g., Engin, 2017; Zhoc et al., 2018). These mixed findings regarding EI are consistent with what previous researchers have found when testing EI as a predictor of academic achievement, SDL, and/or general success outcomes (e.g., Koc, 2019; Zhoc et al., 2018). As discussed in Chapter 2, mixed findings for EI as a predictor of academic success outcomes (e.g., GPA) are common in the literature, regardless of which conceptualization of EI (ability, mixed, trait) or learning environment (ground, online) was assessed (MacCann et al., 2019; Mayer et al., 2016; Petrides & Mavroveli, 2018). Some reasons for why EI did not predict OS in the current study are presented below.

EI a predictor of OS? EI did not predict OS in the current study, even though it has in other online learning studies (e.g., Berenson et al., 2008; Buzdar et al., 2016). One explanation could be the small to moderate effect size (MacCann et al. (2019). In the present study, the association between EI and OS was positive and significant, but also small to moderate (*r* = .12). MacCann et al. (2019) found in their meta-analysis that EI (ability, mixed, and trait) correlated with academic performance (e.g., GPA), but the overall effect size (Pearson *r*) was small to moderate (95% CI [.17, .22]). Just as MacCann et al. (2019) demonstrated, the small effect size could explain why EI did not predict OS in the current study. Other explanations for these mixed findings on whether EI predicts academic success outcomes relate to the EI measure selected for the study and the sample variance (i.e., demographic characteristics), which are discussed in more detail below.

***EI measures*.** Another explanation why EI did not predict OS in the present study could be a result of the EI measure (MacCann et al., 2019). The current study used a trait EI measure (TEIQue-SF) in lieu of an ability (e.g., MSCEIT) or mixed EI measure (e.g., EQ 2.0). Other researchers who used ability- and/or trait-based EI measures have found that EI predicted academic success and/or life success outcomes (e.g., SDL) in either learning environment (e.g., Engin, 2017; Zhoc et al., 2018). In contrast, some researchers found that ability- and/or trait-based EI measures do not associate with nor predict success outcomes as well as mixed EI measures in either a ground or online learning environment (e.g., Han & Johnson, 2012; Koc, 2019). In a meta-analysis comparing results across studies on academic performance (e.g., GPA) using ability, mixed, and/or trait EI measures, MacCann et al. (2019) found only two common elements of EI, emotion understanding and emotion management, predicted academic performance when the effects of IQ and personality were controlled for in the model. These common EI elements are found in all three approaches to EI (ability, mixed, and trait), but in varying degrees across EI measures, which could help to explain the mixed findings of EI as a predictor of academic success.

Sample variance. The sample variance could also be a reason why EI did not predict OS in the present study (MacCann et al., 2019). The sample of the current study consisted of mostly female graduate students (90%, 96% respectively). In the research literature, females tend to have higher levels of EI, and more tertiary studies tend to have higher percentages of female participants (Koc, 2019; MacCann et al., 2019). In their meta-analysis, MacCann et al. (2019) found smaller effect sizes of overall EI for tertiary samples and those with higher percentages of females. The sample of the present study consisted of both (tertiary studies and higher percentages of females), which could explain the smaller overall effect of EI and why EI did not predict OS.

SDL as a predictor of OS. As hypothesized, and consistent with the literature, SDL positively and significantly predicted OS in the current study. Previous researchers have identified SDL as a significant predictor of academic success for adult learners in both ground (e.g., Cazan & Schiopca, 2014; Zhoc et al., 2018) and online (e.g., Lai, 2011; Schulze, 2014) learning environments. One reason for this could be because SDL has been described as the basis of all learning (Cazan & Schiopca, 2014; Chan, 2018; Song & Bonk, 2016; Williamson, 2007). All learners will have varying degrees of SDL competencies and skills because of their unique backgrounds and experiences (Candy, 2000; Knowles et al., 1973/2015; Sumuer, 2018). For this reason, increasing levels of SDL in all learners may help them transition from pedagogy (teacher-directed) to andragogy (self-directed) learning in either a traditional classroom (Knowles et al., 2015; Zhoc et al., 2018) or online (Schulze, 2014; Sumuer, 2018) learning environment.

In addition, because SDL was found to be a predictor of OS, the current study supports previous research (e.g., Doe et al., 2017; Kerr et al., 2006; Lee & Choi, 2011) on the importance of other learner characteristics (i.e., SDL) in the academic success of adult learners taking online courses as part of their degree program. Some researchers (e.g., Lai, 2011; Song & Bonk, 2016; Sumuer, 2018) have even posited that online learning is more conducive for the SDL process than the traditional learning environment. These researchers and others (e.g., Doe et al., 2017; Knowles et al., 1973/2015; Zhoc et al., 2018) have emphasized the need to assess students' SDL as a key factor in appropriate placement in classes and learning environments (ground, online) that better align with the students' instructional and support needs in higher education.

EI as a predictor of SDL. In the current study, EI predicted SDL. Research on both EI and SDL as predictors is scarce in the literature (Koc, 2019; Zhoc et al., 2018). Despite this, there are several possible explanations for why EI predicted SDL in the present study. First, Bar-On (2006) found higher levels of independence (which he defined as being self-directed) facilitated and improved EI. As demonstrated in the current study, EI and SDL were positively and strongly correlated (r = .55), with higher levels of EI significantly associated with higher levels of SDL. Another explanation for why EI predicted SDL in the present study could be because both EI and SDL consist of cognitive, metacognitive, and affective traits and skills (Engin, 2017; Koc, 2019; Zhoc et al., 2018). In addition, the active, process-based, and emotional-social aspects of learning in either environment (ground, online) may help to develop and support both EI and SDL, which in turn, can improve academic success (Bar-On, 2007; Garrison, 1997; Koc, 2019; Rogers, 1980/1995; Zhoc et al., 2018).

Because the current study found EI strongly correlated with SDL (e.g., Buzdar et al., 2016; Engin, 2017), and that EI predicted SDL (e.g., Engin, 2017; Zhoc et al., 2018), then it was possible for a mediation relationship to exist between them (Baron & Kenny, 1986; Field, 2018). The results of the mediation analysis are discussed below.

Mediation Analysis

SDL as a mediator. As hypothesized, the present study found that SDL mediated (influenced) the relationship between EI and OS using PROCESS, a bootstrap resampling method with replacement developed by Hayes (2018). The indirect effect can be interpreted because it does not include a zero (95CI [.001, .008]). The very small indirect (mediated) effect (ab_{ps} = .004) was unexpected given Bar-On's (2006) mixed EI model and the findings of previous research (e.g., Buzdar et al., 2016; Engin, 2017; Zhoc et al., 2018). These are explained in more detail in the sections below.

Bar-On's (2006) model. Bar-On (2006) was the first to observe a connection between EI and SDL. After 17 years of research, he identified independence (which he defined as being self-directed) as a facilitator of EI (Bar-On, 2006). In other words, higher levels of SDL improved levels of EI (Bar-On, 2006). At the time, he explained that he did not pursue this line of research because these two constructs, EI and SDL, were not linked in the literature (Bar-On, 2006). Instead, Bar-On (2006) continued his research on the impact of EI on life success but making the distinction between EI constructs and EI facilitators in his model and in his measurement scale.

***Previous research*.** Empirically, Bar-On (2006), Cazan and Schiopca (2014), Koc (2019), and Zhoc et al. (2018) suggested that SDL could be a mediator, or an influencing variable, between psychological traits (e.g., EI) and academic achievement (e.g., GPA). For instance, Zhoc et al. (2018) examined the indirect effects of SDL on the relationship between EI and academic success in the traditional learning environment and found that EI correlated and predicted academic success through the influence of SDL. In other words, SDL mediated the relationship between EI and academic achievement (i.e., GPA) as well as between EI and generic learning outcomes (i.e., critical-thinking) in a traditional classroom environment.

***SDL as a mediator of EI and OS*?** For the current study, it is possible that the very small indirect (mediated) effect results from the unique characteristics of the sample examined in this research. For example, most participants in the present study were female graduate students who have already demonstrated their academic potential prior to acceptance in their graduate degree programs. In addition, most participants, regardless of age, gender, or education level, possessed higher levels of EI, SDL, and GPA. As previous researchers have suggested (e.g., MacCann et al., 2019), the higher levels of these traits combined in the sample could have minimized any effect (direct or indirect) of EI and/or SDL on OS, operationalized as GPA.

Given this, the very presence of an indirect (mediated) effect of SDL on the relationship between EI and OS in the current study suggests that even among adult learners with higher levels of EI, SDL, and GPA, it would be beneficial to assess and implement EI and SDL in the online classroom. Previous research supports the positive impact of above average EI and SDL skills on academic success (e.g., Zhoc et al., 2018) and the importance of implementing them within online course curriculum and/or training programs (Bawa, 2016; Kauffman, 2015; Majeski et al., 2017; Noor & Hanafi, 2017; Pool & Qualter, 2012).

The findings of the present study also support previous researchers (e.g., Kerr et al., 2006; Lee & Choi, 2011; Zhoc and Chen, 2016) that have identified the need in higher education to assess learner characteristics (e.g., EI, SDL) and then match students with the most appropriate learning environment and instructional strategies. This practice could not only help to improve student course satisfaction and academic success, but it could also decrease attrition rates in higher education (Bawa, 2016; Doe et al., 2017; Kauffman, 2015; Kerr et al., 2006; Lee & Choi, 2011; Peck et al., 2018).

The limitations of the current study and future research recommendations are discussed in the sections below.

Limitations of the Study

The sample examined in the present study (N = 282) consisted of experienced online adult learners who had above average levels of EI, SDL, and OS, operationalized as GPA. Therefore, the results of the study may not generalize to other adult learner populations (i.e., male adult learners, undergraduates). As mentioned previously, most of the participants were female graduate students. One reason for this could be because three of the five social media groups (i.e., Facebook, LinkedIn) used for recruitment were focused on graduate students, with two of the three groups comprised of all female members. Also, because the sample was mostly graduate students, they had already demonstrated previous academic success (e.g., higher GPAs) by gaining, and maintaining, acceptance into their degree programs.

In addition, because of the nonexperimental nature of the study, causality was not determined. Correlational, regression, and mediation analyses can only help support claims for associations between variables and how these may be causal in nature (Hayes, 2018). Furthermore, even though EI and SDL have been found to positively correlate in the literature with each other (e.g., Engin, 2017) and with academic success, such as GPA (e.g., Zhoc et al., 2018), other variables could be at work that were not included in the proposed and tested mediation model.

Last, social desirability bias, where participants' may answer survey questions in ways that they believed the questions should be answered, may have presented as a confound for the variables in the present study because all of the variables were measured using self-report (Cox, 2016). For instance, GPA was self-reported and may not have represented actual academic performance. However, because most of the participants were graduate students, higher GPAs are required for their degree programs. Therefore, this could explain the skew in GPA scores (*M*= 3.76, *SD* = .365) and why the mode GPA reported was 4.0. Recommendations for future research are discussed below.

Recommendations

With the demand for online education remaining steady, but attrition rates for online courses remaining higher than ground courses, more research is needed into online student success. This research focused on adult learners who were taking online courses as part of their degree program and were either members of a fully online university's participant pool or recruited via social media websites (e.g., Facebook, LinkedIn). Previous researchers who have examined the relationships between EI and/or SDL and OS (as GPA or OLR) did not target adult learners who attended fully online institutions of higher education and/or adult learner groups on social media (e.g., Berenson et al., 2008; Buzdar et al., 2016; Engin, 2017). In consideration of the growing demand for online education, and open access courses (e.g., MOOCs), more research is needed to examine this population.

When tested in both ground and online learning environments within the context of higher education, EI and SDL have been shown to be predictors of student success outcomes (e.g., Berenson et al., 2008; Buzdar et al., 2016; Cazan & Schiopca, 2014; Engin, 2017; Lai, 2011; Zhoc et al., 2018). To date, the present study was the first to examine EI and SDL as predictors of OS (operationalized as GPA) as well as the indirect effects of SDL on the relationship between EI and GPA in the online learning environment. The results of the current study support the proposed mediation model (see Figure 1 in Chapter 1), which suggests that EI and SDL are important factors in the academic success of adult online learners. However, the given sample consisted of mostly female graduate students. In their meta-analysis, MacCann et al. (2019) found lower effects of EI in studies with higher percentages of tertiary students and/or with female participants. Future research should explore the impact of EI and SDL on academic achievement in other populations of adult learners (e.g., males, undergraduates) taking online courses as part of their degree program.

In addition, for the present study, a trait EI measurement scale (TEIQue-SF) was used to measure EI in participants. Engin (2017) used the TEIQue-SF to measure EI with similar results in the online learning environment. Zhoc et al. (2018) used an ability EI-based measure (EIS) and found similar results to Engin (2017) in the traditional learning environment. Zhoc et al. (2018) also found SDL mediated (influenced) the relationship between EI and academic achievement (GPA). However, EI researchers (e.g., Mayer et al., 2016; Petrides & Mavroveli, 2018) have found ability- and/or trait-based EI measures may not associate or predict academic achievement as well as mixed EI measures. In their recent meta-analysis, MacCann et al. (2019) found EI (ability, mixed, and trait) correlated with academic performance (e.g., GPA), but the overall effect was small to moderate. Mayer et al. (2016) posited how the mixed findings on the relationship between ability EI and academic performance could be a result from not all the constructs in ability EI being identified. Petrides and Mavroveli (2018) explained how trait EI measures associate and predict personality factors better than academic achievement. In lieu of these mixed findings, it would be beneficial for future researchers to further explore the relationship between EI, SDL, and OS using a mixed EI measure (e.g., Bar-On's EQ 2.0, Goleman's ESCI).

EI theoretical considerations. To better understand the impact of EI on academic and life success, more research is needed into what constitutes EI, and then perhaps its effect on other learner characteristics (e.g., SDL) and academic success (e.g., GPA) could be better understood. For instance, Schutte et al. (2011) reconceptualized ability and trait EI as being complementary dimensions of adaptive emotional functioning. In their dimensional model, ability EI may support the development of trait EI, in that higher levels of ability EI may predispose individuals to display more trait EI characteristics (Schutte et al., 2011). In other words, a person can have a mix of ability and trait EI, which means EI can be influenced by both genetic and environmental factors. In the literature, higher levels of EI, measured as either ability EI or trait EI, are associated with greater psychological well-being and persistence (Mayer et al., 2016; Petrides et al., 2016; Schutte et al., 2011).

In addition, Mayer et al. (2016) noted it is possible for ability EI to be a part of a higher-order emotional-social construct, which was originally theorized by Thorndike (1920) and then further developed by Bar-On (2006) in his 1988 dissertation and mixed model of EI. Bar-On (2006) defined EI as an interrelated set of intrapersonal and interpersonal competencies, skills, and facilitators that combine to determine human behavior. However, after 17 years of research, Bar-On (2006) discovered some constructs in his mixed EI model were only facilitators of EI (e.g., independence). Future research should determine the constructs that warrant inclusion in the construct of EI and whether EI is ability- or trait-based, or a mix of the two.

SDL and EI. In following with others before him (i.e., Dewey, Knowles, Rogers), Garrison (1997) observed how opportunities to learn SDL enhance cognition and metacognition, which in turn, help to create those educational conditions (or elements) conducive to developing lifelong learners. More specifically related to the present study, adult learners with higher levels of SDL often have higher levels of EI (Kauffman, 2015; Koc, 2019; Zhoc et al., 2018). Both EI and SDL include a range of cognitive (e.g., attention, problem-solving), metacognitive (e.g., planning, evaluating progress), and affective (e.g., related to emotions) attributes (Koc, 2019; Rager, 2009; Zhoc et al., 2018). These skills are also often interrelated and positively correlated in the literature (Bar-On, 2006; Koc, 2019; Rager, 2009; Zhoc et al., 2018). Future researchers should explore in greater detail the cognitive and motivational dimensions of EI and SDL in both traditional and online learning environments.

Other learner characteristics. Previous researchers (e.g., Schulze, 2014; Sumuer, 2018) have found other learner characteristics (i.e., English speaking ability, use of Web 2.0 tools) to predict SDL in the online learning environment. Schulze (2014) found that SDL predicted online course completion through the indirect effect (mediation) of participants' English speaking ability. Schulze (2014) noted that this effect could be explained by how participants were required to have some English speaking ability. Sumuer (2018) found that SDL predicted the efficacy in technology (SDLt) through the indirect influence (mediation) of participants' use of Web 2.0 tools for learning. In following with the literature (e.g., Doe et al., 2017; Kauffman, 2015; Kerr et al., 2006), future researchers should consider these possible individual differences in their exploration of EI and/or SDL as factors in the OS of adult learners.

This research adds to the current literature by examining and providing statistical relationships between EI, SDL, and OS in adult learners. For other researchers interested in this field of study, the results of the present study may encourage the exploration of other specific predictor and mediator variables in future investigations of the relationships between EI, SDL, and OS. Such research can inform administrators and stakeholders in higher education to develop online courses and programs that build EI, SDL, and other positive cognitive, emotional, and behavioral patterns to help support the learning needs of adult learners.

Implications

Adult learners are part of the population who seek out online learning to better their life circumstances, skills, and/or employment opportunities (Bawa, 2016; Hassan et al., 2014; Knight, 2019; Vayre & Vonthron, 2017). Although the demand for online learning remains higher than ground courses, attrition rates for online courses have also remained higher than on campus courses, with 40% to 80% of online students failing and/or dropping out (Bawa, 2016; Choi & Park, 2018; Kauffman, 2015; Peck et al., 2018). Previous research studies on adult learners (graduate, undergraduate) have shown that higher levels of EI and/or SDL lead to better academic performance and higher course satisfaction (e.g., Berenson et al., 2008; Chan, 2018; Goodwin, 2016; Koc, 2019; Lai, 2011; Song & Bonk, 2016; Zhoc et al., 2018). The results from the current study support this in that the participants were adult online learners in degree programs with above average EI, SDL, and OS (i.e., GPA). Findings from the current study have implications for adult learners, online course developers, and administrators and faculty in higher education.

Adult learners appear to become more self-directed, and learn more deeply, when they are learning something self-initiated versus being directly taught by someone else (Knowles et al., 1973/2015). Also, it is important that learning outcomes be of immediate value to adult learners both personally and professionally. Knowles' (1975) defined SDL as a process where adult learners "take the initiative without the help of others [during] their own learning experiences," especially those outside of the traditional classroom (p. 18). The SDL process is dependent upon the context of learning and the needs of the learner (Candy, 2000; Garrison, 1997; Knowles, 1975, 1984; Meyer, 2010; Song & Hill, 2007). In this sense, both context and learner needs should be considered in the factors that influence academic success, such as course design, instructional methods, and peer engagement (Bawa, 2016; Kauffman, 2015; Kerr et al., 2006; Lee & Choi, 2011; Song & Hill, 2007). Knowles (1975, 1984) and others (e.g., Candy, 2000) found that teaching SDL skills to adult learners increased their academic performance. In support of Knowles' SDL theory, researchers have also found that SDL abilities and skills can be taught and improved with awareness and practice in both traditional classroom (e.g., Macaskill & Denovan, 2013; Nasir et al., 2014; Zhoc et al., 2018) and online (e.g., Chan, 2018; Lai, 2011; Sumuer, 2018) educational settings.

In turn, teaching SDL strategies to adult learners can increase EI, which may help to improve motivation, self-efficacy, self-management, emotional regulation, persistence, and satisfaction in either the traditional or online learning environments (Boyatzis, 2002; Koc, 2019; Rager, 2009; Zhoc et al., 2018). Even though in the current study EI did not predict OS (operationalized as GPA), improving EI in adult learners could also be valuable for administrators, faculty, and stakeholders in higher education. EI skills can help increase adult learners' emotional understanding and regulation, which in turn can increase their academic satisfaction and success in either learning environment (Berenson et al., 2008; Brown et al., 2016; Goodwin, 2016; Kauffman, 2015; MacCann et al., 2019). For students taking online courses, improving EI could help to reduce the high attrition and dropout rates, which in turn, would increase retention and student satisfaction with their overall university experience (Bawa, 2016; Berenson et al., 2008; Kauffman, 2015; Koc, 2019; Majeski et al., 2017; Zhoc et al., 2018).

This research could assist online educators and course developers to better understand the impact of EI and SDL on the academic and life success of adult learners. By providing a better understanding of how EI and SDL skills can influence the performance of adult online learners may allow them to offer adequate support, curriculum, and instruction to improve the well-being and academic success of adult learners. This research could also help the focus in the literature for the assessment and identification of online learner characteristics and needs as well as ways to offer course design, instruction, and support to adult learners.

Conclusion

The USDOE (2014), along with online education researchers (e.g., Allen & Seaman, 2017; Bawa, 2016; Kauffman, 2015; Peck et al., 2018) have emphasized the need for an improved understanding of online learning to increase retention and graduation rates, and ultimately, the productive employment of all students. There are gaps for identifying learner characteristics to better promote online student performance, completion, and success (Choi & Park, 2018; Kauffman, 2015; Kerr et al., 2006; Knight, 2019).

The current study answered the call for more research on adult learner characteristics, needs, and strategies in the online learning environment to improve online course design, delivery, and online instructor training (Bawa, 2016; Kauffman, 2015; Kerr et al., 2006; Majeski et al., 2017; USDOE, 2014; Vayre & Vonthron, 2017). Results indicated that among adult learners studied, SDL predicted OS and mediated (influenced) the relationship between EI and OS, although the indirect (mediated) effect was small. Though not intended, this study was conducted on mostly female graduate students. Further, these adult learners had above average EI, SDL, and OS. Due to the unique characteristics of the sample, the generalizability of the findings was limited.

In alignment with the theoretical frameworks of this study (Bar-On, 2006; Knowles, 1975, 1984), both EI and SDL include cognitive (e.g., problem-solving), metacognitive (e.g., planning), and affective skills (e.g., emotional understanding) that can be taught and improved with increased self-awareness and practice, as described in the literature (Bar-On, 2007; Berenson et al., 2008; Knowles, 1975, 1984; Lai, 2011; Zhoc et al., 2018). More specifically related to the present study, Bar-On (2006) and others (e.g., Boyatzis, 2016; Goleman 1995/2005) found that teaching EI skills to learners of all ages increased their independence (self-directedness) and academic performance. In other words, teaching EI skills improves SDL. Other researchers (e.g., Candy, 2000; Knowles et al., 1973/2015; Macaskill & Denovan, 2013; Zhoc et al., 2018) have found that improving SDL skills in adult learners increases their academic success and helps them to become lifelong learners and better managers of their daily lives. Like EI, improving SDL could also help to reduce the high attrition rates in online education (Bawa, 2016; Doe et al., 2017; Kaufman, 2015; Peck et al., 2018).

Recently, researchers have found that online learning helps develop metacognition (e.g., planning) and cognition (e.g., problem-solving) skills, which in turn help to develop motivation and self-efficacy, which then lead to increases in retention, satisfaction, and success (Doe et al., 2017; Hobson & Puruhito, 2018; Kauffman, 2015; Peck et al., 2018; Song & Bonk, 2016; Vayre & Vonthron, 2017). In this way, the active, process-based, and emotional-social aspects of online learning may help develop and support EI, SDL, and OS (Berenson et al., 2008; Engin, 2017; Goodwin, 2016; Song & Bonk, 2016). Through the assessment and implementation of EI and SDL skills into online course design, placement, curriculum, and instruction, more adult learners may benefit from improved academic performance, school satisfaction, and lifelong success.

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Appendix A: Research Participation Invitation

My name is Amanda Coté, and I am a doctoral candidate at Walden University. I am conducting a study on the attitudes and experiences of adult online learners. This research is a partial fulfillment of the requirements for my PhD in Educational Psychology at Walden University. Adult learners (18 years or older) who have completed at least one online course and one quarter/semester towards a degree program (undergraduate, graduate) are invited to participate to help expand our understanding of online learning and academic success.

Participation in this research is completely voluntary and anonymous. There will be no repercussions should you choose not to participate in this study, and you may exit the study at any time without consequences. If you agree to be in this study, then you will be directed to an anonymous online questionnaire that will take approximately 20-25 minutes to complete. The data collected will not contain personal identifiable information and will only be accessed by me, the researcher; it will not be shared with anyone else. To further protect your privacy, a consent signature is not requested.

Interested participants can click on the link below which will direct them to an informed consent page that provides more details about the study.

(Link was removed for publication)

Please feel free to share this invitation to participate with other adult online learners who meet the eligibility requirements and who might also consider participating in this research.

Thank you very much.

Best Regards,

Amanda Coté
Walden University PhD candidate

Appendix B: Demographics Questionnaire

Directions: Please answer the five demographic questions below. Note that your answers will remain anonymous and secure.

1. Please enter your age. _______

2. Select your gender.
   - o Female
   - o Male

3. Select your current level of education.
   - o Undergraduate Student (seeking an Associate's or Bachelor's Degree)
   - o Graduate Student (seeking a Master's or Ph.D./Doctorate Degree)

4. Enter the total number of online courses that you have taken for your current degree program. _______

5. Enter your GPA (in number format, i.e., 1.23). _______

Appendix C: SDLRS Usage Approval Correspondence

From: [redacted]
Sent: Sunday, March 8, 2020 8:03 PM
To: Amanda Cote
Subject: RE: Dissertation student seeking permission to use the Self-Directed Learning Readiness Scale for Nursing Education
Attachments: SELF-D~2.DOC

Dear Amanda

You have my permission to use the SDLRS to use in your expressed study. Instrument attached.

Regards,

[redacted]

From: Amanda Cote [redacted]
Sent: Saturday, 7 March 2020 5:30 AM
To: [redacted]
Subject: Dissertation student seeking permission to use the Self-Directed Learning Readiness Scale for Nursing Education

Dear [redacted],

I am a doctoral student at Walden University in the area of educational psychology. My research is examining the indirect relationships between emotional intelligence, self-directed learner readiness, and online success (course completion, GPA) in adult learners attending a fully online university.

I am writing to you for permission to use the 40-item Self-Directed Learning Readiness Scale for Nursing Education developed in 2001 by Fisher, King, and Tague. If you could formally give me your permission to use the survey via email, I would greatly appreciate it.

Thank you for considering my request to use your survey for my dissertation research. Please let me know if you need any additional information.

Respectfully,

Appendix D: TEIQue - SF Usage Approval Notice

http://psychometriclab.com/obtaining-the-teique/

Permission notice:

All TEIQue forms, versions, and translations are available free of charge for academic research purposes only. Provided there is no commercial usage, TEIQue instruments can be used for research purposes without permission. Please do not email us to request permission for usage in academic or medical research, as this is unnecessary. However, any commercial or quasi-commercial usage of any TEIQue instrument or related materials is **strictly prohibited, unauthorized and illegal**. For commercial applications, click **here**.