THE RELATIONSHIP OF PERCEIVED LEARNING AND SELF-REGULATED LEARNING OF UNDERGRADUATE STUDENTS AND THE CURIOSITY SCORES GENERATED BY PACKBACK

by

Rosemarie Rizzuto

Liberty University

A Dissertation Presented in Partial Fulfillment

Of the Requirements for the Degree

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ABSTRACT

Institutions work to improve their retention rates. Research supports academically and socially integrated students are more likely to develop a commitment to the institution and persist to graduation. Historically these theories emphasized perceived learning and self-regulated learning as contributing factors for student retention. Curiosity is a motivational factor that improves student engagement and academic integration. Discussion boards are used with face-to-face, online, and hybrid courses. Instructors use the virtual workspace to build a collaborative community for students to engage with one another, the instructor, and the course material. Packback uses artificial intelligence (AI) to heighten student engagement on discussion board posts by providing immediate feedback to students and publishing a leader board with curiosity scores. Through the lens of Connectivism and the Community of Inquiry Model for online learning, this predictive correlational study explored the relationship of perceived learning and self-regulated learning of students enrolled in an undergraduate political science course and the curiosity score generated by Packback. The study involved a convenience sample from a land grant institution located in the southeastern United States . The Cognitive, Affective, and Psychomotor (CAP) survey measured perceived learning using a seven-point Likert scale. The Online Self-Regulated Learning Questionnaire (OSLQ) measured self-regulated learning behaviors using a five-point Likert scale. Packback's Curiosity Score is generated through an algorithm using presentation, credibility, and effort. A multiple regression analysis demonstrated a lack of sufficient evidence to support a predictive relationship between perceived learning and self-regulated learning (predictor variables) upon curiosity scores (criterion variable) generated by Packback.

Keywords: Self-regulated Learning, Perceived Learning, Curiosity Scores, Packback

Copyright Page (Optional)

Dedication

This dissertation is dedicated to my husband Tony, and my two daughters, Sammy Rose and Angelina Marie, who encouraged me in word and action throughout the process. You all took turns in giving me the physical, emotional, and spiritual support I needed to persevere from beginning to end. I thank you for helping me to talk out ideas, vent my frustrations, and celebrate the milestones. You gave me the strength to carry on. I love you!

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List of Abbreviations

Artificial Intelligence (AI)

Cognitive, Affective and Psychomotor (CAP)

Community of Inquiry (COI)

Comparative Fit index (CFI)

Creativity, Critical and Reflective Thinking (C & CRT)

Deprivation-type curiosity (D-type)

The Durbin Watson statistic (DW)

Epistemic Curiosity Scale (ECI)

Functional magnetic resonance imaging (MRI)

Interest type curiosity (I-type)

Non-normed fit index (NNFI)

Online Self-regulated Learning Questionnaire (OSLQ)

Personal Learning Environment (PLE)

Root mean standard error of approximation (RMSEA)

Sum of Error of Estimates (SEE)

CHAPTER ONE: INTRODUCTION

Overview

The purpose of this quantitative correlational study was to explore the relationship of perceived learning and self-regulated learning of undergraduate political science students and their curiosity scores generated by Packback. Chapter One includes background information about student retention and the influence technology has on enrollment, pedagogical practices, and learning goals. Included in the background is an overview of the theoretical framework for this study. The problem statement identifies the absence in the literature addressing artificial intelligence (AI) coaching on topics of perceived learning and self-regulated learning with online discussion boards as implemented by Packback. The purpose and significance of the study are followed by the research question. Chapter One concludes with a list of essential terms and definitions referred to throughout the paper.

Background

Higher education is a gateway to economic opportunity, social mobility, and full civic participation (Allen & Norma, 1995; Cahalan et al., 2020). Credential degree earnings often translate to increased income, access to better health care, job satisfaction, and a longer life span (Cahalan et al., 2020; Toutkoushian & Paulsen, 2016). Higher graduation rates impact the local community, the state, and the country (Fraysier et al., 2020). Institutions focus on strategies to increase student retention. Professors incorporate technology as a tool of instruction to aid, motivate, and engage learners.

Before World War II, higher education focused on educating the elite, and graduation rates were high (Hunsaker & Thomas, 2013; Kember et al., 2021). Once access to higher education increased, the graduation rate declined. Freshmen's attrition rates of 25% became concerning in the 1970s (Cahalan et al., 2020; Thelin, 2011). The 1972 amendments to the Higher Education Act expanded government regulatory control in exchange for financial aid funding known as the Pell Grant (Gándara & Jones, 2020; Geiger, 2016). Institutions added professional advising, expanded student services, and invested in other resources to help students persist and graduate. The 1990 Right to Know Act required all higher education institutions receiving Title I funds to report on data points, including graduation rates (Gándara & Jones, 2020; S. 542, 1990). Researchers continued to study factors, including student integration, faculty to student ratios, engagement factors, and course design to identify factors that could improve persistence (Fraysier et al., 2020; Hunsaker et al., 2013; Huo et al., 2022). According to Vilkova & Shcheglova (2021), self-regulated learning, specifically environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation, are significantly correlated with higher educational outcomes.

Universities allocate funding for resources to support students' academic, physical, and emotional well-being with the goal of enhancing the overall college experience and increasing attrition (Joanis et al., 2020). Secretary Spelling's Commission Report emphasized performance results for all higher education institutions seeking accreditation (Commer, 2021; Kinzie, 2019; U.S. Department of Education, 2006). The report charged institutions with providing quality education that is accessible, affordable, transparent, and accountable. Criticism from the report created uncertainty and anger throughout universities across America (Commer, 2021; Budd, 2007). However, the change did occur. Spelling introduced an era of data-driven decision-making focused on student outcomes that impacted policies and finances (Commer, 2021; Kinzie, 2019; Liu, 2017).

The Obama administration introduced an interactive college scorecard that published data points for each university, including cost, graduation rates, loan default rates, average amount borrowed, and employment (Commer, 2021; Hafer et al., 2021; U.S. Department of Education, 2013). Revisions made to the scorecard provided over 1700 data points, including completion rates and post-college earnings of alumni (Commer, 2021; U.S. Department of Education, 2016). Graduation rates are published on college scorecards to provide transparency for potential students (Oztekin, 2016; Pike & Robbins, 2020). Thirty-three states adjusted their performance funding to create incentives for public institutions to improve student success (Pike et al., 2020). The college scorecard and performance funding provided an indirect path for graduation rates to impact an institution's revenue. The access to persistence information has not increased retention, but it highlights the attrition problem to the public. Students and their families are informed consumers when they enter the market for higher education.

As institutions evolve to meet new mandates, technology transforms every aspect of individual’s lives. Smart mobile devices and streaming databases led to globalization. Technology makes higher education more assessable for people. The learning management systems create an engaging learning environment, with email, multimedia capabilities, and a community forum that empower students to connect and collaborate on coursework (Coates et al., 2005; Soegoto & Rinaldy, 2020). In 2018, almost 7-million scholars, representing 35.3% of higher education students, were enrolled in at least one distance learning course at a degree-granting institution (National Center for Education Statistics, 2019). Many institutions incorporate distance learning as part of their strategic plan to increase their revenue (Allen & Seaman, 2016; Saunders et al., 2020). The digital age changes education and institutions’ need to adjust their practices and policies to maximize the technological benefits and meet the customers' expectations.

Increasing the completion rate for higher education helped make the United States globally competitive (Budd, 2007; Capano, 2011; Fraysier et al., 2020). With less federal funding available, students need to borrow from their future to obtain a degree that will provide them with a career and financial stability. Too often, people leave their investments and dreams before they come to fruition. Students acquire debts they need to repay; and they do not always leave with a degree or sought-after skills (Goldrick-Rab & Labaree, 2021). Joanis et al. (2020) reported that, by the end of 2019, the United States will have an estimated 1.6 trillion dollars in outstanding student loan debt. Generally, students who do not graduate earn half as much as a person with a bachelor's degree, are more likely to experience unemployment, have a lower standard of living, and are less likely to have healthcare (Cahalan et al., 2020; Oztekin, 2016; Toutkoushian et al., 2016). Low persistence rates lead to a stagnant economy and limit socioeconomic mobility (Fraysier et al., 2020; Toutkoushian et al., 2016).

Technology enables higher education institutions to accommodate more learners and address the inequality in accessibility to higher education by expanding online learning opportunities. Unfortunately, there are additional obstacles interfering with equality. These hindrances include disparities in academic readiness, student's ability to interact with the necessary technology, and accessibility to devices and the Internet (Athens, 2018; Fraysier et al., 2020; Warf, 2019; Weidlich & Bastiaens, 2018). Students who lack exposure to web technologies or learning management systems struggle when introduced to unfamiliar platforms before interacting with the integrated course material (Kumar & Owston, 2016; Vasilescu et al., 2020; Woo et al., 2021; Warf, 2019). Additionally, internet access is not readily available in all areas (Kumar et al., 2016; Lee, 2017; Warf, 2019). Research using these indicators reveal that black males comprise the demographic group with the highest risk of not completing online courses based on these indicators (Athens, 2018; Fraysier et al., 2020; Xu & Jaggars, 2013).

Technology allows knowledge to grow exponentially, doubling every 12 hours (Chamberlain, 2020). This fact influences the focus of learning practices based on the needs and preferences of the learner. Siemens introduced a learning theory entitled Connectivism in 2004, which Downes further developed (Chamberlain, 2020). Many refer to the theory as a learning theory for the digital age since it incorporates ideas from the non-linear theories of chaos, network and complexity, and self-organization. Connectivism posits that learning does not require more information, but rather, the ability to connect informational data sources. Connectivism assumes the scholar can find and decipher relevant information quickly by accessing connections between ideas and concepts (Chamberlain, 2020; Goldie, 2016; Reese, 2014; Siemens; 2004). Students need to develop analyzing and synthesizing skills so the quality of information can be evaluated and embedded where needed (Corbett & Spinello, 2020; Siemens, 2004). Autonomy, connectedness/interactivity, diversity, and openness are the four foundations of learning outlined in the theory (Corbett et al., 2020, Downs, 2019). Knowledge is personal, context-sensitive, yet collaborative (Chamberlain, 2020).

COI also extends the Constructivist learning theory to an online platform (Chamberlain, 2020; Cleary, 2021; Flynn et al., 2015). COI focuses on three aspects of presence in a virtual environment. Teaching presence includes course design, activities, and direct instruction (Garrison, 2017; Restall & Clark, 2021). Social presence addresses the level of open communication, affective expression, and group cohesion. Cognitive presence refers to the amount of meaning constructed through reflection and discourse within the community. The interaction between these three elements of presence establishes the learning environment.

Technology altered the educational landscape. Higher education institutions adjusted to the digital age by expanding course modalities, modifying course design, building infrastructures, and incorporating technological advancements into the curriculum (Lowenthal & Moore, 2020; Makani et al., 2019). The role of the instructor and the student also changed. Teachers are facilitators, coaching students as they decipher web-based information (Corbett et al., 2020). Students autonomously work to establish their network connections (Corbett et al., 2020; Downes 2019). Research suggests an association between Connectivism and an increased ability to learn, which Downes contributed to the increase in student self-management and access to diverse worldviews.

Problem Statement

College attrition rates have political and economic consequences for our county, hinder social mobility, and limit financial growth and overall well-being (Fraysier et al., 2020; Toutkoushian et al., 2016). Federal and state governments implement data-driven financial incentive programs to motivate institutions to improve their completion rates and overall effectiveness (Pike et al., 2020). Higher education institutions work to accommodate students' schedules by increasing distance learning opportunities and calendar flexibility (Allen et al., 2016; Kember et al., 2021). Despite these efforts, completion rates have only marginally increased. More than 35% of the students who begin a journey to obtain a bachelor's degree are unsuccessful after six years (National Center for Education Statistics, 2019).

Discussion boards are an essential tool used in higher education with face-to-face, hybrid, and online course formats. The virtual environment creates a community that serves to substitute or enhance in-class interactions. Instructors use discussion boards to promote student communication, collaboration, and engagement, through critical thinking and meaningful dialog. Research supports the role discussion boards play in building community (Cleary, 2021; Watt, 2016), fostering student engagement (Ding et al., 2020; Lane, 2014; Li, 2019; Watt, 2016), and increasing student interaction (Ding et al., 2020; Watt, 2016). Still, the discussion board's efficacy is highly scrutinized due to the lack of meaningful student participation and the extensive time required by instructors to monitor the boards (Champion & Gunnlaugson, 2018; Ding et al., 2020). Packback uses AI to monitor posts generated by students, providing feedback for instructors and students in real-time that includes a gamified component of earned curiosity points on a Learner Leaderboard in the form of a curiosity score (Hudson et al., 2020). There is limited research on using gamification approaches with online discussion boards (Ding et al., 2018; Ding et al., 2020). Scholars suggested research leading to an increase in discussion board effectiveness would benefit instructors and students (Fehrman & Watson, 2021; Ringler et al., 2015).

Due to the concerns for student retention and the increasing use of AI coaching applications in higher education, it is important to investigate the impact AI has on perceived learning, self-regulated behaviors, and curiosity, three factors associated with course satisfaction and higher completion rates (Alqurashi, 2019; Barnard et al., 2008; Rovai, 2003). Bates, Cobo, Marino & Wheeler (2020) reported that some argue AI does not develop higher-order thinking skills, such as critical thinking, problem-solving, creativity, and knowledge management, which are the claimed benefits associated with discussion board posts. Zawacki-Richter et al. (2019) concluded that after reviewing 146 articles from a pool of 2656 publications between 2007-2018, AI learning applications tended to embrace a behaviorist philosophy and lack input from educators. AI studies seemed to focus on the application and the algorithms rather than the effect on student learning or the interaction with specific student characteristics (Bates et al., 2020; Luckin & Cukurova, 2019). The problem is that more research is needed to determine if curiosity scores can be predicted from a linear combination of perceived learning and self-regulated learning (Bates et al., 2020; Cox 2021; Luckin & Cukurova, 2019; Zawacki-Richter et al., 2019).

Purpose Statement

The purpose of this quantitative predictive correlational study was to explore the relationship of the predictor variables, perceived learning, and self-regulated learning of undergraduate political science students and the criterion variable, curiosity score generated by Packback application (Gall, Gall & Borg, 2007; Joyner et al., 2018; Rockinson-Szapkiw et al., 2019; Warner, 2013). Perceived learning is the self-reported measure of a change in knowledge based on reflective processes (Bacon, 2016; Thomas et al., 2019). Perceived learning was measured using the overall Cognitive, Affective, and Psychomotor (CAP) score obtained by a survey instrument (Harrell & Wendt, 2019; Rovai et al., 2009). Self-regulated learning is the ability of a learner to establish a productive environment for learning, set academic goals, manage time, seek help from peers and instructors, monitor work, and evaluate academic progress (Araka et al., 2020; Barnard, 2010a). This cyclical process involves goal-oriented activities, thoughts strengthened by motivation, emotion, and perseverance, which is followed by reflection of one's performance (Harati et al., 2020). Self-regulated learning will be measured using the Online Self-Regulated Learning Questionnaire (Araka et al., 2020; Barnard et al., 2009).

Curiosity is the drive to acquire new information and embrace novel experiences while eliminating a gap in one's knowledge (Berlyne, 1954; Gómez-Maureira & Kniestedt, 2019;

Kashdan et al., 2009; Litman, 2008). Packback generates a curiosity score for every post and response based on presentation, credibility, and effort (Packback, 2022). The study population includes volunteer undergraduate students enrolled in a political science course taught face-to-face, hybrid, and online during the spring semester of 2022 at a public university in Alabama.

Significance of the Study

This study's significance is to add to the literature base about characteristics associated with student persistence in higher education by looking at perceived learning, self-regulated behaviors, and curiosity when Packback's AI technology responds to their discussion board posts. There are several published qualitative studies on the use of AI feedback on discussion boards. However, a limited number of quantitative studies address AI, specifically Packback, on students' perceived learning, self-regulated behaviors, or curiosity. Unlike most published research that addresses AI in educational settings, this study addressed student outcomes rather than the application or algorithm (Bates et al., 2020). Hudson et al. (2020) conducted research with Packback on two different platforms, which yielded conflicting results on average word count measures, the number of cited resources, and participation rates. Identifying the relationship between students' self-regulated behaviors, perceived learning, and curiosity scores on discussion boards adds to the research about effective pedagogical practices for using discussion boards in higher education, as Ringler et al. (2015) and Luckin et al., (2019) stated is needed.

This study is essential for expanding scholarship on the impact of AI innovations, specifically Packback technology, in educational settings, by allowing students, instructors and institutions to make informed decisions about financial expenditures on relevant technology (Paulsen & McCormick, 2020). Correlational data about perceived learning, self-regulation and curiosity benefits students' performance, pedagogical practices, and course design (Baker & Smith, 2019; Bates et al., 2020). This research provides educational feedback addressing the impact AI applications have on student learning (Bates et al., 2020). The possibilities and limitations of AI in this capacity will be explored (Baker, 2019). The study informs the larger conversation of AI usage regarding the technology's social, ethical, pedagogic, and management issues (Cox, 2021; Picciano, 2019).

Research Question

RQ1: How accurately can curiosity scores be predicted from a linear combination of perceived learning (cognitive, affective, and psychomotor) and self-regulated learning (environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation) for undergraduate political science students?

Definitions

The terms pertinent to the study are listed below.

1. *Affective learning* – The domain in Bloom's taxonomy that addresses the growth of attitudes, emotions, and behavior (Rovai et al., 2009: Testers et al., 2020).
2. *Artificial Intelligence* - A technology capable of engaging in human-like activities, including learning and adapting (Popenici & Kerr, 2017; Rybinski & Kopciuszewska, 2021).
3. *CAP* – An instrument used to measure the perceived cognitive, affective, and psychomotor learning reported by students (Harrell & Wendt, 2019; Rovai, 2009)
4. *Connectivism* – A learning theory for the digital age (Corbett & Spinello, 2020; Siemens, 2004)

5. *Discussion Board* – A virtual environment for students to construct knowledge independently and with a community of other learners about course topics (Champion et al., 2018; 2017; Fehrman & Watson, 2021).
6. *Distance Learning* – A course taught asynchronously, off-campus, and may require a digital device (Casado-Aranda et al., 2021; Rovai, 2003).
7. *Environment Structuring* – Creating a physical space ideal for maximum productivity (Araka et al., 2020; Barnard et al., 2009).
8. *Goal-Setting* – An achievement outcome that motivates a person to engage in a course of action (Von Suchodoletz et al., 2020).
9. *Offloading* – A strategy used to minimize the cognitive demands of retaining information by utilizing an external record for the data (Clark & Mayer, 2011/2016; Corbett & Spinello, 2020).
10. *Packback* – AI discussion board monitoring program that provides immediate feedback to students on their post and uses a gaming component to generate a curiosity score (Hudson et al., 2020)
11. *Perceived Learning* - Self-reported measures of the increase in knowledge and skills gained during an academic experience or exercise (Thomas et al., 2019).
12. *Persistence* – Students' ability and desire to complete their studies and obtain a degree (Kember et al., 2021; Rovai, 2003).
13. *Retention Rate* – The percent of students who continue in an institute of higher education until they graduate (Hunsaker et al., 2013; Kember et al., 2021).
14. *Seek-help* – A personal initiative to improve learning by adapting strategies and being persistent (Araka et al., 2020; Zimmerman, 2002).

15. *Self-evaluation* – The ability to accurately perceive the quality of one's work or performance so one can adjust future actions (Araka et al., 2020; Zimmerman, 2002).
16. *Self-regulated learning* - Proactive and reactive student-initiated steps and engaged thought patterns that support cognitive gains (Araka et al., 2020; Zimmerman, 2008).
17. *Task Strategies* – The ability to plan and carry out effective activities that bring one closer to their goal (Araka et al., 2020; Zimmerman, 2002).
18. *Time Management* – The discipline to allocate time and remain focused on strategically planned activities designed for goal achievement (Araka et al., 2020; Barnard -Brak et al., 2010a; Zimmerman, 2002).

CHAPTER TWO: LITERATURE REVIEW

Overview

The purpose of this literature review was to present the impact technology has on the landscape of higher education, learning theories, and course design. The chapter opens with the theoretical framework for student retention and moves to the role technology plays in expanding higher education opportunities. Connectivism (Siemens, 2005) and Community of Inquiry (Garrison et al., 1999), foundational theories for this study, are discussed. A thorough review of the literature connected to self-regulated learning, perceived learning, twenty-first century thinking skills, curiosity, and discussion boards are presented. An explanation of Packback, a specific discussion board platform, is included before a summary of the synthesized literature concludes the chapter.

Theoretical Framework

This chapter presents two different theoretical frameworks: those related to persistence theories in higher education and those related to learning theories. The persistence theories evolved from a student's need to assimilate to an institution academically and socially (Bean, 1980; Huo et al., 2022; Tinto 1975) to more recent approaches focused on the institution developing an inclusive environment concerned with accommodating the student's academic and social needs and preferences (Gabi & Sharpe. 2021; Luyt, 2013; Kerby, 2015). This shift in retention strategies result from research that supports correlations between students' motivation and retention rates (Simpson, 2013; Szymkowiak et al., 2021), and studies that show a positive association between perceived learning and self-regulated learning with course satisfaction and persistence in higher education (Alqurashi, 2019; Rovai, 2003; Stephen et al., 2020; Zimmermann, 2002). Learning theories, such as Connectivism and Community of Inquiry, support technology use, learner autonomy, various forms of interaction, and metacognitive processes applicable for learners during the digital age (Brieger et al., 2020; Mattar, 2018; The Learning Society, n.d).

Persistence Theories for Higher Education

Student persistence is a concern for all institutions. Several theories identified variables that influence the decision-making process involved in student attrition. Tinto's theory of integration (1975) that evolved into the institutional departure model posited that persistence is the result of aligned motivation with the student's academic ability, which matches the academic and social characteristics of the institution (Behr et al., 2020; Cabrera et al., 1992; Terenzini et al., 1985; Tinto, 1993). An individual's motivation includes their background (family expectations and socioeconomic status), individual attributes (gender, ethnicity, and ability), and pre-college schooling, which impacts an individual's commitment to their career goals and their institution of higher education (Behr et al., 2020; Tinto, 1975; Tinto 1993). Goal commitment correlates with grade performance and intellectual development, which research suggested leads to academic integration (Behr et al., 2020; Terenzini et al., 1985; Pascarella & Terenzini, 1991; Tinto, 1975; Tinto, 1993). Institutional commitment involves strengthening social integration by increasing interactions with peer groups and faculty (Schaeper, 2020; Tinto, 1975; Tinto, 1993).

These goals and commitments have a symbiotic relationship with academic and social integration (Behr et al., 2020; Schaeper, 2020; Terenzini et al., 1985; Tinto, 1975; Tinto, 1993). Research suggested academically and socially integrated students are more likely to develop a commitment to the institution and persist to graduation (Andrade et al., 2020; Astin, 1985; Cabera et al., 1992; Terenzini, 1985; Tinto, 1975; Tinto & Pusser, 2006). Some argue that goal commitment based on previous behavior, attitudes, and individually accepted norms towards education affect the ability to endure to the goal (Ajzen, 2012; Huo, Messenger & Miller, 2022; Ilyas & Zaman, 2020). External factors, distractions, and adversity impact an individual's level of commitment to the goal based on the perceived result (Behr et al., 2020; Fishbein & Ajzen, 1974; Tinto, 1975; Tinto, 1993). A premise to commitment-making rests in a theory of cost-benefit analysis (Baker, 2019).

The student attrition model originated from a theory used to explain employee turnover in an organization (Bean, 1980; Tight, 2020). Bean (1980) substituted grade point average, student development, and career possibilities for wages. Like Tinto's research, the study supported the influential role institutional commitment has on student persistence (Bean, 1980; Bean, 1982; Huo et al., 2022; Tinto, 1975; Tinto, 1993; Whitten et al., 2020). Bean identified variables impacting attrition in a later study, including intent to persist, attitudes, institutional fit, and external factors, such as family approval, peer encouragement, transfer opportunities, and finances. The intent to leave was the most vital determinant of attrition (Bean, 1982; Boddy, 2020; Cabrera et al., 1992). The negative correlations with loyalty to the university, concern about an institution being the best place to obtain the degree, and practical value for career selection, provide additional reasons a person intends to leave the institution (Bean, 1982; Huo et al., 2022; Whitten et al., 2020).

Critics of Tinto's theory (1975) suggested he minimized the role external factors play in the decision-making process, which provides limited predictability validity (Bean, 1985; Behr et al., 2020; Cabrera et al., 1992; Neumann & Finaly-Neumann, 1989; Terenzini et al., 1985; Tight, 2020). Scholars criticize persistence theories for the limited applicability for juniors and seniors who had previously integrated themselves academically and socially (Bean, 1985; Behr et al., 2020; Kerby, 2015; Neumann et al., 1989; Tight, 2020). Theorists pivoted their focus to explore the impact of student preparedness and student learning experience upon persistence (Huo et al., 2022; Kerby, 2015; Kodama et al., 2018; Neuman et al., 1989; Tight, 2020). The research suggested that course design should involve interaction, outside classroom opportunities, and quality learning experience that yield direct and indirect benefits for students (Gabi et al., 2021; Luyt, 2013; Kerby, 2015; Neumann et al., 1989; Pascarella et al., 1991; Tinto, 2012). The academic environment should allow for the mindset of curiosity to grow, time for students to examine their thoughts, and reflect on their performances (Maksum et al., 2020). Research supported perceived growth, an inclusive environment for interactions, opportunities for students to engage in their academic program, and the quality of course content and instructional activities, as dominant predictors for junior and senior persistence behaviors (Andrade et al., 2020; Gabi et al., 2021; Kerby, 2015; Smith & Van Aken, 2020). Other studies emphasized the value of considering learning characteristics and the attributes of the current generation when discussing policy, student needs, retention strategies, and instructional designs (Prensky, 2001a.; Prensky, 2001b; Moore et al., 2017; Szymkowiak et al., 2021).

Those considered to be in the same generation have a shared context that shaped their worldview (Cartwright-Stroupe & Shinners, 2021; DiMattio & Hudacek, 2020; Seemiller & Grace, 2017). These students have similar characteristics and perspectives, even if they have different life experiences. Millennials, sometimes referred to as Generation Y, include those born between 1982 through 2005. These students enjoy team-oriented and collaborative assignments. Millennials also enjoy flexibility with their assignments, multimedia presentations, close relationships with authority figures, and online connectedness (Eckleberry-Hunt & Tucciarone, 2011; Miller & Mills, 2019; Seemiller & Clayton, 2019). Generation Z, sometimes referred to as the Net Generation, are digital natives, born between 1995 and 2010. Technological advancements shaped this generation creating a ‘we centered mentality’ convinced they can save the world with self-identified characteristics of loyalty, thoughtfulness, determination, compassion, open-mindedness, and responsibility (Mahesh et al., 2021; Seemiller & Clayton, 2019; Seemiller et al., 2017). This generation thrives with video-based learning, which resulted in the success of Ted Talks and U-Tube videos (Cartwright-Stroupe & Shinners, 2021; Miller & Mills, 2019; Seemiller et al., 2017). They enjoy assignments that require intrapersonal communication prior to group sharing. Generation Z look for community engagements and internships as part of their educational process (Cartwright-Stroupe & Shinners, 2021; Mahesh, Bhat & Suresh, 2021; Miller & Mills, 2019; Seemiller et al., 2017).

During the twentieth century, universities responded to the needs of business by preparing students to meet the demands of the workforce necessary for economic growth (Cheng, 2015; Krishnamoorthy & Keating, 2021). At the time of the research, the job market was less stable. Jobs, the economic market, technology, and social environments were constantly changing, requiring individuals to engage in self-management by being autonomous and lifelong learners (Cheng, 2015; Rotatori et al., 2021). Evidence of this workforce shift was seen with the post-industrial employer who sought individuals who solve problems, make critical decisions, communicate effectively, and possess interpersonal, networking, and digital skills (Cheng, 2015; LeRoux, 2002; Rotatori et al., 2021). The relevancy of universities in this knowledge-driven society is based on their ability to prepare students for success in the current market of their time (Cheng, 2015; Krishnamoorthy & Keating, 2021; LeRoux, 2002; Seemiller et al., 2017). Students need skills and strategies that equip them to manage the constant flow of information that shapes their lives (Cheng, 2015; Rotatori et al., 2021; Seemiller & Grace, 2017).

Non-traditional enrollment also increased, and persistence models examined the predictability of attrition patterns in this population. A non-traditional student has one or more of the following characteristics: part-time enrollment status, older than 24, or is a non-resident of the institution (Bean & Metzner, 1985; Gulley, 2021). Bean et al. (1985) theorized that non-traditional students look for practical outcomes rather than social outcomes (Stephen et al., 2020). External factors, such as educational background, finances, family, and job responsibilities, have a substantial impact on persistence; therefore, many theories incorporate them (Andrade et al., 2020; Bean et al., 1985; Stephen et al., 2020; Tinto, 1993). Since non-traditional students face external factors that challenge persistence, self-regulation, self-efficacy, and self-directedness are important determinants for their retention (Stephen et al., 2020).

As distance learning evolves, theories of persistence and learning theories need to adapt to include growing modalities of learning. Rovai (2003) combined Tinto's theory (1993) with Bean and Metzner's (1985) persistence models to create one composite model for distance learning (Stephen et al., 2020). Rovai's (2003) model included student characteristics (age, ethnicity, and gender), academic experience, and skills before entering higher education, along with internal and external factors after program admission (Stephen et al., 2020). Rovai combined Tinto and Bean's internal factors with self-esteem, program clarity, resource availability, and pedagogical factors. External factors include work and family responsibilities, opportunities to transfer, and life crises. Commonalities among persistence theories emphasized perceived learning benefits and goal commitment as contributing factors for student retention (Alqurashi, 2019; Stephen et al., 2020; Vanslambrouck et al., 2017).

Learning Theories

Behaviorism, Cognitivism, and Constructivism were popular learning theories of the 20th century (Cleary, 2021; Corbett et al., 2020). Behaviorists believe knowledge acquisition is externally driven and require explicit conditions for learning (Corbett et al., 2020; Harasim, 2017). Cognitive theories support internally driven learning and consider the learner's mental processes that interact with the stimulus to explain a learner's response (Corbett et al., 2020; Harasim, 2017; Siemens, 2005). These two theories ignore individual differences and variations with interrelated components of learning (Corbett et al., 2020; Saba et al., 2017; Siemens, 2005). Constructivists believe knowledge is continuously constructed by individuals through interaction with the community, making it dynamic and conditional (Cleary, 2021; Corbett et al., 2020; Harasim, 2017; Siemens, 2005). Pedagogical practices for Constructivism include student-centered active learning experiences, scaffolding, and collaboration (Corbett et al., 2020; Harasim, 2017; Siemens, 2005). Constructivists maintain that learning requires active critical thinking, which may include collaborative and co-regulated processes (Cardak, 2018; Feyzi Behnagh & Yasrebi, 2020). Connectivism supports the social learning aspect of Constructivism and extends it to the networked world (Corbett et al., 2020; Duke et al., 2013). Feyzi Behnagh and Yasrebi (2020) argued that effective integration of learning technology provides opportunities for collaboration and creates new way of learning.

Technology development created a need for new learning theories to direct pedagogical practices that incorporate technology and explain the changes in context for learning (Bell, 2011). Educational research discovered the potential benefits of online communities and networks on student engagement (Bell, 2011; Cleary, 2021). Connectivism suggests that learning is a complex and nonlinear process, contradicting the foundation of the earlier theories (Saba et al., 2017; Jacobsen, 2019). Like Constructivism, Connectivism believes learning is social, active, reflective, and occurs in context (Brieger et al., 2020; Flynn, Jalali & Moreau, 2015). This theory extended the limits of Constructivism by incorporating networking, nonlinear knowledge development with the concept of offloading information by storing data in computers, and databases, instead of solely in the human brain (Downes, 2019; Mattar, 2018; Siemens, 2004). Offloading information is a strategy used to minimize the cognitive demands of retaining information by utilizing an external record for the data (Clark & Mayer, 2016; Cleary, 2021; Jacobsen, 2019).

Connectivism

Siemens (2005) argued that learning theories developed before the digital age are inadequate since they do not consider the impact of social networking technology (Corbett et al., 2020). The digital learning theory abandons the idea of knowledge acquired through reason and experience, since knowledge can be obtained through another's experience shared through a network connection (Corbett et al., 2020; Harasim, 2017; Siemens, 2005). A network is a connection between nodes, also referred to as entities. Nodes are individuals, organizations, groups, resources, and communities that vary in size and influence, which depends on the number of individual connections within the system (Corbett et al., 2020; Siemens, 2005). There are three diverse levels of nodes: neural, conceptual, and external. The neural level consists of neurons, the conceptual level consists of ideas and concepts, and the external level include people and informational sources (AlDahdouh, 2021). Nodes that are popular or acknowledged for their expertise gain influence and strength that can be transferred to other networks (Corbett et al., 2020; Siemens, 2005). Connectivism supports the acquisition of competence from formed connections with updated networks. These networks are decentralized and employ theories of chaos, network and complexity, and self-organization (Corbett et al., 2020; Downes, 2010; Harasim, 2017; Siemens, 2005). Connectivists focus on the learner's ability to connect with different networks where information is accessible and continuously multiplies (Dreamson, 2020; Siemens, 2005; Strong & Hutchins, 2009). These theoreticians believed learning is a process of network formations (AlDahdouh, 2018; Dreamson, 2020; Kotzee & Palermos, 2021). Knowledge acquisition is unpredictable and the navigation of networks creates a rippling effect on the community of knowledge (Demir et al., 2019; Siemens, 2005). Connections between contrary ideas leads to intellectual growth and innovation (Siemens, 2005; Tham et al., 2021).

There are four distinct stages of network connections. These stages include aggregation, remixing, repurposing, and feed forward (AlDahdouh, 2021; AlDahdouh, 2018; Downs, 2019; Kop et al., 2011). Aggregations involves searching for content by building reliable connections with information resources. During the remixing stage, the learner applies the information to the situation using their own lens. Repurposing involves creating an artifact with the remixed information. The last stage, feed forward, encourages the learner to share their gained knowledge by posting their artifacts or hosting discussions that contribute to the collective knowledge based on the understanding gained in the process (AlDahdouh, 2021; AlDahdouh, 2018; Downs, 2019; Kop et al, 2011).

Network learner uses higher order thinking skills, such as creativity, critical, and reflective thinking (C & CRT) to develop and maintain their personal learning environment (PLE) on personal computers or mobile devices (Cardak, 2018; Carter et al., 2019). C & CRT are interrelated skills that collaborate with one another and manifest in varying degrees during the learning process (Akpur, 2020; Cardak, 2018). Critical thinking is the process focused on determining beliefs and actionable steps while reflective thinking organizes the learning with context and understanding (Proctor, 2020). A study conducted by Akpur (2020) found a positive and significant relationship between creativity, critical thinking, and reflective thinking, along with evidence that supports each one of these elements having positive and significant predictive power on academic performance. Cardak (2018) identified eight steps in the process, which include selection, organization, connection, investigation, creation, sharing, following, and interacting. The process is not dependent on any one skill or the sequence implemented. Connectivism focuses on networks, maintaining those networks, creating new nodes, and the decision-making process (Cardak, 2018; Tham et al., 2021).

Technology and the internet impacted education by connecting learners to knowledge beyond their experience through networks (Corbett et al., 2020; Goldie, 2016; Reese, 2014; Siemens; 2004). The ability to find and decipher relevant information quickly by accessing connections between ideas and concepts is vital (Corbett et al., 2020; Goldie, 2016; Reese, 2014; Siemens; 2004). Connectivism accounts for the social environments rapidly updating data, which requires one to continuously engage in decision-making influenced by peers, technology, and media (Corbett et al., 2020; Siemen, 2005). Learners engage in the process formally and informally (Corbett et al., 2020; Dunaway, 2011; Greenhow et al., 2009). They obtain knowledge and contribute information to the networks (Corbett et al, 2021; Downes, 2019; Dunaway, 2011; Kotzee & Palermos, 2021). Knowledge is personal, context-sensitive, yet collaborative (Corbett et al., 2020; Dunaway, 2011; Siemens, 2005; Tham et al., 2021). Connectivism prioritizes the ability to identify, access, and leverage information sources, or networks, over fixed knowledge (Cleary, 2021).

Learners need to recognize connections, make decisions, and synthesize gathered information (Corbett et al., 2021; Goldie, 2016; Reese, 2014; Siemens; 2004). Connectivism provides pedagogical principles for online learning (Goldie, 2016; Siemens, 2004; Utecht & Keller, 2019). These principles include diversity of opinions, specialized nodes of information sources, learning in non-human appliances, a celebration of the capacity to know rather than what is already known, the ability to develop, nurture, and maintain connections, and possess accurate and up-to-date knowledge (Goldie, 2016; Siemens, 2004; Utecht & Keller, 2019). The teacher is no longer the sole source of information. Instructors need to support and motivate students to read, make observations, question, analyze, evaluate, and then create (Brieger et al., 2020; Maksum & Khory, 2020). The role of the instructor is to manage interactions and provide support for network navigation (Brieger et al., 2020; Corbett et al., 2020; Dunaway, 2011; Siemens, 2005). The learning climate the teacher establishes influences the thinking patterns of students (Maksum & Khory, 2020).

Critics argue that online learning is not a viable option for education because it separates the learner from the teacher and their peers while limiting collaboration, which suggests diminishing student engagement, participation, and activity (Chen et al., 2020; Kotzee & Palermos; 2021; Reese, 2014). Theorists claim that connectivism does not explain higher-order thinking, the digitally illiterate learner, the development of connections, or the impact network connections have on a learner's physical or social development, as seen in behavioral performances or moral decision making (AlDahdouh, 2017; Corbett & Spinello, 2020; Dennis, 2020; Harasim, 2017; Kop & Hill, 2008; Tham et al., 2020). Downes (2019) contended that social networking and digital technologies have become ubiquitous since the introduction of the theory, eliminating many concerns. Retaining information on an external device eliminates the cognitive load caused by the information data but creates a need to remember the location of the data (Lu et al., 2020). In a study conducted by Lu et al., offloading information led to false recollection of related information.

Theorists warned against the increase dependence on technology for information storage. (Lu et al., 2020; Puddifoot & O'Donnell, 2018). Offloading information has been found to reduce mnemonic activity, learner engagement, and negatively impacts learning because it creates missed opportunities for the human-mind to link information (Lu et al., 2020; Puddifoot et al., 2018). The human memory system is designed to perform necessary functions required for a person to internalize information, link data together from numerous sources, produce abstract representations, engage in knowledge consolidation, and update prior knowledge (Lu et al., 2020; Puddifoot et al., 2018). These researchers speculated that transference of knowledge occurs after memories with commonalities are linked together and the human-mind identifies patterns. Research supported the need to engage with these cognitive processes before offloading the information so the gained knowledge can be applied to new situations (Lu et al., 2020; Puddifoot & O'Donnell, 2018).

Siemens (2005) and Downes (2019) agreed that Connectivism is a work in progress that provides a blueprint for others to follow (Dennis, 2020; Dron & Anderson, n.d.; Kotzee & Palermos, 2021; Siemens, 2005). Current technologies influence the structure and direction of education and should be considered for instructional practices (Dreamson, 2020; Siemens & Conole, 2011). Scholars criticized Connectivism for not being rigorous enough to be considered a learning theory and claim it is a pedagogical practice instead (Clarà & Barberà, 2014; Cleary, 2021; Harasim, 2017; Tham et al., 2021). Downes (2019) argued that these criticisms are not widespread. Some theorists debated that Connectivism be used in conjunction with other learning theories to develop their application to a globalized and networked world (Duke et al., 2013; Corbett & Spinello, 2020). Ravenscroft (2011) suggested that combining Connectivism with Constructivism emphasizes the value of dialog, strengthening the theory (Cleary, 2021; Ravenscroft, 2011; Tham et al., 2021). Researchers hypothesized that digital networks make connections, social relationships, and dialogue, creating a sociotechnical framework that provides opportunities for Social Constructivist activities to occur (Cleary, 2021; Ravenscroft, 2011; Tham et al., 2021).

Connectivism explains how technology impacts education by highlighting the need for new instructional practices that include learning communities and networked technologies (Cleary, 2021; Dreamson, 2020). The Community of Inquiry model compliments the theory of Connectivism by adding the Social Constructivist component (Cleary, 2021; Ravenscroft, 2011). Connectivism explains how technology impacts education by highlighting the need for new instructional practices that include learning communities and networked technologies, while the Community of Inquiry model emphasizes social and participatory learning with current information in a virtual democratic space (Cleary, 2021; Ravenscroft, 2011). Commonalities amongst the theories include a respect for diverse opinions through discourse and critical dialog, connection to specialized and conceptual information sources, and the goal of contributing to the collective knowledge (Cleary, 2021; Garrison et al., 1999; Ravenscroft, 2011).

Community of Inquiry

The Community of Inquiry theory (COI) originated with a study about professional discourse in a text-based, computer-mediated discussion board (Garrison et al.,1999; Krzyszkowska & Mavrommati, 2020). The researchers investigated the different impact on learning when written language is used instead of spoken word (Restall & Clark, 2021). Oral communication tends to be spontaneous and less structured when compared to text-based communication (Garrison et al.,1999; Krzyszkowska & Mavrommati, 2020). The researchers argued that written communication provides time for reflection of thought, which encourages discipline and rigor in thinking. Written communication is considered a lean medium for interactions since it must convey meaning without additional support transmitted though tone, inflection, and non-verbal social cues. Garrison et al., (1999) hypothesized that writing may be essential when engaging in meaningful learning about complex issues (Jansson et al., 2021).

COI is grounded in the premise that learning happens in communities. Through course design and pedagogy, face-to-face, blended, and online learning communities are established (Garrison et al., 2000; Garrison, 2017; Hilliard & Stewart, 2019; Moore, 1993; Ngubane-Mokiwa & Khoza, 2021; Rovai, 2002; Tinto, 2016). People in these communities develop a sense of trust and belonging as they engage in critical analysis of subject matter, questioning, and the challenging assumptions (Garrison et al., 2001; Hilliard & Stewart, 2019; Moore,1993; Ngubane-Mokiwa & Khoza, 2021; Rovai, 2002). COI identifies cognitive presence, social presence, and teaching presence as three necessary and interconnected components within the community that are vital for success in higher education (Garrison et al., 2000; Garrison, 2017; Hilliard & Stewart, 2019). These elements and their interactions are equally important for establishing a productive learning environment (Restall et al., 2021).

Cognitive presence is the learner's ability to engage in critical thinking when faced with a problem or situation (Garrison et al., 2000; Garrison, 2017; Jansson et al., 2021). The learner reflects on the topics, searching for information by repeatedly taking personal thoughts into a shared world (Garrison et al., 2000; Harrell & Wendt, 2019). This process enables the learner to coherently integrate new knowledge and apply it to a new situation. This component involves higher order thinking within the community. Numerous studies have connected cognitive presence with course satisfaction, perceived learning, and self-regulated learning (Garrison et al., 2001; Garrison, 2017; Sadaf et al., 2021).

Cognitive presence consists of four phases of critical inquiry: trigger event, exploration, integration, and resolution (Garrison et al., 2001; Harrell & Wendt, 2019; Sadaf et al., 2021). The trigger event is the learning challenge presented by the instructor or peer. During exploration, the learner shifts between individual reflection and group social analysis of ideas, which may consist of brainstorming, questioning, and sharing of information (Garrison et al., 2001; Guo et al., 2021; Sadaf et al., 2021). The student evaluates the applicability of ideas for a situation during the integration phrase. During the resolution phase, a dialog leads to a solution based on the consensus with the community of inquiry.

Social presence is the ability to project personality characteristics through expressions of emotion, open communication, and group cohesion (Garrison et al., 2000; Guo et al., 2021). It is the affective communication that leads to development and social bonds that create a sense of belonging. The members of the community need to feel confident and secure to openly express their ideas about a common goal or purpose (Garrison & Arbaugh, 2007; Guo et al., 2021; Harrell & Wendt, 2019). Social presence is the evolution of relationships with acquaintances with a social-emotional component to established personal relationships in a cohesive group. These communities of learners are intellectually focused while confidently engaging in purposeful and respectful communication, often referred to as discourse (Garrison et al., 2007; Guo et al., 2021; Ngubane-Mokiwa & Khoza, 2021). The challenge for a community of inquiry is to be inclusive, respectful, and supportive while being critical, contradictory, and skeptical (Garrison, 2017; Guo et al., 2021).

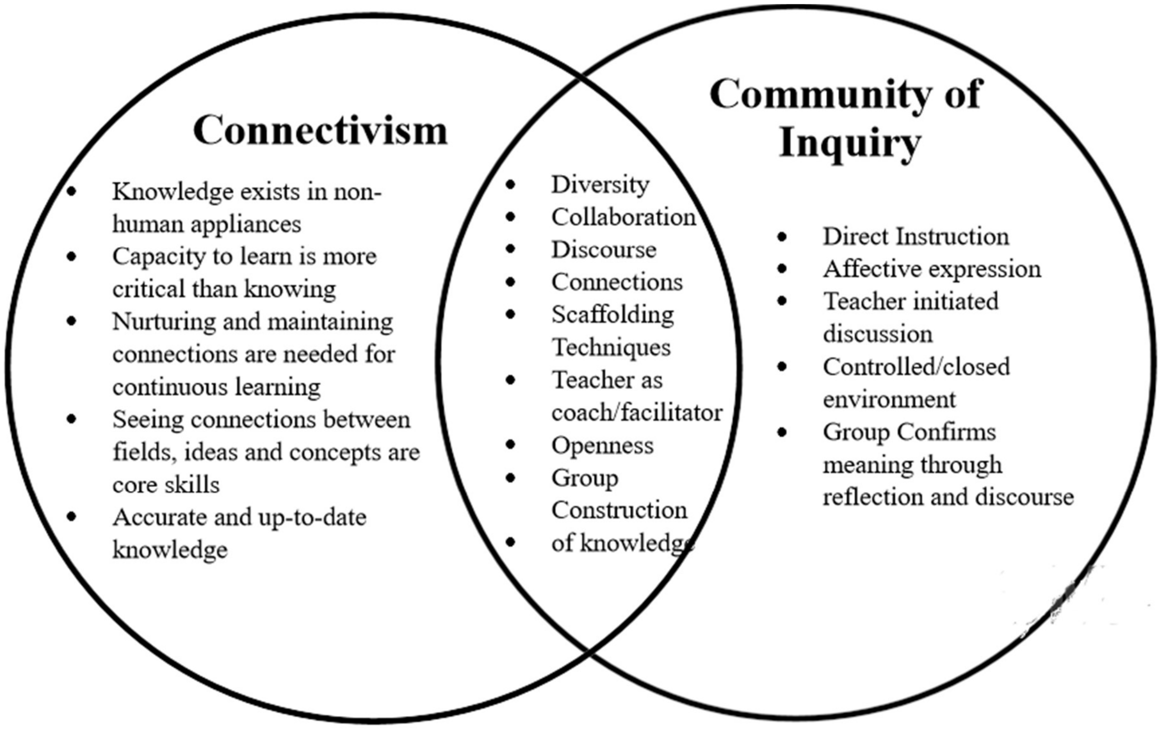
There are three stages of social presence in the development of a community of learners

(Garrison et al., 2007; Guo et al., 2021; Jansson et al., 2021). The first stage is affective communication. During this stage, the learners communicate expressing emotions, using humor, personal references with self-disclosure, and goodwill messages (Garrison, 2017; Guo et al., 2021). These correspondences establish a climate of trust for the second stage, which is open communication. The learners openly communicate with one another by acknowledging, complementing, and responding to the contributions of others. Reflective participation and discourse are encouraged during open communication (Garrison, 2017; Guo et al., 2021; Ngubane-Mokiwa & Khoza, 2021). Group cohesion is the final stage and involves community members constructing meanings, engaging in discourse, confirming understandings, and completing collaborative activities (Garrison, 2017; Guo et al., 2021; Ngubane-Mokiwa & Khoza, 2021).

Teaching presence is the balance of cognitive and social issues that involve instructional management, direct instruction, and the art of building understanding through facilitation and intervention (Garrison et al., 2000; Restall & Clark, 2021; Wang & Stein, 2021). This element guides the interaction of the community of learners by clearly defining the parameters and direction of inquiry (Delaney & Betts, 2022; Garrison et al., 2007; Wang & Stein, 2021). Teaching presence consists of three components: instructional design and organization, facilitating discourse, and direct instruction. The instructional design and organization component addresses the curriculum, the course structure, interactions, and evaluations established by the instructor prior to the beginning of the course. The instructor needs to adjust the design and organization throughout the course to be responsive to the developing needs of the learners (Delaney & Betts, 2022; Garrison, 2017; Restall & Clark, 2021; Wang & Stein, 2021). Facilitating discourse requires interaction with all students and the content, during which the instructor ensures the discussions are moving forward in productive ways (Garrison et al., 2007; Restall & Clark, 2021). The instructor needs to engage learners while highlighting and connecting well-reasoned responses so the collective understanding increases (Garrison, 2017; Wang & Stein, 2021). The direct instruction component describes the course content the scholarly leader shares with the students. The instructor checks comments for accuracy, provides explanatory feedback, contributes, and directs discussions, provides sources of information, and scaffolds data to enhance learning (Garrison, 2017; Garrison et al., 2007; Krzyszkowska & Mavrommati, 2020; Wang & Stein, 2021).

COI's presence components work collaboratively to impact the quality of the educational experience and academic outcomes (Restall & Clark, 2021; Wang & Stein, 2021). Elements of COI diminish the transactional distance between a student, teacher, and institution (Delaney & Betts, 2022; Moore, 1993). Transactional distance (TD) is the perceived distance between a student, the course content, the instructor, and the learning institution (Moore, 1993; Wen et al., 2019). TD is a psychological phenomenon that challenges face-to-face and distance programs, which need to overcome (Delaney & Betts, 2022; Weidlich et al., 2018). Transactional distance theory posited that the perception of social distance is mitigated through structure, dialog, and learner autonomy. Researchers argued that these three variables are in a dynamic relationship (Delaney & Betts, 2022; Saba et al., 2017). The measures of these variables are fluid, and their values change interdependently of one another in efforts to respond to the personal needs of the learner.

Figure 1
Comparison of Connectivism and Community of Inquiry



Related Literature

Retention programs should focus on the students' welfare, a commitment to support students' academics, and the formation of social and academic communities that foster student integration (Braxton, 1999; Honicke et al., 2020; Panadero, 2017; Tinto, 1993). An institution's policies and practices should reflect their retention efforts and include new technologies, flexible classroom design, and innovative learning initiatives (Braxton, 1999; Daniel, 2015; Soicher et al., 2020; Tinto, 2012; Watt, 2016). Student-based academic models for learning are evident in course designs (Kang & Zhang, 2020; Soicher et al., 2020). Professional development for instructors and course designers should have approaches focused on student retention that include strategies to improve the quality of the educational experience while enhancing the integration of technology and incorporate self-regulated learning behaviors for the students

(Barrett, 2010; Braxton, 1999; Bond et al., 2020; Luongo, 2018; Makani et al., 2019; Panadero, 2017; Pickett, 2019; Soicher et al., 2020; Tinto, 2012; Zimmerman, 2002). Theorists recommend that students receive training on the learning management system utilized by the institution, along with strategies that develop and strengthen self-regulated behaviors that support learning (Restall & Clark, 2021; Tinto, 2012; Watts, 2016).

Self-regulated Learning Behavior

Studies suggested COI aligns with concepts of self-regulated learning to facilitate collaboration and higher order thinking (Restall & Clark, 2021). Learner's monitor, regulate, and control their thinking and their actions based on the circumstances and goal constraints (Callan & Cleary, 2019; Pintrich, 1999; Restall & Clark, 2021; Zimmerman, 2002). Researchers believe goal commitment is part of an extensive process called self-regulated learning (Barnard-Brak et al., 2010a; Callan et al., 2021; Panadero, 2017; Greene & Schunk, 2017; Zimmerman, 2002). This process requires learners to use metacognition, an awareness of their thinking, to compensate for deficiencies or limitations they experience completing the task (Callan & Cleary, 2019; Clark & Mayer, 2016; Zimmerman, 2002). There are component-oriented models and process-oriented models (Callan & Cleary, 2019; Roth et al., 2015; Šteh & Šarić, 2020). The component-oriented models focus heavily on the cognitive, metacognitive, and resource management strategies, while process-oriented models emphasize coordination, control, and regulation of learning in a recursive cycle (Roth et al., 2015; Šteh & Šarić, 2020). The two models are interrelated and associated with student success (Šteh & Šarić, 2020). Commonalities among self-regulated learning-oriented models include a combination of specific learning processes, levels of self-awareness, and motivational beliefs (Panadero, 2017; Zimmerman, 2002; Šteh & Šarić, 2020). These theories vary in their emphasis on the behavioral, cognitive, metacognitive, motivational, and emotional aspects of learning (Callan & Cleary, 2019; Greene & Schunk, 2017; Schunk & DiBenedetto, 2020).

Zimmerman's (2008) Cyclical Phases Model for self-regulated learning includes forethought, performance, and self-reflection, which determine how the learner activates, adjusts, and sustains learning practices independently or with others (Callan & Cleary, 2019; Schunk & DiBenedetto, 2020; Zimmerman & Moylan, 2009). The forethought phase consists of task analysis and self-motivated beliefs (Callan & Cleary, 2019; Schunk & DiBenedetto, 2020; Zimmerman, 2002). During task analysis, the learner engages in goal setting and strategic planning. Self-motivated beliefs include self-efficacy, outcome expectancy, intrinsic interests, and goal orientation. The performance phase includes self-control and self-observation. The learner engages in task strategies that include behaviors, techniques, and skills, such as self-instruction, help-seeking, environmental structuring, time management, interest incentives, and self-consequences (Callan & Cleary, 2019; Panadero, 2017; Schunk & DiBenedetto, 2020; Zimmerman et al., 2009). Self-reflection completes the cyclical process and includes self-judgment and self-reaction. Other theories emphasize motivational or emotional variables in goal attainment (Callan & Cleary, 2019; Greene & Schunk, 2017; Schunk & DiBenedetto, 2020).

Self-regulation is a process that can be taught to students and correlates with academic achievement (Šteh & Šarić, 2020; Zimmerman, 2002). Stephen et al.'s (2020) research demonstrated that persistence correlates with the combination of self-efficacy, self-regulation, and self-directedness with non-traditional online learners. Poitras and Lajoie (2017) reported that students who invest time in planning, goal setting, and monitoring have better learning outcomes, especially with declarative knowledge than their peers. Students who engage in self-regulated learning strategies tend to be more engaged and autonomous learners (Purarjomandlangrudi &

Chen, 2020). Research supports that self-regulated learning is associated with numerous factors that predict student satisfaction and student retention (Barnard-Brak et al., 2010; Eom, 2019; Šteh & Šarić, 2020; Vilkova et al., 2020). Students who develop self-regulated behaviors benefit from a connectivist environment (AlDahdouh, 2021).

Perceived Learning

Perceived learning is a self-regulatory behavior that results from self-reflection about the impact of instruction. Students often report on three different domains of learning which correlate with the domains of learning outlined in Bloom's Taxonomy. These domains of learning are cognitive, affective, and psychomotor learning (Bloom et al., 1956; Nikolic et al., 2021; Rovai et al., 2009). Cognitive learning is the student's ability to recall, recognize, and comprehend knowledge (Richardson et al., 2017; Suesse et al., 2021). Affective learning measures the degree of interest, positive opinions, emotions, and values toward the assigned work or subject (Ismail & Groccia, 2018; Suesse et al., 2021). Psychomotor learning measures students' ability to apply the information to new tasks or situations (Ismail et al., 2018; Suesse et al., 2021). Research supports the connection between retention rates and a student's level of perceived learning (Rovai, 2003; Guo et al., 2019; Harrell & Wendt, 2019; Wang & Stein, 2021), which connects to social presence, (Guo et al., 2019; Richardson & Swan, 2019; Rockinson-Szapkiw et al., 2016), sense of community (Harrell & Wendt, 2019; Ismail et al., 2018; Rovai, 2002; Richardson et al., 2017), teacher presence (Gray & DiLoreto, 2016; Restall & Clark, 2021), and course satisfaction (Sauder & Mudrick, 2018; Wang & Stein, 2021).

Twenty-first Century Thinking Skills

The United States Department of Labor promoted and defined the term *21st-century skills* in 1991 (Habets et al., 2020; National Research Council, 2012; Nehring et al., 2017). The goal was to focus schools on prioritizing the skills necessary for a globally competitive workforce capable of generating new ideas and innovations (Habets et al., 2020; McKenna, 1991; Nehring et al., 2017; Silber-Varod et al., 2019). The report encouraged graduates to be learners rather than regurgitators of facts (Habets et al., 2020; McKenna, 1991; Silber-Varod et al., 2019). Today, the direction of education remains focused on creating thinkers capable of transferring knowledge, skills, and experiences to unique situations (Clark et al., 2016; National Research Council, 2012; Silber-Varod et al., 2019). Van Laar, Van Deursen, Van Dijk & De Haan (2017) conducted a systematic literature review of 21st-century skills that included 75 articles from 1592 initially screened. Their investigation identified 21st-century core digital skills. Technical information management, communication, collaboration, creativity, critical thinking, and problem-solving were among those skills identified. Ethical awareness, cultural awareness, flexibility, self-direction, and lifelong learning were identified as contextual skills (Silber-Varod et al., 2019). The National Research Council (2012) identified these same competencies in their list of 21st-century skills sought by employers, and current research validates the continued relevance of these skills in the labor market (Habets et al., 2020; Silber-Varod et al., 2019).

Twenty-first-century skills focus on social and cognitive skills (Habets et al., 2020; Silber-Varod et al., 2019). Collaboration and communication are social skills that enhance the cognitive abilities of problem solving and innovation (Habets et al., 2020). Discussion boards provide an environment where social and cognitive skills comingle (Butcher et al., 2020). Cognitive skills are classified as thinking skills that require a far transfer of knowledge, since the learner needs to apply these skills to adapted guidelines appropriate for new situations (Clark & Mayer, 2016; Silber-Varod et al., 2019; Silva Pacheco & Iturra Herrera, 2021). Instruction provides information about the general approach for the task; however, multiple strategies yield a desirable outcome (Clark & Mayer, 2016; Habets et al., 2020).

Cognitive processing skills divide thinking into three categories: creative thinking, critical thinking, and metacognition (Clark & Mayer, 2016; Silva Pacheco & Iturra Herrera, 2021). Creativity requires one to generate novel and valuable ideas to solve unfamiliar problems (Álvarez-Huerta et al., 2021). Creativity correlates with students engaging in deep approaches to learning, earning higher grades, transferring information correctly, and reporting satisfaction with their educational experience (Álvarez-Huerta et al., 2021; Miller & Dumford, 2016; Silva Pacheco & Iturra Herrera, 2021). Suyana, Nadaipah, Sinaga, and Feranie (2019) suggested that creativity develops when students are challenged to imagine novel solutions by combining new knowledge or techniques to a situation. Inquiry-based instructional strategies and training opportunities strengthen creative thinking (Clark & Mayer, 2016; Makhene, 2019; Siburian et al., 2019). Research showed a connection between creativity and critical thinking skills (National Research Council, 2012; Silva Pacheco & Iturra Herrera, 2021).

Critical thinkers question their propositions to determine if they align with reality. The process involves interpreting, evaluating, and engaging with inference skills (Clark & Mayer, 2016; Le, 2019; Silva Pacheco & Iturra Herrera, 2021; Zare & Mukundan, 2015). Research supports the correlation between critical thinking and positive learning results in concept gaining and cognitive ability (Siburian et al., 2019). Studies suggested critical thinking can be taught (Clark & Mayer, 2016; Makhene, 2019; Siburian et al., 2019). Inquiry learning activities, such as organizing research, observing, formulating problems, solving problems, engaging in discourse, and drawing conclusions, have been associated with developing critical thinking skills (Clark & Mayer, 2016; Makhene, 2019; Siburian et al., 2019). Collaboration coupled with reflective thinking positively impacts critical thinking (Erdogan, 2019). Discussion boards are the platform that provides the environment conducive for these tasks.

Metacognition is responsible for managing and regulating the learner's approach to thinking (Clark & Mayer, 2016; Silva Pacheco & Iturra Herrera, 2021). Research suggested metacognitive estimates of one's prior knowledge impacts their level of curiosity drive (Gottlieb et al., 2013; Wade & Kidd, 2019). Three facets of metacognition include knowledge, experience, and regulation of skills (Jin & Ji, 2021; Reber & Greifeneder, 2017). Metacognitive knowledge focuses on the learner's awareness of their thinking processes, strategies, and foundational understanding, while metacognitive skills are responsible for the internal response to learning, including feelings, confidence levels, and judgments on learning (Jin et al., 2021; Reber et al. 2017). Metacognitive skills benefit the application of knowledge, while metacognitive regulation is the ability to continuously summarize, reflect, and evaluate the known knowledge and identify the knowledge that still needs to be learned to improve the practical ability (Jin et al., 2021). Metacognition strengthens student's thinking, correlates with self-efficacy, critical thinking skills, and impacts levels of curiosity (Gottlieb et al., 2013; Jin et al., 2021; Naimnule & Corebima, 2018). Metacognitive knowledge guides information seeking behavior, which results from either a trait or state of curiosity (Brooks et al., 2021; Kashdan & Fincham, 2004).

Curiosity

Curiosity is the drive to acquire new information and embrace novel experiences (Berlyne, 1954; Gómez-Maureira & Kniestedt, 2019; Kashdan et al., 2009; Litman, 2008). This characteristic is considered essential as a survival skill, since it assists in the adaptation of one's environment (Gruber et al., 2019). This intrinsic motivation sparks exploratory behavior, which triggers learning, promotes academic success, and improves the quality of decision-making

(Fandakova & Gruber, 2021; Grossnickle, 2016/2014; Leonard & Harvey, 2007). Curiosity influences academic persistence and engagement and correlates with satisfaction in college and life (Lounsbury et al., 2009; Hulme et al., 2013; Vracheva et al., 2019/2020). Studies on curiosity are reported through philosophical, psychological, educational, and neuroscience lenses, including theories such as drive reduction, optimal arousal, dynamic subsystem regulation, and knowledge gap models (Gómez-Maureira & Kniestedt, 2019; Grossnickle, 2014; Oudeyer et al., 2016; Peterson & Hidi, 2019). Researchers claim the effects of curiosity vary between feelings of pleasure, excitement, reward-related to neurologic and physiological responses, and emotions related to tensions and frustrations resulting from uncertainty or an information gap (Gómez-Maureira & Kniestedt, 2019; Litman et al., 2010; Oudeyer et al., 2016).

Curiosity was originally divided into two categories, perceptual and epistemic dimensions (Berlyne, 1954; Metcalfe et al., 2020; Schmidt & Rotgans, 2020/2021). Perceptual curiosity is an exploratory response to understand objects in the learner's environment, often referred to as collative variables. Epistemic curiosity, sometimes referred to as intellectual, information-seeking, or cognitive curiosity, focuses on the desire for knowledge acquisition, the elimination of uncertainty, and engagement with intellectual activities (Binu et al., 2020; Grossnickle, 2016/2014; Metcalfe et al., 2020). Interest induction (I-Type) epistemic curiosity accounts for the positive responses of gaining new knowledge, while deprivation elimination (D-Type) epistemic curiosity accounts for the elimination of perceived fear of failure due to lack of knowledge (Chang & Shih, 2019; Litman et al., 2010; Metcalfe et al., 2020). I-type curiosity is associated with mastering a goal, while the motivation for D-type curiosity prioritizes performance and situation avoidance (Chang & Shih, 2019; Litman, 2008; Ryakhovskaya et al., 2022/2021). Research studies support a positive relationship between I-type epistemic curiosity and intrinsic motivation, while reporting a negative correlation with extrinsic motivation (Binu et al., 2020). In an earlier study, D-type epistemic curiosity was positively correlated with both forms of motivation, which the researcher attributed to the integration of motives (Litman et al., 2010; Ryakhovskaya et al., 2022/2021).

Researchers further separated curiosity into categories, such as a search for knowledge, search for experience, and search for stimulation, with these dimensions quantified for depth or breadth of curiosity (Ainley, 2019; Grossnickle, 2016). Depth curiosity focuses on a limited number of topics, while breadth curiosity involves smaller inquiries with more topics. Specific curiosity focuses on experiencing the unknown to reduce uncertainty, while diversive curiosity seeks uncertainty to increase arousal and reduce boredom . Different types of curiosities can coexist, be interactive, and have an established hierarchy (Ainley, 2019; Binu et al. 2020; Grossnickle, 2016; Litman et al., 2010; Kashdan, Gallagher, Silvia, Winterstein, Breen, Terhar, & Steger, 2009).

Curiosity traits are personality characteristics that refer to a learner's tendencies that are consistent across varying situations and circumstances (Ainley, 2019; Grossnickle, 2016; Litman & Silvia, 2006). Curiosity as a state is an immediate driving force triggered by collative variables which create a state of arousal resulting from uncertainty, surprise, novelty, and complexity . Leonard et al. (2007) reported that work conducted by Nissen in 1930 with rats demonstrates curiosity as an innate, as well as a learned, characteristic that support learning. Curiosity traits and curiosity states correlate with one another (Ainley, 2019; Grossnickle, 2016; Kashdan et al., 2009; Lamnina & Chase, 2019). Individuals identified with higher levels of curiosity traits reported experiencing curiosity states more frequently and more intensely than those with lower traits of curiosity (Grossnickle, 2016; Kashdan et al., 2009; Lamnina & Chase, 2019).

The information-gap perspective addresses state curiosity as an intrinsically motivated desire for specific data (Loewenstein, 1994; Schmidt & Rotgans, 2020/2021). The theory stateed that curiosity is the result of elevating desired knowledge above one's current level of knowledge. Individuals are dissatisfied with their information gap, which activates their curiosity to resolve the uncertainty . A positive correlation exists between the intensity of curiosity and one's expectation to close the gap (Loewenstein, 1994; Schmidt & Rotgans, 2020/2021; Yu, 2017). Some knowledge on a topic is necessary so curiosity can be present (Kang et al., 2009; Loewenstein, 1994; Wade and Kidd, 2019). Activities that expose gaps in one's knowledge, like Socratic questioning, discussion discourse, or reflection on course lectures, stimulate curiosity (Loewenstein, 1994; Maksum & Khory, 2020; Siburian et al., 2019). A quadratic or inverted U-shape relationship exists between curiosity and one's confidence in their ability to close the information gap (Kashdan & Fincham, 2004; Peterson & Hidi, 2019; Singh & Manjaly, 2021). Tasks that are perceived to be too difficult evoke anxiety and task avoidance. If the task is familiar, the individual approaches with boredom and apathy. In an unpublished study conducted by Lowenstein, Adler, Behrens, and Gillis (1992), the quadratic relationship between curiosity and task challenge was evident as individuals worked to complete a puzzle. As individuals filled the information gap for the puzzle image, their curiosity increased until a point of diminishing returns. Once the individual approached task completion, with the ability to predict the puzzle image confidently, their curiosity decreased significantly (Kashdan & Fincham, 2004). The quadradic relationship has been replicated and reported in diverse settings (Kang et al., 2009; Kashdan & Fincham, 2004; Kidd & Hayden, 2015; Singh & Manjaly, 2021).

Curiosity-driven exploration reduces uncertainty and improves one's ability to predict or control their environment (Oudeyer et al., 2016; Oudeyer & Smith, 2016; Ten et al., 2021). The brain pursues stimuli with intermediate complexity (Oudeyer et al., 2016; Ten et al., 2021). The Learning Progress model hypothesizes that individuals focus on activities of intermediate complexity, which are achievable learning activities that extend their knowledge. Individuals focus on maximizing learning until they reach a plateau, and then they select a different information-seeking activity. Acquiring knowledge triggers an intrinsic reward, which positively impacts their curiosity drive. A self-reinforcing feedback loop exists between learning and intrinsically motivated curiosity, which diverts learners from perceived unlearnable tasks (Holm et al., 2019; Oudeyer et al., 2016; Ten et al., 2021). Wade and Kidd's (2019) research supported the bi-directional relationship between curiosity and learning. Perceived prior knowledge is related to greater curiosity for new information. Curiosity is associated with better learning (Wade et al., 2019).

Neuroscience research on curiosity uses functional magnetic resonance imaging (MRI) to observe brain activity in regions responsible for reward, control, learning, and memory (Cervera et al., 2020; Gruber et al., 2019). Regions of interest included the substantia nigra and the ventral tegmental areas in the midbrain, the nucleus accumbens of the ventral striatum, and the hippocampus (Cervera et al., 2020; Gruber et al., 2014; Kang et al., 2009). The nucleus accumbens regulates emotional and motivational processes, such as reward and pleasure. The hippocampus is a critical contributor to learning and memory creation. These regions of interest work together in the process of learning and memory development. The reward circuit, also known as the mesolimbic dopaminergic circuit of the hippocampal, transports dopamine from the ventral tegmental areas to the nucleus accumbens and amydale. Dopamine is a neurotransmitter that increases pleasure and motivation while assisting learning and memory functions (Cervera et al., 2020; Gruber et al., 2014; Kang et al., 2009). MRI images showed increased activity in and between these regions of the brain during states of curiosity.

To trigger perceptional curiosity, researchers presented ambiguous visual image to individuals. MRI imaging showed brain activity in the anterior insula and anterior cingulate cortex, which are areas sensitive to arousal and conflict (Jepma et al., 2012; Lau et al., 2020). Once the image was apparent, the brain activity moved to the striatum, which is associated with reward processing (Hidi & Renninger, 2019; Jepma et al., 2012; Lau et al., 2020). MRI imaging supports the idea of curiosity triggered by uncertainty yields an increase in aversive arousal (Jepma et al., 2012; Lau et al., 2020). Additionally, the reduction of uncertainty was associated with increased activity in the hippocampus. In a study involving rhesus macaques, images showed that the expectation of receiving information activated dopaminergic midbrain neurons, which suggest reward-seeking and information-seeking share a neural code (Cervera et al., 2020).

Additional studies using MRI imaging supported the benefit of stimulating curiosity before knowledge acquisition (Gruber et al., 2014). Curiosity states enhance learning and memory function for high-interest and incidental material across long retention intervals (Kang et al., 2009; Lau et al., 2020; Shin & Kim, 2019). MRI images show activity in the striatum when intrinsic and extrinsic motivation are present during task performance (Lau et al., 2020; Lee & Reeves, 2017). The midbrain assists memory function for goal-relevant and irrelevant information (Gruber et al., 2014; Lau et al., 2020). Intrinsic satisfaction is relevant to intrinsic motivation (Kidd and Hayden, 2015; Shin & Kim, 2019). Individuals increase mental effort as they become more interested in the task (Lee & Reeves, 2017; Shin & Kim, 2019).

Curiosity is often considered synonymous with situational interest, but they are two different constructs based on origin, biological understanding, and trigger factors (Shin & Kim, 2019). Situational interest is associated with pleasure and enjoyment, triggered by stimulus that entices an individual to approach. Situational interest activates the valuation brain region, which evaluates the impact of the stimulus. The interest activates an opioid system in the brain, associated with increasing the liking of a stimulus, rather than creating a wanting or drive. Satisfied cycles of curiosity can result in an individual developing situational interest.

Web 2.0

Web 2.0 is a term coined in 2005 by Tim O'Reilly to describe platforms and internet services that offered bidirectional capabilities (Isaías et al., 2021; Newman et al., 2016). Web 2.0 empowers users to expand their communities and generate material on the site (Isaías et al., 2021; Lim & Newby, 2019/2020). Users are seen as developers. They access or contribute to the collective knowledge at any time and on any device. Educational institutions successfully implemented the technology to create learning management systems that support learning (Atzori et al., 2020; Isaías et al., 2021). Students and teachers send documents all over the world (Blair & Stafford, 2016; Isaías et al., 2021). This capability opened new opportunities for the students to collaborate (Blair et al., 2016; Lim & Newby, 2019/2020). Through continued innovation and device accessibility, real-time interaction was achieved (Blair et al., 2016; Isaías et al., 2021; Newman et al., 2016).

Web 3.0

Web 3.0 prioritizes ubiquitous connectivity for personal devices (Atzori et al., 2020). Virtual coaches and adaptive programs are new resources being introduced to support student learning (Atzori et al., 2020; Blair et al., 2016). Cameras, sensors, and recording devices, coupled with communication capabilities, have changed how people live, work and play (Lampropoulos et al., 2019; Son et al., 2019). Smartphones and mobile devices provide continuous connectivity between people and things (Lampropoulos et al., 2019; Newman et al., 2016). Cloud computing provides communication between devices and data storage for future processing (Pierleoni et al., 2020). Ubiquitous computing is convenient and efficient, but it creates privacy and security concerns (Son et al., 2019).

Discussion Board

Discussion boards are commonly used for assignments in higher education (Calderon & Sood, 2020; Chen et al., 2018; Covelli, 2017; Kurnaz et al., 2018). They extend or replace face-to-face class interactions. These boards generate conversation, extend students' thinking, encourage student reflection, and build a sense of community (Calderon & Sood, 2020; Chen et al., 2018; Delaney et al., 2019; Kui Xie & Yen, 2011; McKinney, 2018). Virtual environments allow students to create shared meaning from the course material and engage in critical discourse, which yields higher-order cognitive learning (Calderon & Sood, 2020; Garrison et al., 2000; Halabi & Larkins, 2016; Kurnaz et al., 2018; Luyt, 2013; Pickett, 2019; Rovai, 2003). Discussion boards incorporate social and academic integration, suggested ingredients recommended to promote higher education retention rates (Calderon & Sood, 2020; Rovai, 2003; Tinto, 1975; Tinto & Pusser, 2006). They employ a constructivist approach to learning by having students activate their prior knowledge in an original post and allow the social interaction amongst the students to foster understanding (Calderon & Sood, 2020; Covelli, 2017). Discussion boards extend the limits of constructivism by creating a virtual environment where students engage in critical discourse after accessing relevant network connections for up-to-date information. The discussion board becomes a new node of knowledge (AlDahdouh, 2018; Cardak, 2018; Liu et al., 2022/2021).

Discussion boards serve as a vehicle to promote learning, with the benefit of providing students with time to construct cohesive answers (Calderon & Sood, 2020; Kurnaz et al., 2018). Instructors provide feedback on student responses and assess students' understanding of the material from their published posts (Kim & Thacker, 2020). To create a sense of community in an asynchronous environment, institutions use discussion board forums to facilitate interaction among students as an extension or substitute for face-to-face class discussions. The virtual environment allows students to challenge another's thinking (Kurnaz et al., 2018; Washington et al., 2019). The number of discussion board posts positively correlated with classroom community subscales for connectedness and learning (Calderon & Sood, 2020; Rovai, 2003). Online discussion boards promote professional competencies and critical thinking skills (Onyema et al., 2019; Perrotta, 2020; Szabo & Schwartz, 2011) . Courses that utilize online discussion boards report higher student satisfaction rates (Perrotta, 2020; Szabo & Schwartz., 2011).

An increasing number of studies have found that statistically significant correlations exist between perceived social presence, perceived learning, and a sense of community in distance education (Ismail, & Groccia, 2018; Onyema et al., 2019; Richardson et al., 2017; Richardson & Swan, 2019; Rockinson-Szapkiw et al., 2016; Rovai, 2002; Tusks, 2012). Research supported a connection between retention rates and a student's level of perceived learning (Calderon & Sood, 2020; Rovai, 2003), which connects to social presence (Richardson & Swan, 2019; Rockinson-Szapkiw et al., 2016), sense of community developed on the discussion board (Calderon & Sood, 2020; Ismail & Groccia, 2018; Onyema, 2019; Richardson et al., 2017; Rovai, 2002; Rovai, 2003), and course satisfaction (Sauder & Mudrick, 2018). Students who perceive a sense of belonging show increased engagement levels, which correlates with higher retention levels (Purarjomandlangrudi et al., 2020). Students content with the idea of distance learning, who understand the course's purpose and establish productive online communications, have a positive educational experience . Students' course satisfaction positively correlates with higher persistence rates (Alqurashi, 2019; Kuo et al., 2014).

Students' attitudes towards discussion boards are often low (Clinton & Kelly, 2020). In a study conducted by Kui Xie and Yen (2011), discussion boards showed no intrinsic motivation on learners at the onset of the course (Clinton & Kelly, 2020; Kui Xie & Yen; 2011) . Motivation and frequency of posting on the discussion board increase after students form peer relationships and establish the virtual community (Delaney et al., 2019; Kui Xie et al., 2011). Courses assigning a grading incentive of at least 10% of the overall course grade found a higher number of students' weekly posts than courses who did not grade the assignment (Fehrman & Watson, 2021; Rovai, 2003). In other studies, students reported that discussion board assignments are valuable and enjoyable during high engagement levels (Clinton & Kelly, 2020; Kui Xie et al., 2011). Delaney et al. (2019) suggested a positive relationship exists between social factors and intrinsic motivation. Their study found that incentivizing the discussion board heightens motivation and interaction (Delaney et al., 2019; Fehrman & Watson, 2021). Rubric guidance resulted in students' efforts aligning with the professor's expectation and diminished negative comments on course evaluations about discussion board activities (Fehrman & Watson, 2021; McKinney, 2018). Rubrics even heightened professors' satisfaction by decreasing the time required to grade students' posts (Fehrman & Watson, 2021; Kurnaz et al., 2018; McKinney, 2018).

Unfortunately, the discussion board's efficacy has been highly scrutinized (Calderon & Sood, 2020; Champion et al., 2018). Common challenges associated with using discussion board assignments include low student participation and engagement, a limited display of critical thinking, identifying the appropriate amount of instructor interaction, and communicating with others without the benefit of social cues (Aloni & Harrington, 2018; Luongo, 2018). Students sometimes lack the communication skills needed to provide critical feedback respectfully, which is essential for the well-being of the community of learners (Kim et al., 2020). Technologically challenged instructors struggle to fulfill their role with the online format (Luongo, 2018). Sheen, Yekani, and Jordan (2019) found improved academic course outcomes using the discussion board but cited the lack of control of students' posts as a limitation of the technology.

Professors struggle with identifying their role on the discussion board and find themselves overwhelmed with numerous posts to monitor (Aloni et al., 2018; Champion et al., 2018). In a study conducted by Cho and Tobias (2016), teacher interaction on the discussion board did not impact student learning, course outcome, or student satisfaction. Rovai's (2003) research supported this finding and found that the number of instructors' posts did not impact students' posts, while Washington et al. (2019) reported that instructors who interact too often tend to discourage learners from problem-solving independently. The discussion board's utilization increases teaching presence and decreases the perceived distance between the learner and the instructor (Calderon & Sood, 2020; Cho et al., 2016; Covelli, 2017). Research supported the positive impact discussion boards have on student learning, student engagement, student interaction, sense of community, reflective practices, critical thinking, and course outcomes (Ismail et al., 2018; Kurnaz et al., 2017; Onyema et al., 2019; Richardson et al., 2017;

Washington et al., 2019). The best discussion board practices that extend students' thinking still need to be studied (Aloni et al., 2018; Calderon & Sood, 2020).

Packback

Packback extends the discussion board experience by incorporating COI and connectivism principles. The platform provides a place where students interact and engage with one another, course material, and share affiliated information gathered from cited network sources (Packback, n.d.; Rivero, 2017). Packback's virtual environment prioritizes student inquiries and empowers a student to be autonomous (Packback, n.d.). The platform creates a flexible environment conducive for lifelong learning by creating tasks that provide opportunities for students to pursue interests while arousing and satisfying their own curiosity (Derrick, 2003). Using the Socrative method of inquiry and incentivizing gaming components, students ask and answer questions on the platform. According to Rapanta (2018), it is better for students to ask the questions, since they can identify gaps and inconsistencies between imparted knowledge from books and instructors, and the generalized prior knowledge of the group. Snaprud and Helmikstøl (2015), agreed with Rapanta and further suggested that creating questions deepens a student's insight in a topic and encourages their curiosity. Creating a learner-centered process promotes curiosity and supports student's learning (Grossnickle, 2014; Yu, 2017). Packback provides feedback using an AI algorithm to quantify the student interaction on attributes, including critical thinking and curiosity (Heap et al., 2020; Packback, nd.).

Packback assigns students a curiosity score for their posts and features high-quality responses in a newsletter (Heap et al., 2020). The curiosity score reflects the quality of the presentation, the credibility of the sources cited, the depth of the post, and effort displayed by the uniqueness and value added to the discussion (Butcher et al., 2020). Packback provides feedback to the learner that encourages reflective thinking and promotes self-directed learning. The platform reports the level of skill and knowledge necessary, according to Blooms' Taxonomy, to answer the question the student poses (Packback, n.d.). Technology is used in two ways. The gaming technology incentivizes the activity with a leaderboard highlighting posts that earned the highest curiosity points. The digital assistant coaches students in ways that will improve their curiosity scores. The technology provides feedback in real-time while students are posting and later with a follow-up email (Rivero, 2017). The virtual assistant grades the assignment on academic discourse, which assesses and encourages critical thinking (Packback, n.d.). AI technology keeps the conversation going while the instructor spends time coaching students (Heap et al., 2020). Research studies suggested that Packback posters exhibited increased student engagement, higher levels of course satisfaction, improved retention rates, higher overall course grades, and fewer failing grades (Packback, n.d.). The studies suggested that Packback users provide more citations, demonstrate critical thinking in their discussion board posts, and have longer and an increased occurrence in students' posting, than students using other learning management systems.

Artificial Intelligence

The success of Packback, as with all AI technologies, depends on the user's acceptance (Kim et al., 2019/2020). In a study conducted by Kim et al. (2020), perceived usefulness and perceived ease of communication with AI technology positively predicted favorable attitudes towards using an AI teaching assistant. Institutions, instructors, and students need to perceive the benefit and the ease of using the technology before developing a positive attitude toward implementing the technology (Kim et al., 2019/2020). AI cannot be used independent of a human teacher but in the compacity that complements the teacher (Heap et al., 2020; Kim et al., 2019/2020; Popenici & Kerr, 2017). Instructors and students need training on the implementation of all new technology (Kim et al., 2019/2020). Additional research with artificial intelligence is needed to understand the impact it has on student learning (Shyr et al., 2019).

Artificial intelligence (AI) is a technology capable of engaging in human-like activities, including learning, and adapting (Popenici & Kerr, 2017; Zawacki-Richter et al., 2019). Applying the concept of the Internet of things, AI can obtain data from external devices for machine learning and combine it with data from social media and information on a local device (Kaplan & Haenlein, 2019). The device considers all data sources to create a schema for recognizing patterns, making predictions, and anticipating appropriate actions to implement (Kaplan & Haenlein, 2019; Popenici et al., 2017). The AI system controls, moves, and manipulates its program based on the learned information (Kaplan & Haenlein, 2019). Universities can utilize AI applications as virtual teaching assistants capable of answering and adapting to their individual needs.

AI assist instructors with time management (Kim et al., 2020; Popenici et al., 2017; Zawacki-Richter et al., 2019). Technological capabilities create simulated experiences, instructional tutoring systems, adapted learning programs, analytics that identify students in need of additional support and automate the instructor's tasks (Zawacki-Richter et al., 2019). AI algorithms can analyze data in real-time so teachers better leverage nuances and meet student's needs by providing individualized scaffolded instruction (Luckin & Cukurova, 2019; Zawacki-Richter et al., 2019). Technological capabilities should not interfere with pedagogically sound practices and should require human oversight (Bates et al., 2020; Zawacki-Richter et al., 2019).

Research on automated essay scoring compared to human graders using fluency, conventions and word choice attributes yielded similar scores for undergraduate students with and without disabilities (Buzick et al., 2016; Zawacki-Richter et al., 2019). A later study involving an academic writing analysis program with pharmacy students utilizing AI technology to assess formative work yielded similar results as human evaluators (Lucas et al., 2019). The technology provides immediate feedback to the student to enhance their reflective ability and promote self-directed learning. The students' perceived benefits from the AI technology included improved reflective writing, confidence, and the ability to critique their work. Packback technology works in a similar way.

AI technology in higher education lags compared to other fields. Some oppose the implementation of AI technology in higher education because they fear it dehumanizes the learning experience (Cox, 2021). Existing literature focused on AI lacks longitudinal studies, implementation studies, impact studies, and design-based studies (Zawacki-Richter et al., 2019). A systematic review of the AI literature highlights only a few authors from educational backgrounds and a limited number of research articles showing any evidence-based influence of AI on teaching and learning outcomes in higher education (Bates et al., 2020; Zawacki-Richter et al., 2019). Researchers suggested for educators to partner with AI developers to incorporate pedagogical practices in future application to yield improved academic outcomes and improve the user experience.

Gamification

Gamification is an instructional design strategy that adds game-like elements to a non-game activity (Bai et al., 2020; Dichev et al., 2020; Ding et al., 2018; Looyestyn et al., 2017). These elements include points, badges, leaderboards, challenges, avatars, and performance feedback. The goal of gamifying educational activities is to increase motivation, engagement, and the learner’s experience. Inconsistent and inconclusive data addressing the effectiveness of gamification have been published (Ding et al., 2017; Ding et al., 2018). Ding (2019) suggested the inconsistencies found in the efficacy of gamified learning systems may be the result of the specific gamification and research design. Yet, studies reported connections among learning analytics coupled with digital badges leading to increased student motivation by recognizing and validating student learning through gaming components (Bai et al., 2020; Mah, 2016).

Two different systematic reviews involving gaming found evidence supporting an increase in student engagement and improved outcome with gamification, especially for single, short-term event occurrences (Bai et al., 2020; Looyestyn et al., 2017). The efficacy diminished over time. Utilization of the leaderboard was found to be highly effective, followed by skill badges (Ding, 2019; Looyestyn et al., 2017). The researchers attributed the success of the leaderboard to the element of competition, social comparison, and tangibility (Looyestyn et al., 2017). Other researchers argued that gaming promotes goal setting, fulfills a need for learners to be recognized, and provides feedback on learner's performance (Bai et al., 2020).

Research investigating the effects of gamification with online discussion boards found improved levels of engagement with the gEchoLu application (Ding et al., 2018). This application provides gaming features, such as badges, experience points, leaderboards, progress bars, reactions, and awards. Students receive e-mail notifications when they earn a badge or receive activity on their post. This study found increased engagement and participation resulting from the leaderboard and earned badges as reported in the systematic review. In a later study, Ding (2019) found gamification only impacted the quality of the discussion board post and the number of comments posted if the learner was aware of the gamification component of the assignment.

Socrative Method of Inquiry

Socrates was a teacher, philosopher, and the originator of the Socrative method of inquiry (Hlinak, 2014; Mejia, 2020/2022). This pedagogical practice is sometimes referred to as elenchus or the elenctic method and is designed to stimulate creative and critical thinking skills (Boghossian, 2006; Hlinak, 2014; Makhene, 2019; Mejia, 2020/2022; Yip, 2021). The instructor guides the student to see the weaknesses in their thinking and gaps in their knowledge while encouraging them to formulate better supported ideas (Boghossian, 2006; Dinkins & Cangelosi, 2019; Hlinak, 2014; Loewenstein, 1994; Mejia, 2020/2022). The approach is grounded in the idea that truth is obtained through discourse and the elenctic or questioning process (Hlinak, 2014; Mejia, 2020/2022). A presupposition of the Socratic process, as with connectivism, is that knowledge exists independently from the learner and that agreed upon deductions correspond to a shared knowledge of the group (Boghossian, 2006). Obtaining the truth is a life-long journey (Boghossian, 2006; Yip, 2021).

The Socrative method of inquiry is a learner centered cyclical instructional strategy involving questioning used to encourage reflective behaviors and non-judgmental attitudes towards opposing opinions (Acim, 2018; Friesen & Stephen, 2016; Rapanta, 2018; Yip, 2021). Students search for the truth through discourse and logical reasoning based on inferences (Acim, 2018; Boghossian, 2006; Le, 2019; Nussbaum 2021; Yip, 2021). The learner thoughtfully considered presented statements while evaluating and synthesizing the facts. The process relies on participants engaging in dialogue, specifically constructing and critiquing arguments until truth is realized and the fallacy of their prior thinking has been exposed (Acim, 2018; Boghossian, 2006; Le, 2019; Mejia, 2020/2022; Nussbaum 2021; Yip, 2021). It is important to establish a democratic culture where students interact freely and directly with one another

(Friesen & Stephan, 2016; Rapanta, 2018; Yip, 2021). Students debate the viable solutions, engaging in reasoning, which guides them to plausible arguments that support a variety of solutions . The goal is to find the truth which has the best defendable explanation (Rapanta, 2018; Yip, 2021).

During the initial phase of the Socrative process the learner engages in exploration and discovery of the topic. Then the student reflects and personally examines their position on the issue. The group participates in an open discussion until an agreed upon truth becomes apparent (Dinkins & Cangelosi, 2019; Rapanta, 2018; Yip, 2021). This final phase requires the truth to be challenged by creating generalizations of the claims (Mejia, 2020/2022). The instructor uses questioning strategies to move the conversation forward (Mejia, 2020/2022; Yip, 2021).

Socratic questions allow for multiple answers, which lead to additional questions (Dinkins & Cangelosi, 2019). These questions can focus on clarifying a person's articulated position or obtaining more detail about a statement (Makhene, 2019; Yip, 2021). Questions challenge the validity of facts or the trustworthiness of a source (Dinkins & Cangelosi, 2019; Yip, 2021; Zare & Mukundan, 2015). The instructor may question the link between the statements or the relevancy of a comment to the original question (Dinkins & Cangelosi, 2019; Zare & Mukundan, 2015). Questions are designed to encourage the student to examine the depth while considering the breadth of all possible viewpoints and applicable perspectives . The process requires critical analysis and evaluation of one's beliefs while challenging the learner to provide evidence for their position (Dinkins & Cangelosi, 2019; Makhene, 2019; Yip, 2021; Zare & Mukundan, 2015). Packback uses AI technology to coach students in real time to ask questions that are rooted in a Socratic philosophy (Packback, n.d.).

Researchers claim the Socratic method helps students to strengthen their arguments, improve cognitive strength, and develop their critical thinking skills (Dinkins & Cangelosi, 2019; Hlinak, 2014, Makhene, 2019; Mejia, 2020/2022; Shahsavar et al., 2013; Yip, 2021; Zare & Mukundan, 2015). Technology enhanced learning systems claim to use a Socratic inquiry model to enhance critical thinking (Le, 2019). These systems control dialog and claim to ask questions based on a Socratic pedagogical philosophy. The conversational agents, otherwise known as cognitive assistants, are programed to deepen understanding, increase reflection, and strengthen critical thinking. Studies using conversational agents show significant improvements in reasoning skills and an increase in student engagement with discussion board posts. Le argued that technology enhanced learning systems have not yet demonstrated Socratic questioning abilities with conversational agents. A Socratic conversational agent needs to respond to students in a way that encourage them to test their hypothesis, provide a counter argument, or check for contradictions. Learning systems need to include these capabilities in these programs before they can accurately claim using Socratic techniques.

Summary

This chapter outlined how persistence theories for higher education pivoted from students needing to adapt to the institution of higher education to the institution needing to meet the needs and preferences of the student (Gabi et al., 2021; Luyt, 2013; Kerby, 2015; Neumann et al., 1989; Pascarella et al., 1991; Tinto, 2012). The philosophical change in learning theories and pedagogical practices is apparent in course design and aligns with the needs of the job market (Corbett et al., 2020; Dunaway, 2011; Siemens, 2005). Connectivism and COI are learning theories appropriate for this time when web 3.0 technology is commonplace in people's lives (Strong et al, 2009). It maximizes the availability of information from numerous networks for students to navigate (Corbett et al., 2020). Students are more autonomous in their learning, as they find new ways to connect to their instructor, peers, and course content (Siemens, 2005; Wen et al., 2019). Connectivism and COI support the interaction of students on discussion boards, where students challenge one another's thinking by engaging in critical discourse using material synthesized from a variety of networks (Kurnaz et al., 2017). Packback, an AI application, supports students' learning by challenging the quality of their responses and piques curiosity surrounding course content (Heap et al., 2020; Packback, n.d). Research supported Packback's claim to increased student engagement, yield higher levels of course satisfaction, improved retention rates, and course grades (Packback, n.d.).

CHAPTER THREE: METHODS

Overview

Chapter Three describes the quantitative, correlational research design selected to investigate the relationship between perceived learning and self-regulated learning behaviors of undergraduate political science students and curiosity scores generated by Packback. The research questions with corresponding null hypotheses are shared. The chapter describes the target population the sample represents and the setting for the study. Information about the instruments used to measure the variables is included. The chapter outlines the procedures and the rationale for selecting a multiple regression research design for data analysis.

Design

This quantitative, correlational design study will examine the relationship between the predictor variables, perceived learning and self-regulated learning, and the criterion variable, curiosity scores generated by Packback. The two predictor variables for this study are perceived learning and self-regulated learning. Perceived learning is the recognized change in one's knowledge, skills, confidence, and ability after instruction (Rovai et al, 2009). Self-regulated learning is active and intentional behaviors engaged by learners to promote their learning (Barnard-Brak et al., 2010; Schwam et al., 2021). Curiosity is the criterion variable. Curiosity is the quantified evaluation of the presentation, the credibility of the sources cited, the depth of the post, effort displayed by the uniqueness, and value added to a discussion board forum (Butcher et al., 2020).

Correlational research is a non-experimental research design that explores the direction and magnitude of the relationship between two or more quantitative variables (Curtis et al., 2016; Warner, 2013). According to Curtis et al. (2016), correlational research is guided by a conceptual framework that informs the possible relationship between the variables. Correlational studies include at least one predictor variable and one output or criterion variable that are clearly defined (Curtis et al., 2016; Gall et al., 2007). The researcher quantifies the relationship with the correlational coefficient, which is the variance of change in one variable, or combination of variables, and the corresponding change in another variable (Warner, 2013). These variables need to be measured using an ordinal, interval, or ratio scale (Curtis et al., 2016). The instrument used to measure the variables needs to produce reliable data that is objective, accurate, valid, free from error, and usable. The sample involved in the research should accurately represent the target population so the findings can be generalized. Data analysis, the final component of correlational research, yields correlation scores for each predictor measure with the criterion score (Curtis et al., 2016; Gall et al., 2007; Warner, 2013).

This non-experimental, quantitative, correlational research study explores the relationship between perceived learning and self-regulated learning and curiosity scores generated by Packback (Joyner et al., 2018; Plonsky & Ghanbar, 2018). This correlational design was selected to identify the magnitude of the connections between the variables (Gall et al., 2007; Warner, 2013). The predictor variables were measured using a self-reported questionnaire. Self-reported measures of one's perception are a valid measure of learning (Chesebro et al., 2000; Corrallo, 1994; Harrell & Wendt, 2019). Research supports that perceived learning yields comparable results as direct learning measures while avoiding previous knowledge, class policies, and restricted scales found in course grades (Corrallo, 1994; Harrell & Wendt, 2019; Rovai et al., 2009). Perceived learning refers to students' perspective on their gain in knowledge and ability based on self-assessment (Nikolic et al., 2021; Rovai et al., 2009). Self-regulation is a cyclical process students employ when planning, monitoring, and reflecting on their progress (Šteh &

Šarić, 2020). Curiosity is defined as intellectual, information-seeking, or cognitive thirst focused on the desire for knowledge acquisition, the eliminate of uncertainty, and engagement with intellectual activities (Binu et al., 2020; Grossnickle, 2016/2014; Metcalfe et al., 2020). Curiosity was measured by a computer algorithm based on the quality of the presentation, the credibility of the sources cited, the depth of the post, and effort displayed by the uniqueness and value added to a discussion board post (Butcher, Read et al., 2020).

Research Question

RQ1: How accurately can curiosity scores be predicted from a linear combination of perceived learning (cognitive, affective, and psychomotor) and self-regulated learning (environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation) for undergraduate political science students?

Hypothesis

The null hypothesis for this study is:

H_0: There will be no significant predictive relationship between the criterion variable, curiosity score as measured by Packback, and the linear combination of the predictor variables, perceived learning as measured by the Cap Perceived Learning Scale and self-regulated learning as measured by the Online Self-Regulated Learning Questionnaire for undergraduate political science students.

Population, Participants, and Setting

Population

The demographic for the population included 30,444 students, of which 24,628 students were undergraduates (National Center for Education Statistics, 2020). The institution's demographics included 79.2% white, 5.5% Black/African American, 3.4% Hispanic/Latino, 2.3% Asian, 3.1% were other, and 6.7% were not resident aliens. There were 1,375 full-time and 231 part-time instructional faculty members. Students enrolled in only face-to-face instruction accounted for 78% of the student population. In comparison, 21% of students enrolled in some distance learning, and 1% enrolled in only distance learning. The four-year graduation rate for the freshman class of fall 2012 was 50%, which rose to 78% after six years. The retention rates for the incoming freshman class of 2017 were 90% for full-time students and 75% for part-time students in the fall of 2018. There were 19 full-time political science faculty members and several part-time and adjunct professors at the university, which offered a major and a minor in political science.

Participants

A convenience sample was used for this study. Convenience sampling refers to the selection of participants based on accessibility and willingness (Scholtz, 2021; Zhao, 2020/2021). This is the most common form of sampling within the social sciences. According to Gall et al. (2007), the sample size for this study required a minimum of 66, when assuming a medium effect size with a statistical power of 0.7 at the 0.05 alpha level. One hundred and eighty-eight students had access to the questionnaire for forty-eight hours. A total of 96 participants submitted the survey. Upon examining the surveys, 24 participants had either incomplete data or inaccurate responses for average curiosity scores. The sample comprised 37 males and 33 females, ranging in ages from 18 to 33+, from a three-credit political science course, Foundations of Business Marketing. The self-reported demographics of the 70 participants included in the sample included 80% White or Caucasian, 8.6% Black or African American, 5.7% Asian, 1.4% Native Hawaiian or Other Pacific Islander, 1.4% Multi-racial and 2.9% Preferred not to say. Self-reported class standings for the course included 1.4% Freshman students, 2.9% Sophomores, 48.6% Juniors, and 47.1% Seniors enrolled in the classes, ranging in ages from 18 to 33+. Self-reported measures for GPA included 4.3% of participants reported having a 4.0, 65.7% of the students reported having a GPA between 3.0 to 3.99, 30% of the students reported have a GPA between 2.0 to 2.99.

Setting

Recruitment for this study's participants included students from a public university in Alabama enrolled in a political science class in southeast, Alabama during the spring semester of 2022 invited to take part in the study. The professor of the courses involved in the study had a Ph.D. in political science. She had more than five years of experience using Packback and had attended several Packback training classes. The course integrated discussion board assignments using the Packback environment throughout the semester.

Instrumentation

Three instruments were used in this study. The instruments included the CAP Perceived Learning Scale to measure the predictor variable of perceived learning (Rovai et al., 2009). Perceived learning is the result of self-reflection about the impact of instruction on a learner's understanding and ability (Harrell & Wendt, 2019). Online Self-Regulated Learning Questionnaire (OSLQ) was used to quantify the predictor variable of self-regulated learning on a virtual platform (Barnard et al., 2009; Schwam et al., 2021). Self-regulated learning is defined as a students' ability to regulate their learning by engaging in environment structuring, goal setting, time management, help-seeking, task strategizing, and self-evaluative behaviors. Packback's algorithm measured the criterion variable curiosity (Packback, n.d.). The Curiosity Score is defined by the quality, credibility, depth, uniqueness, and value added by a student to a discussion board forum.

CAP Perceived Learning Scale

The purpose of the CAP Perceived Learning Scale was to measure the cognitive, affective, and psychomotor perceived learning of the participants. The CAP Perceived Learning Scale met the study's needs because of its ability to measure instruction's impact across different learning modalities. It did so by measuring the perceived learning from three domains outlined by Bloom's Taxonomy (Bloom et al., 1956; Harrell & Wendt, 2019; Rovai et al., 2009). The first domain was cognitive learning, which measures comprehension and recall of information (Bloom et al., 1956; Rovai et al., 2009). The second domain was affective learning, which addresses the attitudes towards learning, and the final domain was psychomotor learning, which measures behavioral changes resulting from gained knowledge.

The development of the CAP Perceived Learning Scale began as an 80-item instrument, reduced to a 21-item scale, and reduced again to a nine-item questionnaire. The psychometric test scale was used with students using face-to-face, blended, and online instruction and had a Flesch-Kincaid grade level score of 7.5, suggesting its potential use with multiple populations (Agrawal & Krishna, 2021; Lowell & Alshammari, 2019/2018; Park et al., 2022; Rockinson-Szapkiw et al., 2016; Rovai et al., 2009; Şahin Kızıl, 2021). Confirmatory factor analysis was conducted to confirm construct validity and dimensionality of the instrument (Rovai et al., 2009). Reliability analysis for combining subscales using Cronbach's coefficient alpha was 0.79, which was deemed acceptable for internal consistency (Harrell & Wendt, 2019; Rovai et al., 2009). Cronbach's coefficient alpha for cognitive perceived learning was 0.86; for affective perceived learning, it was 0.87, and for psychomotor, it was 0.22. The Perceived Learning Loss Scale was negatively correlated with the Perceived Learning Loss Scale (Rovai et al., 2009). Studies using CAP Perceived Learning Scale supported the role perceived learning plays in predicting final course grades and course satisfaction (Li, 2019; Rockinson-Szapkiw et al., 2016).

The CAP Perceived Learning instrument is a nine-item questionnaire which utilizes a seven-point Likert scale, with a response of zero representing "Not at all" and a response of six representing "Very much so" (Harrell & Wendt, 2019; Rovai et al., 2009, p. 10). The CAP Perceived Learning instrument's overall score range is zero to 54, with the maximum score for each domain of 18. A high perceived learning score indicates strong feelings of perceived learning. Statements one, two, and five on the CAP Perceived Learning instrument measured cognitive learning, statement four, six, and nine measured affective learning, and statements three, seven, and eight measured psychomotor learning. Statements two and seven needed to be inversely scored.

The CAP Perceived Learning Scale was administered online as part of the overall questionnaire administered to students. The directions were included with the questionnaire (Rovai et al., 2009). This portion of the study’s questionnaire took about five minutes to complete. The researcher scored the question,s as outlined in the CAP scale. The researcher requested written permission from Rovai et al. to use the CAP Perceived Learning measurement scale for this study (See Appendix A).

Online Self-Regulated Learning Questionnaire

The purpose of the OSLQ was to obtain a psychometric measure of students' ability to regulate their learning behavior on a virtual platform. The instrument consisted of six subscales: environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation (Barnard et al., 2009; Schwam et al., 2021). Environment structuring refers to establishing a physical space conducive for maximum performance (Ejubović & Puška, 2019). Goal setting is a forethought decision to achieve a goal. Time management is proactively committing sufficient time to a task for completion (Theobald, 2021). Help-seeking behaviors involves knowing and pursuing the necessary support to complete a task, while task strategies include the application of various approaches and tactics that help one advance towards the goal (Ejubović & Puška, 2019). Self-evaluation refers to one's ability to accurately assess the performance on the task (Theobald, 2021).

The measurement was designed for hybrid or online course formats (Barnard et al., 2009). The 24-questions were selected from a collection of 86 questions reviewed for internal consistency (Barnard et al., 2009; Schwam et al., 2021). The researchers' repeated the study to demonstrate internal consistency of scores (Barnard et al., 2009). OSLQ has been used in several studies (Bruso et al., 2020; Handoko et al., 2019; Schwam et al., 2021; Rivers et al., 2022/2021) and adapted for several languages, such as Turkish, Romanian, Russian, and Chinese (Korkmaz & Kaya, 2012; Cazan, 2014; Martinez-Lopez et al., 2017; Fung et al., 2018).

The chi-square goodness-of-fit statistic, the Tucker Lewis Index, and the Comparative Fit Index (CFI) all supported the model's ability to fit the data in hybrid and online course formats (Barnard et al., 2009; Schwam et al., 2021). The CFI for each variable was reported as follows: environment structuring 0.57, goal setting 0.53, time management 0.94, help-seeking 0.79, task strategies 0.83 and self-evaluation 0.81 (Barnard et al., 2009). The model's paths were significant, yielding standardized values of 0.43 to 0.77 for hybrid course format and 0.46 to 0.84 for online course format. These results support the instrument's construct validity for hybrid and online course formats (Barnard et al., 2009; Schwam et al., 2021). Reliability analysis for combining subscales revealed Cronbach's coefficient alpha 0.90 when used in hybrid course settings and 0.92 when used in online courses format, which is deemed acceptable for internal consistency (Barnard et al., 2009). Cronbach's coefficient alpha for subscales ranged from 0.67

to 0.90 for hybrid course format and 0.87 to 0.96 for online course formats, which are deemed sufficient for score reliability on the subscale level. Internal reliability for environment structuring was 0.92, for goal setting was 0.95, for task strategies was 0.93, for time management was 0.87, for help-seeking was 0.96 and for self-evaluation was 0.94.

There are four environment structuring questions, five goal setting questions, four task strategy questions, three time-management questions, four help-seeking questions, and four self-evaluation questions (Barnard et al., 2009). Each question is scored using a five-point Likert scale, with one representing strongly disagree and five representing strongly agree with statement (Barnard et al., 2009; Schwam et al., 2021). The OSLQ's overall score range is 24 to 120, with higher scale scores indicating higher self-regulation by students in online or hybrid course formats. The OSLQ was administered online as part of the overall questionnaire administered to students. The directions noted the change in the Likert scale among the two instruments. This portion of the study’s questionnaire took about fifteen to twenty minutes to complete. The researcher scored the questions, directly reporting the Likert score marked. The researcher requested written permission from Barnard et al. to use the Online Self-regulating Learning Questionnaire for this study (See Appendix B).

Packback’s Curiosity Score

The purpose of the curiosity score was to measure the quality of the questions and responses posted on Packback (Packback, n.d.). Packback uses an AI algorithm to calculate the curiosity scores, with evaluations of the students' presentation, credibility, and depth on their discussion board posts. Posts that are unique, engaging, open-ended, and explorative earn high points for effort. The quality of the sources cited by the student which support their ideas determine the credibility points. Presentation refers to the formatting, legibility, images, video, and other supplemental resources included with the post to make it more interesting and informative. AI technology uses Bloom's Taxonomy to determine curiosity points. Posts that focus on remembering and understanding earn fewer points than posts using application, analysis, evaluation, or creation with the assigned topic. Each Packback assignment requires three posts. Each post is worth 100 points for a total of 300 points. The Learner Leaderboard uses the accumulated points for the assignment to determine a student's ranking. In two different studies with essay writing, automated scoring, and human scorers, results yielded revealing very high rates of agreement and consistency between the automated engine and expert human scorers in areas on idea development and writing convention, supporting the claim that AI technology has the capability to complete the task (Massachusetts Board of Elementary and Secondary Education, 2019; Ramalingam et al,, 2018).

Procedures

The researcher asked the Alabama institution for permission to survey students for the study (See Appendix C). Once the participating institution granted permission, the researcher submitted the completed research packet to Liberty University's Institutional Review Board (IRB) and waited for approval before completing additional actions. Once the IRB committee approved the study, the research began (See Appendix D).

The population selected for the study included undergraduate students enrolled in a political science course, Foundations of Business Marketing, that used Packback at least four times throughout the course. The researcher asked the professor to post the questionnaire on the course page. The professor agreed to offer an extra credit rounding point for students who participated in the study. This was one of several opportunities afforded to the students throughout the semester to earn the extra credit rounding point. Upon confidentially submitting the survey, students were sent a second survey so they could submit their email for the extra credit rounding point.

Students who clicked on the link to participate in the survey first saw the survey cover letter (See Appendix E) describing the purpose of the research, the survey time requirements of about 20 minutes, and ensured students that participation was voluntary and that no repercussions would occur if they did not participate. The letter communicated to students that their responses were secure and reiterated that they were free to stop participating at any point during the survey. The letter instructed the participant to click on the link to the survey, which indicated their agreement to participate in the study, bringing them to the first questions in the survey. The second page confirmed the participants' willingness to participate and ensured that the student was 18 years or older. If a participant was under the age of 18, the survey would end, and the student wase sent a link for the extra credit rounding point.

The third page of the survey included the nine CAP learning scale questions. The fourth page contained the 24 questions from the OSLQ. The fifth page consisted of four multiple-choice questions about the student's Gender, Ethnicity, Class Standing, reported GPA, and an open ended question about their Average Curiosity Score generated from Packback. The final page of the correspondence expressed the researcher's gratitude for their participation in the study. Participants were instructed to submit the survey at the end of this page. Upon submitting the survey, students were sent a confirmation email with a link so they could submit their email to the professor for the extra credit rounding point. After the survey ended, the researcher collected all the data and analyzed it using IBM SPSS 26 software application.

Data Analysis

Multiple linear regression was used to analyze the data. This design was appropriate when the study had more than one continuous predictor variable and one continuous criterion variable. Multiple linear regression is commonly used in educational research to examine a combination of two or more predictor variables and determine the magnitude and statistical significance of the relationship between the variables in the study (Gall et al., 2007; Plonsky & Ghanbar, 2018). The versatility of the multiple linear regression statistical analysis allows for different scales when comparing variables about their predictive values on the criterion variable (Plonsky et al., 2018). According to Warner (2013), multiple linear regression measures the predictive usefulness of each predictor variable while controlling for other possible linear relationships with other predictor variables. This statistical procedure enables researchers to study the interrelationship of three or more variables at one time to determine which predictor variable is the best predictor of the criterion variable. (Gall et al., 2007; Plonsky & Ghanbar, 2018). The analysis cannot establish causation (Gall et al., 2007; Plonsky et al., 2018; Vetter & Schober, 2018).

The two predictor variables for this study were perceived learning and self-regulated learning. The criterion variable was curiosity scores. A multiple linear regression was appropriate for this study because it can show the correlation between perceived learning and self-regulated learning with curiosity scores. The analysis determined the magnitude and statistical significance of the relationship between the variables (perceived learning and self-regulated learning) to predict individually, and in combinations, the curiosity scores of undergraduate students generated by Packback.

The researcher inputted the data in the IBM SPSS 26 software application. Preliminary data screening was conducted by comparing data from the spreadsheet with the information from the Google Form Spreadsheet. The researcher corrected any discrepancies in the data and identified missing data values. Incomplete surveys were eliminated and later reported. The mean scores and standard deviation on the CAP Perceived Learning scale and OSLQ, and the curiosity score generated by Packback, was compiled to detect trends (Green et al., 2017).

There are eight assumptions tests required for a multiple regression research design (Laerd Statistics, 2015). The first two assumptions were met because there were two predictor variables and one criterion variable, all of which were entered as continuous measures in SPSS 25 software application . Each participant in the study yielded an independent score from other participants, so the assumption of independence of observations was met.

The next set of assumption tests for multiple regression included bivariate outliers, multivariate normal distribution, and the absence of multicollinearity among the predictor variables (Gall et al., 2007; Warner, 2013). The researcher visually examined a series of scatter plots between each predictor variable (perceived learning and self-regulated learning) and each predictor variable (perceived learning and self-regulated learning) with the criterion variable (curiosity scores). The researcher looked for extreme bivariate outliers to ensure the assumption of bivariate outliers was met. Then the scatter plots were reviewed again to look for a linear relationship, a classic cigar shape, between each pair of predictor variables, and each predictor variable with the criterion variable. If the variables were not linearly related then the power of the test is reduced. The assumption of non-multicollinearity was assessed to ensure the two predictor variables (perceived learning and self-regulated learning) were not highly correlated with one another. If the absence of multicollinearity was not met, then the two predictor variables provided the same information about the criterion variable. If the Variance Inflation Factor was greater than 10, it was too high, the assumption was not tenable and multicollinearity existed between the predictor variables. An acceptable value for VIF is between 1 and 5. The effect size for the overall model was calculated using f^2 and reported (Warner, 2013). The researcher looked for a medium effect size using $f^2 \geq 0.15$. The null hypothesis was rejected at the 95% confidence level.

Summary

Chapter Three outlinds the quantitative, correlational research design used to study the relationship of perceived learning and self-regulated learning behaviors of undergraduate political science students, and curiosity scores generated by Packback. The researcher presented the research questions and the null hypotheses. The target population was described. The indicators used to measure perceived learning and self-regulated learning behaviors were defined, along with a description of the instruments used to measure these variables. The researcher presented the steps and procedures for data gathering and shared the plan for data analysis.

CHAPTER FOUR: FINDINGS

Overview

This study aimed to examine whether the relationship between the perceived learning and self-regulated learning of undergraduate students can predict their curiosity scores generated by Packback. The predictor variables were perceived and self-regulated learning. The criterion variable was the curiosity scores generated by Packback. Chapter Four begins with the research question and the null hypothesis. Findings from the data analysis are reported. The researcher conducted a multiple linear regression to address the research question.

Research Question

RQ1: How accurately can curiosity scores be predicted from a linear combination of perceived learning (cognitive, affective, and psychomotor) and self-regulated learning (environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation) for undergraduate political science students?

Null Hypothesis

The null hypothesis for this study is:

H_0: There will be no significant predictive relationship between the criterion variable, curiosity score as measured by Packback, and the linear combination of the predictor variables, perceived learning as measured by the Cap Perceived Learning Scale and self-regulated learning as measured by the Online Self-Regulated Learning Questionnaire for undergraduate political science students.

Descriptive Statistics

Descriptive statistics were obtained using IBM SPSS Version 26 software. The final sample ($N = 70$) consisted of females ($n = 32$; 45.7%) and males ($n = 38$; 54.3%). Almost half of the participants were seniors (*n* = 33; 47.1%), followed by juniors (*n* = 34; 48.6%). Very few participants were sophomores (*n* = 2; 2.9%) or freshman (*n* = 1; 1.4%). Table 1 shows the descriptive statistics for the predictor variables, perceived learning, and self-regulated learning, as well as the criterion variable, curiosity scores.

Table 1

Descriptive Statistics for Predictor Variables and Criterion Variable

Group	*n*	*M*	*SD*
CAP Score	70	33.97	7.12
OSLQ Score	70	84.77	15.73
Curiosity Scores	70	76.57	10.09

Results

A multiple regression was used to test the null hypothesis to determine if a relationship exists between a linear combination of perceived learning and self-regulated learning and curiosity scores. Multiple regression was completed at the 95% confidence level, with the assumption of linearity, assumption of multivariate normal distribution, and the assumption of the absence of multicollinearity being met. These assumption tests determine if the data is appropriate for a multiple regression research design (Warner, 2013).

Data Screening

Data screening was conducted on the predictor and criterion variables. The researcher sorted the data on each variable and scanned for inconsistencies. A total of 96 participants responded to the survey. Upon examination of the data, 24 participants had either incomplete data or inaccurate responses entered for average curiosity scores. These responses were removed from the sample to decrease the probability of Type I and Type II errors (Warner, 2013). IBM

SPSS Version 26 diagnostic testing identified one data point in curiosity, with a standard residual of -3.39 and an outlier in curiosity that was inconsistent with other data points. The researcher removed these cases.

Hypothesis

The null hypothesis stated that there will be no significant predictive relationship between the criterion variable, curiosity score as measured by Packback, and the linear combination of the predictor variables, perceived learning as measured by the Cap Perceived Learning Scale and self-regulated learning as measured by the Online Self-Regulated Learning Questionnaire for undergraduate political science students.

Assumption Testing

The assumption of independence of residuals ensures that the observations in a multiple regression are unrelated. This assumption was met, as each observation represented responses from a different student. As reported in Table 3, there was independence of residuals, as assessed by the Durbin-Watson (DW) statistic of 2.06. This assumption of independence was met.

A matrix scatterplot and a plot of studentized residuals against predicted values of curiosity were used to examine the assumption of linearity between each predictor variable (perceived learning and self-regulated learning) and the criterion variable (curiosity scores). The results showed no concerning outliers, and the assumption of linearity was met. See Figure 2 and Figure 3 for the matrix scatterplots and the plot of studentized residuals against predicted values of curiosity.

Figure 2

Matrix Scatterplot for Predictor Variables and Criterion Variable

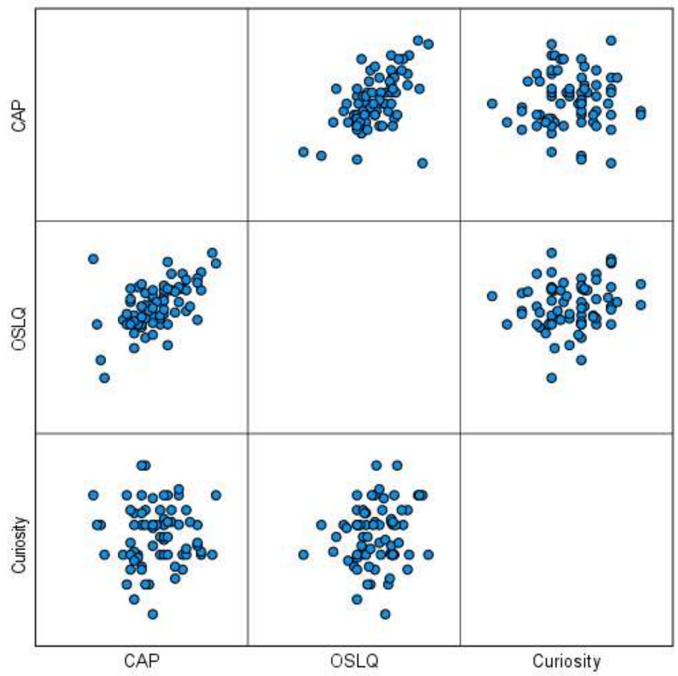
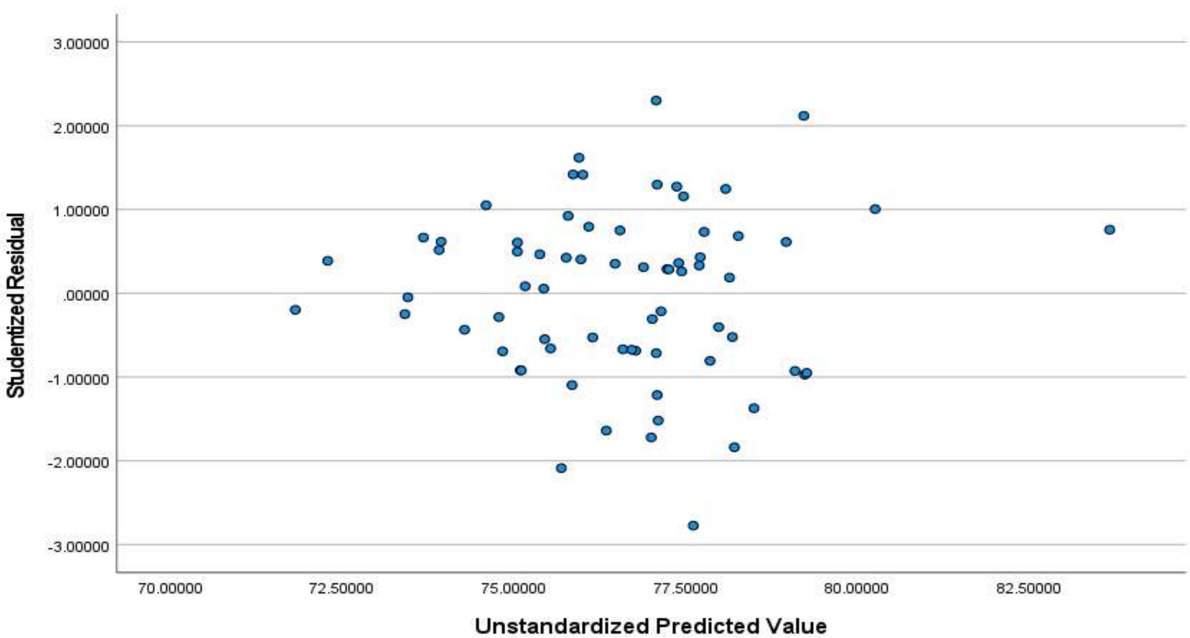


Figure 3

Scatterplot of Residuals against Predicted Values of Curiosity

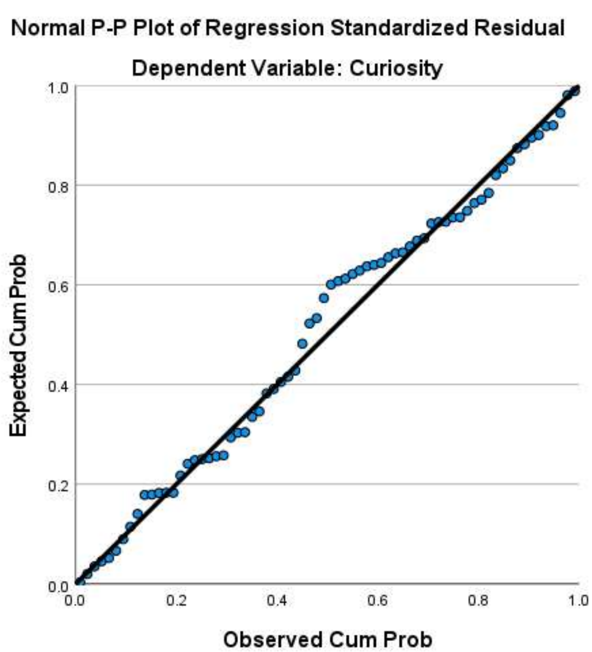


The assumption of homoscedasticity ensures that the variance is equal for all values of the predicted variables. See Figure 3 to view the scatterplot, which shows the residuals are randomly dispersed, indicating homoscedasticity based on the visual inspection of a plot of studentized residuals versus unstandardized predicted values (Laerd Statistics, 2015). Figure 3 shows linearity, as most data plots fall around the 0 line on the y-axis. The assumption of homoscedasticity is tenable.

The assumption of multivariate normal distribution requires examining the data to ensure a linear relationship between each pair of variables. The matrix scatterplot confirmed the linear relationship between each variable with a cigar shape display between each variable. To check for the assumption of normality of the residuals, see Figure 4, the P-P Plot of Regression Standardized Residuals, which illustrates that the residuals are normally distributed. Hence, no transformations need to occur, and the assumption of normality is tenable.

Figure 4

Normal P-P Plot of Regression Standardized Residual



The assumption of bivariate outliers was tested using the matrix scatterplot to ensure no extreme outliers existed between predictor variables or predictor variables and criterion variables. See Figure 1, the matrix scatterplots show no extreme bivariate outliers. The assumption of bivariate outliers was met.

The assumption of non-multicollinearity assumes that the predictor variables are not correlated amongst themselves. The Tolerance and Variance Inflation Factor (VIF) assessed this assumption. As shown in Table 2, the CAP score for Tolerance = 0.72; VIF = 1.40 and the OSLQ score for Tolerance = 0.72; VIF 1.40. The assumption of non-multicollinearity was met, as the Tolerance values were between 0.10 and 1.00 and VIF values were below 10 for each predictor variable. The result indicated no violation.

Table 2

Collinearity Statistics[a]

Model		Tolerance	VIF
1.	(Constant)		
	CAP Scores	0.72	1.40
	OSLQ Scores	0.72	1.40

a. Criterion Variable: Curiosity

A multiple regression was used to evaluate the hypothesis. The Null Hypothesis stated that there would be no significant predictive relationship between the criterion variable, curiosity score as measured by Packback, and the linear combination of the predictor variables, perceived learning as measured by the Cap Perceived Learning Scale, and self-regulated learning as measured by the Online Self-Regulated Learning Questionnaire for undergraduate political science students. Based on the results, the researcher failed to reject the null hypothesis where at a 95% confidence level, F (2, 67) = 1.23, p = 0.30. Results of the multiple regression are presented in Table 3. The Pearson correlation coefficient (r = 0.19) and the R^2 coefficient reflect a small effect size that only 3.5% of the variance in curiosity was predicted by the linear combination of perceived learning and self-regulated learning. This analysis determined that the linear combination of the predictor variables, perceived learning, and self-regulated learning, were not found to be significantly correlated to the criterion variable, curiosity scores.

Table 3

Multiple Regression Model Summary of Curiosity Scores

Model	R	R^2	Adjusted R^2	SEE	DW
1	0.19	0.035	.006	10.05	2.06

a. Predictors: Perceived Learning and Self-regulated Learning
b. Dependent Variable: Curiosity

Table 4

ANOVA for Perceived Learning, Self-regulated Learning, and Curiosity Scores

Model		*SS*	d*f*	*MS*	*F*	*p*
1						
	Regression	247.49	2	123.75	1.23	0.30
	Residual	6770.35	67	101.05		
	Total	7017.84	69			

a. Dependent Variable: Curiosity
b. Predictors: (Constant), OSLQ, CAP

Summary

Chapter four explains the statistical results of this correlational study, including the descriptive statistics. This study aimed to determine whether a predictive relationship existed between the linear combination of perceived and self-regulated learning and the curiosity scores generated by Packback. The researcher failed to reject the null hypothesis based on the results of this study.

CHAPTER FIVE: CONCLUSIONS

Overview

Chapter Five will discuss how the results of this study support or contradict other studies and theories. The study's implications will explain how the research has contributed to the existing knowledge on perceived learning, self-regulated learning, and curiosity. A discussion of the limitation and the implications of the findings is included in this chapter, along with recommendations for future research.

Discussion

This correlational study aimed to examine how accurately a linear combination of perceived learning and self-regulated learning (predictor variables) can predict curiosity scores generated by Packback. The null hypothesis for this study stated that there would be no significant predictive relationship between the criterion variable, curiosity scores generated by Packback, and the linear combination of the predictor variables, perceived learning, and self-regulated learning. Data collection included an online questionnaire with the nine Likert questions from the CAP Perceived Learning scale and the 24 questions from the OSLQ. The data was transferred to IBM SPSS 26 software and analyzed using a multiple regression. The analysis indicated no predictive relationship between the combination of perceived learning and self-regulated learning upon curiosity scores generated by Packback $F(2, 67) = 0.97$, $p < 0.38$ with a 95% confidence level.

Wade and Kidd's research (2019) suggested that learners' perceived knowledge strongly drives their curiosity. According to the study, a learner's curiosity should pique when they are close to discovering the required information. A correlation between perceived learning and curiosity was supported when the information or explanation was simple and considered valuable

(Liquin & Lombrozo, 2022). A different study suggested a relationship between curiosity and self-regulated learning with cognitive ability (Feraco et al., 2022; 2021). The goal of this study was to build upon the body of existing literature about perceived learning and self-regulated learning with curiosity.

A multiple regression analysis addressed the research question of how accurately curiosity scores can be predicted from a linear combination of perceived learning and self-regulated learning for undergraduate political science students. The R^2 for the predictor variables of perceived and self-regulated learning was 0.035. The lack of statistical significance indicated that perceived and self-regulated learning did not explain a significant proportion of variation in the curiosity scores generated by Packback. Thus, there is not enough evidence to reject the null hypothesis. The lack of a statistically significant predictive relationship between perceived learning and self-regulated learning with curiosity scores generated by Packback contradicts previous studies with each individual predictive variable and other measures of curiosity.

Research suggested that academically and socially integrated students are more likely to develop a commitment to an institution and persist to graduation (Andrade et al., 2020; Astin, 1985; Cabera et al., 1992; Terenzini, 1985; Tinto, 1975; Tinto & Pusser, 2006). External factors, distractions, student preparedness, and adversity impact an individual's level of commitment to their academic goals based on their perceived result (Behr et al., 2020; Huo et al., 2022; Kodama et al., 2018; Tight, 2020; Tinto, 1975; Tinto, 1993). The relevancy of universities in our knowledge-driven society is based on their ability to prepare students for success in the current market (Cheng, 2015; Krishnamoorthy & Keating, 2021; LeRoux, 2002; Seemiller et al., 2017). Students need skills and strategies to manage the constant flow of information that shapes their lives (Cheng, 2015; Rotatori et al., 2021; Seemiller & Grace, 2017). Technology altered society, especially in the areas of education and learning at all levels. However, one must question if an abundance of offloaded information is equivalent to the intellectual gains of internalized knowledge when discussing 21st-century skills.

This study is grounded in two theories: Connectivism and Community of Inquiry. Connectivism suggested that learning is a complex and nonlinear social process (Cleary, 2021). Connectivism emphasizds the ability to identify and access information sources over fixed knowledge (Goldie, 2016; Siemens, 2004; Utecht & Keller, 2019). This process leads to offloading information to nonhuman devices. According to Lu et al. (2020), offloading information has been found to reduce mnemonic activity and learner engagement, while negatively impacting one's knowledge because it creates missed opportunities for the human mind to link information leading to perceived learning.

Connectivism values access to real-time data through nodes over fixed information (Corbett et al., 2020; Kotzee & Palermos, 2021). The Community of Inquiry values the social interaction and discourse that occurs amongst students as they establish a shared understanding of the material (Garrison, 2017; Guo et al., 2021; Ngubane-Mokiwa & Khoza, 2021). Learning has become a collaborative process, generally considered a benefit; however, it diminishes individual responsibility and accountability for internalized learning.

Packback prioritizes individual student inquiries by creating tasks that allow students to pursue interests while arousing and satisfying their curiosity. By having students create their own discussion board questions, they are identifying gaps and inconsistencies between imparted course material and the generalized prior knowledge. Snaprud and Helmikstøl (2015) research suggested that, creating questions deepens a student's insight into a topic and encourages curiosity. Packback changed the traditional practices implemented on the discussion board to support student engagement, perceived learning, and reflective practices (Butcher et al., 2020). Surprisingly, the results of the study do not suggest a statistical relationship exists between perceived learning and self-regulated learning with curiosity scores.

Connectivism and the Community of Inquiry theories encourage cooperation and collaboration of thought, which are skills fostered in higher education institutions to prepare students to enter the workforce. Students, who are digital natives, navigate the internet to locate the needed information required to address the discussion board post. Data is quickly gathered, and the student restructures the data to contribute to a group understanding of the information. Students use their critical thinking skills to find, evaluate, and reconstruct the data, but they lack the opportunities for the human mind to link the information. The data remains in the virtual environment, and the satisfaction gained from perceived learning is lost, while reflection on learning is limited. Students return to the evolved shared understanding as a new node or connection in the future. The virtual application that stores knowledge creates missed opportunities for students to internalize the learning and reflect on the information.

Implications

This study adds to the existing knowledge that addresses the impact technology has on education. Increased connectivity introduced students to virtual coaching and adaptive programs at the expense of diminishing internalized cognitive processing. Personal learning has been redefined. Personal learning spaces have been introduced with the development of virtual environments and platforms where learners place information for later access. Offloading information eliminates the human memory system from the learning equations. The lack of an association between perceived learning and self-regulated learning with curiosity scores, supports research addressing the negative impact offloading information has upon learning (Lu et al., 2020; Puddifoot et al., 2018). Additionally, this study supports the criticism about connectivism not being rigorous enough to be a learning theory but rather an instructional process (Cleary, 2021; Tham et al., 2021).

Packback redesigned the discussion board to create an environment for collaboration, discourse, critical thinking, and d learning. These are 21st century skills that have been associated with perceived learning and self-regulated learning (Makhene, 2019; Silva Pacheco et al., 2021). The implications of this study suggest that no statistically significant relationship exists between the linear combination of perceived learning and self-regulated learning with curiosity scores generated by Packback. This study reduces the gap in the literature about the role perceived learning and self-regulated learning have on Packback scores.

Discussion board efficacy continues to be scrutinized (Calderon et al., 2020). Prior research supports the positive impact discussion boards have on student learning and reflective practices (Ismail et al., 2018; Onyema et al., 2019; Washington, 2019). The data from this study contradicts these studies, implying a need for additional research. Additional information about best practices for discussion boards and the benefits of discussion board platforms is needed.

Limitations

Practical limitations involving this research include the sample selection, the instruments used, and the study design. This research examined the predictive relationship between perceived learning, self-regulated learning, and the curiosity scores generated by Packback, with 70 students enrolled in political science classes in a southeastern university.

This study used a convenience sample, which is a limitation (Gall et al, 2007). Students who decided to participate in the study may have a different perspective on perceived learning and self-regulated learning and may have received a different range in curiosity scores compared to students who decided not to participate in the study. Even though the sample size of 70 exceeds the minimum requirement of 66 participants required to ensure a 95% chance of detecting a correlation between perceived learning, self-regulated learning, and curiosity scores, it is still a limitation. A larger sample size would increase the representation of the population, which would increase the statistical significance of the analysis. Obtaining the sample from a single course limits the scope of the study. Students enrolled in the political science course, Foundations of Business Marketing, may have different study habits than students enrolled in different courses and in different disciplines. Additionally, students enrolled at a southeastern university may have different academic behaviors than students in other geographical regions, which contributes to the limitations of the study. These limitations hinder the generalizability of the results, since the sample may not be representative of the greater population of students in America or around the world.

Another limitation for this study includes the 7-point and the 5-point Likert scale instruments used to measure the predictor variables, perceived learning, and self-regulated learning respectively. Likert scales measure a single trait, without reflecting on the complexity of human opinion (Heo et al., 2022). Participants may hold different values to the points on the Likert scale, and some respondents may avoid choosing extremes, even if they are the most accurate representation of their beliefs (Heo et al., 2022). Extreme response styles differ across cultural and ethnical groups (Dolnicar, 2021; Heo et al., 2022). Responses on Likert scales have the potential to be influenced by prior questions (Heo et al., 2022). Dolnicar (2021) reported that Likert scale respondents provide the same answers to the same survey questions in 47% of the cases for 7-point Likert scales and in 57% of the cases on 5-point Likert scales. These statistics suggest low test-retest reliability. Finally, Likert scales are self-reported measures. Participants may create an unintentional bias that matches the way they want to be perceived (Gall et al., 2007).

Another limitation of the study results from the design. Correlational studies indicates if a relationship exists between variables. Correlational research does not address causation or directionality of the relationship between variables (Gall et al., 2007). This research design provides information about relationships that can be followed-up with a controlled experiment.

Recommendations for Future Research

Future research may want to:

1. Explore the predictive relationship between the curiosity scores generated by Packback and an epistemic curiosity instrument.

2. Increase the sample size of students who complete the survey by including a variety of courses at different universities in various locations. Additionally, changing the administration time of the survey to the middle of the semester may lead to less cases being eliminated from the study.

3. A qualitative study is warranted to dig deeper into the topics of perceived learning, self-regulated learning (predictor variables) and curiosity (criterion variable) when using Packback.

4. Conducting a comparison study addressing students' opinions of discussion boards that includes the CAP and OSLQ questionnaires to two different groups. The first group will be familiar with the use of Packback, and the second group will be unfamiliar with Packback.

5. A controlled experiment comparing Packback scores between students who were instructed on self-regulated learning strategies with those who did not receive instruction on self-regulated behavior.

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APPENDIX A: Letter to use CAP Perceived Learning Scale

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APPENDIX B: Letter to Use the Online Self-regulatory Questionnaire

Re: [EXTERNAL] Request to use the Online Self-regulated Learning Questionnaire

Rizzuto, Rosemarie [redacted]
Sat 4/2/2022 9:17 AM
[redacted]

Thank you.

Rosemarie Rizzuto

From [redacted]
Sent: Saturday, April 2, 2022 9:10 AM
To: Rizzuto, [redacted]
Subject: Re: [EXTERNAL] Request to use the Online Self-regulated Learning Questionnaire

You don't often get email from lbarnardbrak@ua.edu. Learn why this is important

Please feel free to use or modify the instrument. Thanks, [redacted]

[redacted]

From [redacted]
Sent:
To: [redacted]
Subject: [EXTERNAL] Request to use the Online Self-regulated Learning Questionnaire

[redacted]

I am a doctoral candidate at Liberty University in Lynchburg, Virginia. I am working on a dissertation that will examine the relationship of curiosity scores generated by Packback, with perceived learning and self-regulated learning. I am writing to request permission to use the Online Self-regulatory Questionnaire discussed in the article, *Measuring Self-regulation in Online and Blended Learning Environments,* 2009.

I would truly appreciate your consideration of my request.

With Regards,

Rosemarie Rizzuto

Doctoral Candidate, Liberty University

Rosemarie Rizzuto

APPENDIX C: Letter to [redacted] University

[External] Re: [EXT] Re: Request to conduct research at [redacted] with classes that use Packback

[redacted]

Mon 5/2/2022 6:46 PM

To: Rizzuto, Rosemarie [redacted]

[EXTERNAL EMAIL: Do not click any links or open attachments unless you know the sender and trust the content.]

You gave my permission to collect data in my department.

[redacted]

Sent from my iPhone

On May 2, 2022, at 5:15 PM [redacted] wrote:

CAUTION: Email Originated Outside of [redacted]

[redacted]

Department Chair of Marketing

[redacted]

Dear [redacted]

As a graduate student in the School of Education at Liberty University, I am conducting research as part of the requirements for a doctoral degree. The title of my research project is *The Relationship of Perceived Learning and Self-regulated Learning of Undergraduate Students and the Curiosity Scores Generated by Packback*. My research aims to examine the relationship between these variables and discussion board practices.

I request permission to conduct research in your department by inviting students enrolled in marketing classes that use Packback to participate in the study. The data will examine the relationship between perceived learning and self-regulated learning of undergraduate students and the curiosity scores generated by Packback. Participants will be presented with an informed consent document before participating and completing the attached survey.

Thank you for considering my request. If you choose to grant permission, respond by email t[redacted] A permission letter document is attached for your convenience.

Sincerely,

Rosemarie Rizzuto

Doctoral Candidate, Liberty University

Rosemarie Rizzuto

APPENDIX D: IRB Approval

Date: 6-21-2022

IRB #: IRB-FY21-22-925
Title: The Relationship of Perceived Learning and Self-Regulated Learning of Undergraduate Students and the Curiosity Scores Generated By Packback
Creation Date: 4-4-2022
End Date:
Status: Approved
Principal Investigator: Rosemarie Rizzuto
Review Board: Research Ethics Office
Sponsor:

Study History

Submission Type Initial	Review Type Limited	Decision Exempt - Limited IRB

Key Study Contacts

Member [redacted]	Role Co-Principal Investigator	Contact [redacted]
Member [redacted]	Role Principal Investigator	Contact [redacted]
Member [redacted]	Role Primary Contact	Contact [redacted]

APPENDIX E: Survey Cover Letter

Hello,

I am pursuing my doctorate at Liberty University in Higher Education Administration and Leadership. I hope to contribute to the scholarship on the impact of AI technology, specifically Packback, in higher education settings.

Data suggest that perceived learning in a course is correlated with student satisfaction for the course. Student satisfaction is associated with higher persistence rates. Additionally, student success also correlates with self-regulated learning. The purpose of my research is to investigate the relationship discussion board practices, specifically Packback, have on perceived learning and self-regulated learning since it could also impact student persistence and graduation rates.

I am writing to invite you to participate in my study by completing an online survey about your perceived learning and self-regulated learning in your political science class. Participation is voluntary and confidential. The survey will open May 6th and it will close on May 8th.

You will not need to answer personal identifying information during the survey. The questionnaire will take about 15 to 20 minutes to complete. The study includes 39 Likert Scale questions and five multiple-choice questions. If you wish to stop answering the questions at any time during the survey, you can exit out of the study with no repercussions. Your teacher has agreed to grant you an extra bonus rounding point for your participation.

If you have questions about my research, contact me at [redacted] If you agree to participate in the survey, click here.

Sincerely,

Rosemarie Rizzuto
Doctoral Candidate, Liberty University