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ADAPTIVE DELIVERY AS A MEANS TO INCREASE STUDENT ENGAGEMENT AND LEARNING OUTCOMES

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DEDICATION

I dedicate this dissertation to my wife Amaris and daughter Maya who went through this whole process with me and learned the trials and tribulations of a doctoral student. I am here because of your belief in me. To my mother who sacrificed her whole life and taught me to be the man I am. Lastly, I would also like to remember my father who left too early in my life but always said, “Your education is the only thing that cannot be taken from you.”

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ABSTRACT OF THE DISSERTATION

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The process of education involves at its core level the support of Learning, which leads to the acquiring of skills, knowledge, values, and habits. Technology has allowed educators and learners to move to a digital platform. These electronic learning platforms, previously classified as distance learning, have their advantages but also their pitfalls. The adaptive modification of learning systems can provide the student's needs by educators even when the student is outside of the classroom. Community colleges are faced with a dilemma of funding and mission. To survey they to need act as agents to find their own solution. This research study provides an approach to identifying the learning style based on a Learning Style Scale (LSS) developed by Abdollahimohammad and Jaafar (2014). A sample group of 163 college students was selected for the study. This quantitative study was broken into multiple evaluation areas. First, the data from the validated instrument was used to cluster students into learning groups. Second, the experiment used learning style clusters to determine the Engagement effects of a lesson presented to those clusters in a sequenced order of their matched learning styles and unmatched style. The impact of this adaptive delivery provides a user interface and experience based on either Auditory or

Visual styles in a feedback method. The feedback adaptation was validated using statistical analysis, and an assessment gauged fluctuations in baseline learning as an improvement and other matched treatment lessons as higher improvement. Statistical analysis provided justification for improved learning outcomes and refuted some criticisms connected to Learning Styles.
Keywords: VAK Learning Style Model; Adaptive System; Learning Styles; Adaptive Lessons; Subject classification codes: 80

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ABBREVIATIONS AND ACRONYMS

IRB	Institutional Review Board
PISA	Programme for International Student Assessment
SPSS	Statistical Program for Social Sciences
VAK	Visual Auditory Kinetic

CHAPTER ONE

INTRODUCTION

In the last decade, community colleges have found the pressure to improve student course completion rates at their institutions by legislatures (Bailey, Jeong, & Choo, 2010). Completions rates and time restrictions on graduation have become the mainstay of policy makers who seek to hold these public institutions accountable to the tax payer. Funding for higher education has been reduced or set to formulas to create accountability in these institutions, which receive their support from taxpayers' dollars. In addition, the amount of funding available has seen declines due to the lack of improvement shown in student completion rates (Cafarella, 2016a).

Community colleges are especially hardest hit due to their open enrollment and lack of restrictive student selection policies. As a result, students who attend these institutions are often under-prepared for college-level work. The majority of students are non-traditional higher education students, as stated by (Bailey , 2009), who "arrive unprepared to engage effectively in the core function of the college." These deficits in learning have caused many institutions to find less expensive alternatives to traditional classroom instruction such as distance learning or "virtual learning."

However, we continue to witness gaps in particular subject areas. These deficits in learning, although can stretch across disciplines, a large population of students are affected by mathematics (Bonham & Boylan, 2012).

A longitudinal study conducted by the National Center for Education Statistics (NCES) found that 42% of students beginning in higher education were underprepared for mathematics and required remediation (National Center for Education Statistics, 2012). As federal and state governments focus more attention on student success and degree completion, developmental programs become a priority for leadership at these institutions (Ariovich and Walker, 2014).

As an agent of the legislature, and in turn the taxpayer; Community colleges must seek solutions that achieve these ends at less cost. Yet, we still see the same methods being recycled again and again. Shall we follow the road we have tread in education for the past hundred years? We seem to draw upon the same ideology that education has languished in that "one size fits all" model. As the research suggests, the student and instructor could find a superior model online if only the experience were personalized (Karagiannis, I., & Satratzemi, M. 2018); adaptive delivery through technology is what we propose. We have an opportunity to leverage technology in tailoring lesson delivery based on learning style to increase Engagement.

In these discussions, you will note that there are disagreements concerning Learning Styles and how Engagement cannot or should be measured by one element. I hope to address these criticisms and to use them to build my methodology based on flaws they use for these arguments. Therefore, I wish to propose steps to helping solve a problem that plagues community colleges in their quest to serve the masses. Finding a solution that will increase Engagement and scores in math courses can make or break a college education in the first or second year. Courses are required not only for a degree award but are a minimum requirement for college-level course work. Unfortunately, these same courses become a "bottle-neck" as some students repeat them over and over to the point of failure. Mathematics, in particular, appears to be a barrier for most of the community college student population (Achieving the Dream, 2006c).

Statement of the Problem

American students ranked 37th among sixty-four nations; this ranking is lower than in previous years. Programme for International Student Assessment (PISA) (2018). Compared to the last 2012 results, the United States was 34th in a smaller sample (PISA) (2012). These trends are alarming and trending downward.

Incorporating this style allows for more accessible Learning, which provides for better outcomes and achievement. Moreover, learners with a strong preference for a specific style will have difficulties if the material is presented, which does not match that style (Bajraktarevic, Hall, & Fullick, 2003). By examining learning style as a variable to unlock potential in a particular subject area (math), we can focus on an under-performing group in this subject. This was confirmed as a beneficial effect of providing students with an adaptive online course that matched their preferred learning style. The students achieved significantly better scores than those who took the course that did not match their style. (Bajraktarevic, Hall, & Fullick, 2003).

What was distance learning has blossomed into the online curriculum for most colleges and universities, not to mention the state-funded virtual classrooms in primary education. Yet, with the millions spent on these systems, this leaves many questions unanswered, course structure, ease of use, and low-cost storage the main goals of these systems? As the research suggests, the problem is that the student and instructor partnership could find a superior model online if only the experience were personalized. (Karagiannis, I., & Satratzemi, M., 2018).

Learning theory states that learning begins with experience. Knowledge is born out of the information and lessons acquired due to task performance within a particular framework. The framework of Education in the US has used operational thinking during arithmetic, which, as research suggests, hinders Learning and transfer (Chesney, & McNeil, 2014). Furthermore, the key to delivering to users via adaptive technologies is relevance. An object or experience is relevant if it relates to prior experience; (Walkington, C., & Bernacki, M. L., 2018) or if it elicits positive emotional reactions; the use of personalized experiences in Learning provides this connection as research suggests.

Leveraging technology would allow for community colleges to raise their completion rates in a twofold manner. Increased Engagement on several levels will allow students to feel more in touch with their learning community and thus achieve longer term learning goals. Increased scores will provide a motivational stimulus to students to complete the courses which seemed out of reach. The latter also presents an opportunity for community colleges to show the legislature a return on tax payer investment.

The Significance of the Study

The Contribution to Business will be the improvement of course delivery by seeking adaption as the goal of presenting material to the learner during a lesson. To allow the instructor to relay the content personally to the online participant and achieve user satisfaction. The overall objective is to deliver superior learning outcomes by increasing math scores of a historically low achieving group in this subject area. By linking customer satisfaction as a significant predictor in learning outcomes, online learning can further become the model, to close the gap between instructor and students.

The first step is to develop a method using a Visual Auditory and Kinetic (VAK) instrument to evaluate and discover the style a student will feel most attuned to helps present the material to the student in an adaptive manner. The next step is to provide an environment where the student can be given the traditional course in math, which has not been altered and follows an established curriculum. The curriculum matches the students' style in stages by allowing for engagement checks. The changing of learning style will also test for mismatches in style, which could present evidence to the actual hindrance in Engagement or frustration on the part of the student. The compilation of these results will provide evidence that links learning styles to increased Engagement.

The importance of providing a bridge between lack of math skills to college-level course work is engaging students at multiple levels (Cognitive, Affective, and Behavioral). Strong mathematical foundations would promote student engagement, which is essential in supporting future professional and academics success for these learners.

Theoretical Perspectives

The theoretical framework for Learning styles has been debated over many years and waxes and wanes. Learning style is the inherent method that a learner prefers to learn (Rogowsky, B. A., Calhoun, B. M., & Tallal, P., 2015). It is an intrinsic attitude and behavior which determines how an individual learns something new (Honey and Mumford 1992). It should be noted that an individual commonly has a main preferred Learning style, yet this can be a mixture of all three (Cassidy, S. 2004). Some establish or develop a great preference for one and have a lesser degree of inclination towards a second. It is less common to find those that have all three styles. The problem faced by educators is how to deliver a customized lesson to each student effectively based on their style. Here is where adaptive delivery would adjust content to allow customized lessons that break the “one size fits all” mold that education has suffered for the last century. The study seeks to establish the efficacy of a feedback loop between instructor and student that was not feasible in all but “one on one” instruction before. Technology will provide the key to lifting this one student, one instructor restriction for individualized instruction.

The Walter Burke Visual Auditory Kinetic Learning Style Model (VAK) would facilitate the clustering of visual, auditory, and kinesthetic learners allowing for an experiment to evaluate the effect of adaptive delivery feedback loops on each student group. After a self-contained lesson, the significant improvement in the assessment score will provide evidence of increased learning based on a moderated learning style lesson presented by adaptive delivery.

Although I have shown how detecting Learning Styles is a vital piece of this research is not the only aspect of this study. Engagement will also be a critical factor in how to measure the success of the study. We will also look at how Engagement in the three forms of Cognitive, Affective, and Behavioral is affected by the independent variable of Learning Style. When a lesson matches the student’s style, will this have a positive effect on Engagement and thus Outcomes (scores) of an assessment. Furthermore, will increase Engagement and Learning style match further impact those scores by mediation?

The overall objective is to achieve improved outcomes by increasing math scores based upon the learning style. This will moderate the delivery of the lesson and achieve a match with the student’s unique ability to learn. Leveraging available technology provides a modern framework and tool that can be scaled to allow the instructor to provide tailored “one-on-one” instruction. The “one on one” system can deliver content, which is unique and offers familiar views of the same problem. The learner will align with the style that matches their frequency of Engagement. The improvement based on this match is proof of the value of using technology for this purpose.

Limitations of the Study

This study did not test the Kinetic group, which involves a more elaborate form of Learning. The research will focus on general students who have baseline characteristics of a specific student population. Exploring broad-spectrum learners, we can allow for generalization, which has been a criticism of previous studies (Massa & Mayer, 2006). This study piloted research using a quasi-experimental method which should be expanded to other areas. As seen in previous research, the trend was focused on specific groups of students tied to convenience samples (i.e., nursing students, business students, or computer science) (Ibrahim & Hussein, 2015). Further studies would include an interface and lesson targeted at Kinetic learners with a focus on literacy.

Positive results in improved lesson scores prove that moderated learning style lessons can improve outcomes, thus justifying their cost. Further testing over a more extended period would prove if longitudinal data can further solidify results.

COVID 19 also played a part in allowing only virtual Learning that was primarily asynchronous in nature. The pandemic forced us away from the traditional classroom and revealed the divisions of those that can thrive in the digital divide and those that falter.

The scope of this study is limited by the characteristics of the demographics of Miami Dade College, where the sample was obtained. The majority of the students attending this institution belong to minority groups, specifically Hispanic and Black students. This is also reflective of the demographics of Miami Dade County. Students self-selected the College Algebra courses where the samples were collected. The courses due to the pandemic were instructor-led or in an asynchronous manner. Due to these conditions, modifications were placed on the experimental design to overcome these limitations.

Summary

The present study proposed a model that explored the relationship among Engagement (Cognitive, Affective, Behavioral), Learning Styles, and adaptive delivery of those lessons in College Algebra classes. Additionally, the study was undertaken to analyze the direct effect of both on the Outcomes of this relationship. The hope is to present viable evidence that this mode of instruction can improve Outcomes and thus completion rates of these courses. The current study arises as a response to fill this gap in the literature as it strives to provide insights on the community college students population. Which also fulfills a baseline subject group, a sector of higher education population markedly underrepresented in research studies.

Chapter two provides a review of the literature that includes further elaboration on a theoretical framework and the findings of prior studies pertinent to building an argument that supports the goal and directions of my research. Chapter three allows for the operationalization of the model and hypothesis development. Chapter four discusses the experimental methodology and the research design of the study. Chapter five presents the analysis and results of the investigation. Finally, Chapter six presents a discussion of the findings, and implications of the body of research.

Research Question

The purpose of this study was to measure the effect of adaptive delivery on a lesson at the community college being researched; one research question will be addressed.

RQ1: Does an increase of Engagement based on adaptive delivery help learning outcomes?

CHAPTER TWO

LITERATURE REVIEW

This chapter includes a discussion of the theoretical viewpoints and studies that relate to this study. The sequence follows the history of community colleges, Learning Style, Instruction in Relation to Learning Style, Engagement, Mathematics in the US, the Role of Adaptive Learning in Mathematics, Learning Independence as a Primary Motivator to Online Learning, the gaps in the literature, and the research model with hypotheses.

History of Community Colleges and Forming the Problem

The community college system was proposed by the Truman Commission in 1948 to fill the need of large numbers of students seeking higher education who traditionally were excluded from four-year universities due to academic admission requirements and higher tuition costs (American Association of Community Colleges, 2016b). Though community colleges have been in existence since 1901, several factors such as the G.I. Bill, post-WWII economic development, and "Baby Boomers" reaching college-age spurred an increase in the number of community colleges (American Association of Community Colleges, 2016b). As a result, community colleges became the choice for the higher education of many financially underprivileged and underprepared learners.

The problem they face was framed with the system on which community colleges themselves were founded. Community colleges have open enrollment and do not conduct entrance exams which presents the crux of our dilemma when improving learning outcomes and completion rates. More importantly, a system that created the baseline for higher education and was created to provide an opportunity to the masses also has unintended consequences.

Over the last thirty years, governments have looked at how to meet the needs of society without spending too much taxpayer money. In response to these pressures, the reaction of these policymakers was to link funding to performance (Williams 1997; van Vught 1997; Layzell 1998, p. 108). However, literature has shown that shifts in funding have a significant impact on the behavior of these institutions as well as their internal processes (Mace, 1995).

Agency Theory and its Effects on Community College Funding

Agency theory is beneficial because it sheds insight into the complex problem that these institutions find themselves in. As an organization, resource allocation will influence the behavior of that entity. Academics and managers in higher education as agents of the principles (legislature) which control funding affect how they deal with risks (Liefner, 2003). Agency theory applies in this relationship situation (Majorne, 2001). The policymakers delegate authority and decision-making control to his or her agent community colleges (Basu, V., & Lederer, A. L., 2011). In the case of educational relationships, (government) are distant yet imposing ever-changing requirements. The agents, community college academics, and administrators need incentives to do the right thing yet find restrictions and moving targets from political administration to administration. For the agent to work in the principal's interest, there has to be a higher alignment between them (Parker, 2011). Furthermore, community colleges are expected to respond to changes in the funding and pivot in the state's resource allocation methods by adopting new strategies to improve student outcomes (Rabovsky, 2012). Therefore, community colleges need to seek solutions contingent on their organizational mission and react accordingly. The goals of institutions, the policymakers, and taxpayers are intertwined as the taxpayers are also tomorrow's students. Creating opportunities is the mantra of many community colleges and should look at themselves to create a viable solution.

My dissertation proposes investigating the relationship between learning style and the student's Engagement in a mathematics curriculum to examine adaptive delivery. The adaptive delivery is the vehicle in which community colleges could, by personalizing instruction, allow for higher Engagement, thus better learning outcomes. But, more importantly, to offer support for what is perhaps my most controversial claim, that Learning styles do have an impact on Engagement and, therefore, Outcomes in retort to opposing research (Rogowsky, 2020, Pashler, 2008).

Learning Style Theory

The literature attempts to define Learning style as the innate preferences of individuals for how they absorb in the learning process (Ehrman and Oxford, 1990; Oxford, 2000). To examine whether it is heredity, environment, educational background, or other factors, a learner will understand and process information differently. To prefer one learning style over another is a reflection of personal selection based on a particular situation. Students, regardless of culture, have a preferred learning style, yet these styles have been broadly categorized. Moreover, even though the literature contains an abundance of research on learning styles and also instruments to evaluate learning preferences, the concept of Learning has been widely debated, and even the definition of their existence is questioned (Felder & Brent, 2005).

Instruction in Relation to Learning Style

Therefore, let us examine the learning style concerning instruction. To find these relations, we need to agree on measuring learning styles in the classroom setting. (Pashler, 2008) states that any valid validation requires robust documentation of specific experimental processes of which learning style-based instruction can be examined. Students need to be divided into groups based on learning styles from which each student can be randomly assigned to receive one of many instruction methods. Then a student should be administered an exam that is given to all students. Lastly, optimal learning can be achieved if each student receives instruction customized to their particular learning style. This experimental treatment will reveal the interaction between learning style and the method of instruction. Learners will achieve the best learning outcomes when taught through an instructional approach that differs from the instructional process producing the best result for students with a different learning style. The instructional method one student finds effective will not suit another (Pashler, 2008). Differentiation in the classroom holds the key to breaking the "one-size fits all" model.

Instructional preference is defined as the individual's tendency to show a favorable attitude or select a particular instructional method (Rider & Smith, 1999). Moreover, individuals have specific learning styles, and instruction will be more effective if based on the preferred sensory modality students use to process or absorb information. Although Learning may vary over time, determining a student's learning style is significant in determining the learning preference, as noted by (Pakkala, Ganashree, & Raghavendra, 2014). In studies by (Raines, Brabham & Aycock, 2007), they state that although students are an essential component in the learning process, their preference for learning is usually not considered. For which they conclude that learning instruction must be based on the interests of the students.

The "one-size-fits-all" paradigm has little effect, and educators need to use diverse methods to deliver instructions, which cater to the different preferences of students (Cools & Belens, 2011). An implication is also noted that a mismatch of instruction and learning preference will cause students to get wearied or inattentive, resulting in their discontinuing a class or, worse, leaving a program (Yusop & Sumari, 2015). Therefore the belief that students' preferences should be considered is supported by (Prosser & Trigwell, 1998; Biggs, 2003; Ramsden, 2003; Sadler-Smith & Smith, 2004). Their argument that interest in the students' learning preference is needed, but appropriate assistance should be provided to help students achieve their learning goals (Bambacas & Sanderson, 2011).

Engagement – Cognitive, Behavioral, and Affective

Cognitive Engagement is defined as the degree to which students are willing and able to take on a learning task. In addition, the number of effort students is eager to invest in working on that task (Corno & Mandinach 1983) and the length of time they persist on said task (Richardson and Newby 2006; Walker et al., 2006). The measure or operationalization of Cognitive Engagement has been traditionally seen by the extent to which students complete assignments, class attendance, extracurricular participation in activities, or their extensive interaction with instructors, and their motivational level while engaging in classroom discussions (Appleton et al., 2006).

To this end, using an instrument to measure cognitive Engagement will allow for "situational cognitive engagement." The departure from traditional measures which do not stress the contextual dependence of the measure. The capture of a dynamic aspect of Engagement during class, a cognitive engagement check can be employed (Blumenfeld et al. 2006; Corno and Mandinach 1983; Volet 1997; Wolters 1999), and this will rely how willing they are to persist on the task at hand (Ainley et al. 2002; Pintrich and De Groot 1990; Prenzel 1992; Richardson and Newby 2006; Walker et al. 2006). As an added variable, the cognitive Engagement can also look at the flow, which would reveal being fully emerged in Learning and forgetting everything around oneself (Csikszentmihalyi 1975; Csikszentmihalyi and Csikszentmihalyi 1988). Immersion in the task to the point of loss of time sense reveals the depth of this form of Engagement.

Next, we need to examine the Behavioral component of Engagement that is so often valued for its noticeable effect. The Behavioral emphasizes the time, effort, or participation of the learner. Interestingly, the Behavioral perspective causes us to miss valuable information, giving us a deeper understanding of the learning experience. We do not suggest that the Behavioral dimension is without merit; this dimension explains part of the complex and multidimensional picture of student engagement. Mainly behavior explains the relationships between teaching practice and student behavior (Kahu, 2013).

Behavioral Engagement at its heart has three facets: positive conduct, which includes attendance; involvement in learning, including time on task and asking questions; and more participation in extracurricular activities, which will lead to involvement (Fredricks, Blumenfeld, and Paris 2004). As the research states, these facets lead to visible success, as noted in Finn's participation model (Finn, 1993) in extracurricular activities.

Affective Engagement is a strength of the psychological approach and is often an approach that is overlooked (Askham, 2008). The focus of this form is Engagement is the sense of belonging (Libbey, 2004). Affective Engagement emphasizes the difference between active and intrinsic motivation, which, as you will discover, creates pleasure and interest in learning. Although the literature seems to give credence to the active form of Behavioral and Cognitive these forms of Engagement are often task-based. The simple form of learning whose sole purpose is to garner higher grades and qualifications than a deep psychological investment in education (Bryson and Hand, 2008).
Consequently, we see that Engagement cannot solely be judged on one aspect or factor. Therefore, to measure Engagement, this study will delve into these three distinct levels and determine each variable as they are influenced by Learning style.

In the literature, there are many references to the impact of Learning style on the learning process. There is an established benefit from material and approaches that match the learning style (Akbulut and Cardak 2012). Failure to match the user to learning style has been shown to create problems from a mismatch between teachers' expectations of students' learning and students' preferred learning styles (Mills et al. 2005). The explanation could lie in that when the learning style is excluded, or one particular style is catered to, students lose interest and are not motivated (Felder et al. 2002).

Using Learning styles adapts the content presentation to the learner (Peter et al. 2010), which is to pair the student with the content in some form of adaptive delivery. Thus, adaptation becomes a matter of programming packages and modules to suit your needs when providing an adaptive product (Kolekar, S. V., Pai, R. M., & Pai M.M., M. 2018).

My interest in this topic stems from the fact that mathematics was a subject I struggled to overcome. The use of adaptive delivery allows for a method using technology already present, Learning Management Systems, multi-platform applications, and mobile instruction. Creating an environment that can personalize the experience of the student and also open avenues to the instructor. I need to ask, "Which method looks less at the subject matter and more at developing a lifelong learner?" How do we stimulate the psychological aspect of Engagement (Affective), which studies state is more long-term (Furlong et al. 2003)?

The presented research leads us to invest more in student Learning styles and feedback from the instructor. Educational entities can use the vast amount of information collected by these systems and establish a pattern of learning style using existing models (Liyanage, Gunawardena, & Hirakawa, M. 2016). Although the Felder Silverman learning style model has been recognized and applied to e-learning environments, its complexity goes beyond the scope of this research. (Liyanage, Gunawardena, & Hirakawa, M., 2016). The uses of an established adaptive delivery would provide a method to offer instruction cost-effectively and to test on a select sample group of students. The subject of math was chosen since it presents a unique dilemma for students. The focus on this subject area will also prove that closing this arithmetic gap further benefits learning the style-adapted system.

The measure of this knowledge can be viewed as through changes in practices or routines (classroom instruction). There is also the measure of performance or the speed at which knowledge is acquired (levels of delineation). Yet all of these measures must be viewed over time to lend perspective of its cycle. For example, a task is converted to knowledge, increases performance, and increases future experience (Argote, L., & Miron-Spektor, E., 2011).

Mathematics Learning in the US

Yet, to draw on previous experiences, we find a hindrance by the practice of operational thinking, which happens early in US arithmetic education. Prior knowledge in a domain helps solve problems presented in that domain but unhelpful if that knowledge is activated as a detriment. For example, using the symbol = balances both sides of an equation in the US is seen as "the answer follows," suggested by (Mcneil & Alibali, 2005). This hindrance allows one to lose the sense of their frame of reference, leading to a collapse of prior knowledge to solve the problem presented in the present day.

The Role of Adaptive Learning in Mathematics

The role of Adaptive Learning in Mathematics can be viewed lightly in the research as noted by cursory reflection into basic math (e.g., Anand & Ross, 1987; Cordova & Lepper, 1996), little research has been conducted on bringing student interests into adaptive technology-based learning environments. To examine a higher level of mathematics such as Algebra bears the importance of this study. Algebra has been seen as a gatekeeper to higher-level mathematics that carries significant implications for students' economic futures (Kaput, 2000; Moses & Cobb, 2001). Algebra allows a student to make an essential transition from working with known quantities to the substitution of symbols to represent unknown quantities, learning other skills like writing, manipulating, and solving algebraic expressions (Common Core State Standards Initiative, 2010). The importance of Adaptive Learning is that instruction may be helpful when presented in the context of the student's interests, which is their predisposition to engage with particular topics, ideas, or concepts (Hidi & Renninger, 2006). Studies show that the presentation of instruction in the context of the students' interest brings about attention, impacts with persistence, and engages (e.g., Ainley, Hidi, & Berndorff, 2002; Flowerday, Schraw, & Stevens, 2004; Hidi, 1990, 2001).

If we look at the movement of technology, some tools propel learning to new heights by closing the distance between the student and the classroom. Web-based platforms represent a progression in learning through the flexibility of occurring anywhere, at any time, and less cost than the face-to-face alternative (Johnson & Aragon 2003; Mayne & Wu 2011). Yet, there is criticism with learning online as opposed to face-to-face. The conversation has been long portrayed as online is second best to traditional face-to-face options. However, the research and evidence have focused on relating to student performance, attrition, and retention with scant attention to the total learning experience, which balances the traditional learning outcome measures side-by-side with student-centered factors, such as students' satisfaction with their learning experience (Mgutshini, T., 2013).

Learning Independence as a Primary Motivator to Online

The repercussion of the body of work on learning styles and technology is that individual students prefer and gain value from learning in technology-rich courses. Yet the research has found that they are different from those who prefer more traditional course work (Aragon, Johnson, & Shaik., 2002)

Moreover, students interested in technology-rich courses are independent learners who prefer a more abstract thought process. The majority of college students are not represented (Cohen, V., 1997). Learning style aside, fully online courses may not provide all the solutions to slumping test scores, yet user satisfaction and customization are steps in the right direction. For this reason, the current research aimed to contribute descriptive data to divide students into clusters based on psychological aspects, which would lead to creating efficiency in e-learning systems that provides adaptive delivery to the individual differences of the students based on their learning style preference. This project will investigate the relationship between learning styles in terms of instructional information processing and personality in terms of auditory, visual, and tactile in undergraduate students from Miami Dade College in Florida. The choice for this subject selection is twofold. Firstly, as the researcher, I would like to look at subjects that set a baseline, as they stated previously, who are the most significant many among college students. Secondly, these subjects are varied in degree selection and do not fall into one classification of a student as previous studies have done. By expanding the group, you generalize the reaction of the sample in the experiment, thus achieve results that could be triggered only in certain groups, such as nursing students, engineers, or accountants. Moreover, a generalized group will bring findings that will sustain the research previously undertaken on specific groups by supporting their conclusions.

Mind the Gap

The gaps I found in the literature are varied. One source looks at particular students (anatomy) and criticizes Learning Styles (Husmann, P. R., & O'Loughlin, V. D., 2019) as discussed in the previous paragraph. Another study (Sharp, Bowker, and Byrne, 2008) states that authors operate on their definitions, theoretical frameworks, models, provide more confusion than answers. Consequently, those that oppose learning styles are inclined to cite (Coffield et al., 2004), as I read carefully did not state learning styles do not exist. On the contrary, the literature confirms we each have a preferred learning style, and these styles could be the impetus for individual, organizational, or even systemic change. A further assertion and the basis for their study in England was to judge if the products that propose learning style inventories are worth the expense, not to refute actual learning preferences among students. Critics of Learning styles are taking part in "cherry-picking," which parts of the Coffield's review agree with and violate that which he warned about in his study. The research was looking at Learning style inventories and whether learning styles were pedagogically sound.

Lastly, one of the charges which resonate throughout the literature states: “There is no connection between identifying learning styles and academic achievement.” To expand on that, students who know their learning style do not perform better than students who do. (Gappi, 2013) attempted to measure learning style and found that students who knew their learning style did not perform any better than those that don’t. In a similar study, the postulation stated that students differ in abilities, background knowledge, interest, and have preferences in how they learn but catering to those preferences will lead to better learning (Riener and Willingham, 2010). Hence, this foundation is enough for some to be critical of using class time in identifying learning styles since it does not correlate to academic achievement. I propose that we first see how students perform if they are not aware of their learning style when absorbing information. More importantly, just because a student does not identify with a particular learning style does not mean they do not use it without realization.

Armed with this, we can nullify some of the criticisms levied on these studies and learning styles in general. For example, previous studies also relied heavily on surveys lacking the benefits of an experimental process (Rogowsky, B. A., Calhoun, B., and Paula T., 2015). My study proposes to tackle many of these criticisms as part of the methodology. I wish to prove significance in Engagement in their varied elements and that scores will be higher between the interaction lesson style and lecture-style when matched.

The importance will give community colleges a method to allow for learning outcomes, course completion, and funding. The methodology for this study will enable me to spend nearly zero dollars by adapting coursework already in existence. Subtle changes in existing lessons to a digital platform that students can access at their convenience added to the leverage of technology. If community colleges were able to replicate these results and raise Engagement and assessment scores, this study would allow for the proof in allocating funds that reflect return on investment of tax dollars. A model of this study could help to take a step in transforming how we present material and how personalization can help to achieve better results. Community colleges need to take any action before the well runs dry.

CHAPTER THREE:

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

Research Model

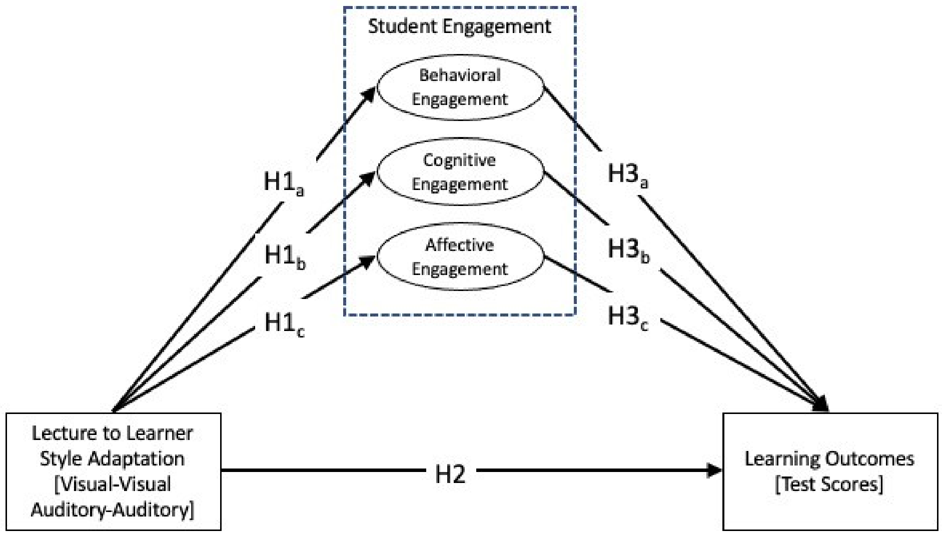

Figure 1: Conceptual model and operationalization of key constructs.

Propositions/Hypothesis Development

As proposed by Creswell (2012), "hypotheses are statements in quantitative research in which the investigator makes a prediction or a conjecture about the outcome of a relationship among attributes or characteristics."

Each hypothesis is based on data gathered from current students enrolled in a community college "bottleneck" courses that impact students and are virtually instructed developmental courses required for graduation.

The hypothesis put forth in this study is based on the research question for this study. These hypotheses are numbered according to the research question and further broken into sub-hypotheses.

Hypothesis One

$H1_a$: Adapting a lecture to a student's preferred learning style will lead to higher behavioral Engagement.

$H1_b$: Adapting a lecture to a student's preferred learning style will lead to higher cognitive Engagement.

$H1_c$: Adapting a lecture to a student's preferred learning style will lead to higher affective Engagement.

Hypothesis Two

H2: Adaptation increases learning (test scores) outcomes.

Hypothesis Three

$H3_a$: Increased Behavioral Engagement of the student will lead to better (test scores) outcomes.

$H3_b$: Increased Cognitive Engagement of the student will lead to better (test scores) outcomes.

$H3_c$: Increased Affective Engagement of the student will lead to (test scores) better outcomes.

Hypothesis Development

As discussed in the literature review, I examined the relationship between conceptual model seen above in Figure 1. My focus was the direct impact of adaptive delivery on the levels of Engagement on learners. The adaptive delivery being the personalization of course material to conform to the student's Learning style or the preferred method in which they prefer to absorb knowledge (Ehrman and Oxford, 1990; Oxford, 2000). This intrinsic method matches a comfort level that I seek to display is essential for the learner (Rogowsky, B. A., Calhoun, B. M., & Tallal, P., 2015). Ignoring this mismatch of instruction will cause students to get wearied or inattentive, with greater consequences for the student and institution (Yusop & Sumari, 2015).

Furthermore, when we examine Engagement we can simply define it as one static construct. Engagement for the purposes of this study has been split into three factors which cover the Cognitive, Behavioral, and Affective as explored by Kahu in her 2013 research. The three aspects treated independently draws the situational aspect of Engagement in a more complete fashion and add context to the measure. Each aspect of Engagement brings a separate factor to allow not only for short term effects such as Behavioral or Cognitive, but also long term learning such as Affective Engagement.

Secondly, the effect of adaptive delivery as a treatment of either Visual or Auditory personalization on scores achieved through assessment pre and posttest. The emphasis on scores provides an immediate validation in the eyes of students and a motivation to continue against adversity (Appleton et al., 2006). Learning outcomes are also very much defined by policy makers as an increase in testing scores and completion of coursework (Williams 1997; van Vught 1997; Layzell 1998, p. 108). Finally we look at the mediation effects of Engagement on Learning Outcomes (scores) as a result of adaptive delivery or perceived personalization. The relationship of increased Engagement can lead to higher outcomes as noted by (Hidi & Renninger, 2006) in their research concerning student interest and its predisposition to engage in particular concepts. The engagement brought about by the presentation of instruction impacts persistence and draws learner attention (e.g., Ainley, Hidi, & Berndorff, 2002; Flowerday, Schraw, & Stevens, 2004; Hidi, 1990, 2001).

CHAPTER FOUR:

RESEARCH METHODOLOGY

In this research, a quasi-experimental design was applied to evaluate the effects of the interaction of adaptive delivery tailored to the student's learning style. Unfortunately, previous studies have been at odds with the measures of learning styles in a classroom setting. Therefore, any validation of learning style-based instruction can only be examined with robust documentation of specific experimental processes (Pashler, 2008). My methodology endeavored to create an experimental process that would refute many of the criticisms of previous studies and how I overcome these.

Sample Frame

The study was conducted in Miami Dade College. Located in the county that bears its name, the institution is one of the four-largest is one of the largest four-year colleges in the United States. It boasts a total enrollment of 51,679 students across its eight urban campuses. Of particular interest, most of the student demographic are Hispanic/Latinx, as summarized in 2019 by the National Center for Educational Statistics for Miami Dade College in (Table 1) below. The larger Hispanic population is indicative of the general population of the area, 69.4%, which aligns with the college itself. The demographics data was summarized in 2019 by the National Center for Educational Statistics for Miami Dade College in (Table 1) below.

I chose a community college based on specific criteria of selecting a population group that would reflect the broadest spectrum of college students. Choosing to attend

Table 1: Demographic Profile of Miami Dade College Student Body

	Percent	Total
Gender		
Male	58%	29,974
Female	42%	21,705
Ethnicity		
White	5%	2,584
Black or African American	14%	7,235
Hispanic/Latino(a)	71%	36,692
Asian	1%	517
American Indian/Alaskan Native	0%	0
Native Hawaiian/Pacific Islander	0%	0
Multiethnic	1%	517
Non-resident alien	6%	3,101
Unknown	2%	1,034
Status		
Full-time	42%	
Part-time	58%	
Total Enrollments	100%	51,679

National Center for Education Statistics Demographic Data, 2019

a community college for students is also a convenient choice: low cost, ease of access, academic programs suited to students' and employers' needs, closeness to students' homes, flexible schedules, a broad range of support services, and links to other levels of educational advancement (Phillippe, K. A., Sullivan, L. G., & American Association of Community Colleges, W. D. 2005). To note that 6.5 million students take courses each fall makes these institutions of higher learning the choice for most learners (Phillippe, K. A., Sullivan, L. G., & American Association of Community Colleges, W. D. 2005). The data reflects that 45% of all undergraduate students in the United States enroll in community colleges.

Furthermore, the selection of this population reflects the first-time students entering college whom 60% require remediation of core academic courses of math, reading, or English before they can proceed to college-level academics (Scherer, J. L., & Anson, M. L. 2014). Thus, the purpose of evaluating a population that would have a higher propensity to repeat and has difficulty with "bottleneck" courses was to assess if adapting delivery would boost specific measures. Bottleneck courses are those that are required to complete a degree or certification and have historical repetition rates.

Functional Math (Area)

This study population consisted of subjects enrolled in an introductory Mathematics course required to complete a degree or certification. Selecting mathematics as a subject area presented the opportunity to tackle the most severe deficit in learning as math has become the lowest achievement point (rank of 37th across 64 nations) among American students (PISA) (2018).

Subject selection occurred through requests to Mathematics departmental chairs. Emails sent to garner support for the study and a recommendation by chairs of the instructional staff who were best suited to participate were the targets of this process.

To expand the sample, I corresponded with professors from the Mathematics Department across all eight campuses requesting their student participation in the research. Professors were asked to provide a class roster absent of names, with specific data points included if at all possible (gender, major, ID number). The ID numbers remained a correlating factor for professor rosters after the study concluded. As a researcher, I was not privy to any system that would allow subject identification through said ID number. The subjects were then provided a link by each professor that led them to a Qualtrics© Online survey/lesson. Qualtrics is a cloud-based platform use to create and distribute web-based surveys.

Subjects of the experiment received a consent form, approved by Florida International University and Miami Dade College, Institutional Review Board (IRB). The form provided an overview of the study, an explanation of the study itself, and its risks. Furthermore, the form explained that the purpose of the study was to measure the effect of improvement in their math score and their Engagement level based on a math lesson. The consent of the subject was given by clicking on a radio button in the form.

Each subject's participation was voluntary, and the confidentiality of their responses was paramount. Those students who choose not to participate were given the option to do so or not to give consent. The subjects who did not consent were removed from the data set for analysis. The data for this research study will be destroyed three years upon its completion.

Respective professors granted extra credit to students upon completing a survey, pretest, treatment lesson, posttest, and closing survey. The extra credit was given to the student at the professor's discretion based on a report that allowed them to reconcile their roster with an excel spreadsheet containing student ID, gender, and major. Students who did not participate were given a substitute lesson by the professor as an assignment.

EXPERIMENTAL DESIGN

Procedures

The quasi-experiment was designed to evaluate the effects of matching learning and lecture-style on the engagement level and outcome of learning in a math lesson. Multiple professors participated in the study; the same math course was also used to control for bias of professors on the subjects.

Furthermore, working during the pandemic required the experiment to be adapted from its proper experimental form. The experiment was delivered in an online model due to the college's COVID-19 Phase 2 pandemic restrictions. This remote model prevented the manipulation from having a unified baseline lecture before the experiment. A pre-conception prompt of the class was used in the Engagement survey instead of a traditional baseline lecture; if it would have been conducted face-to-face by the professor of the course, see Appendix A for the pre-Engagement prompt. The effect of this remote learning required the use of self-contained lessons, which could be accomplished in one sitting by the subject. All classes were self-paced or instructor-led. The self-contained format and pandemic restrictions forced a more compact method of experimentation. I could not control where, when, or how they took the lesson based on these restrictions. Therefore, the convenience sampling of students was selected to test the model and the theoretical framework based on these conditions.

Listed in this section is the background information which describes the processes used to conduct the research. The information sequence is as follows: an overview of research, units of analysis, study design, instrument, scale, data collection procedures, and variables.

Overview of Research

I used a quasi-experimental design to evaluate the effect of adaptive delivery on student engagement and learner outcomes. The focus is the relationship between learning style's influence on a subject's engagement and performance using adaptive delivery during an online lesson. The study was conducted on a broad cross-section of students to allow for a generalized result instead of previous studies. Based on previous studies, the scope and the sample group to the general population were confined to one subgroup of students, such as anatomy students (Husmann et al., 2019), which was, in my opinion, a significant reason this study was carried out with this population group. Furthermore, you will see in Appendix A a listing of majors with the Business major having 9.8%, followed by Biology at 8.6%, and Nursing at 5.5%. The percentages stated are above a significant factor but not encompassing as to dilute the subject group. A more extensive study would allow for the removal of specific majors when they achieve significance.

The study had three components, which were composed of surveys, assessments, and a treatment. The model for the operationalization of the study is presented in Figure 2.

Application	Visual Learner	Auditory Learner	Kinetic Learner
Visual Math Lesson	Learning Results higher	Learning Results baseline	Learning Results baseline
Auditory Math Lesson	Learning Results baseline	Learning Results higher	Learning Results baseline

Figure 2: Experimental Cell Model

The surveys were designed using software developed by Qualtrics© (a survey research company) and were subsequently administered through Qualtrics Online. Qualtrics delivered all surveys, lessons, and assessments in a self-contained format which assigned each participant in a randomized fashion to allow for an experimental treatment environment. Furthermore, to reduce bias from the particular instructor and their method of instruction. Specifically, elaborated instruction can reduce the belief bias effect in syllogistic reasoning but not eliminate it (Newstead et al., 2007).

The research instruments utilized a self-administered English survey questionnaire that consisted of questions adapted from standard scales due to their reliability and validity. In addition, each survey underwent adaption from a previously validated instrument. The adaptation of the survey used suggested modifications based on the literature recommendation by several references listed below.

Scale points between categories in a psychometric instrument are crucial for measuring the instrument and its reliability and validity (Krosnick & Fabrigar, 1997; Wakita, Ueshima, and Noguchi, 2012). In a study by Lissitz and Green (1975), five scale points were the cutting point where reliability leveled off to plateau. Lissitz and Green stated that using scales with more than five points had little effect.

Furthermore, Lagenfeld and Pajares (1993), which modified the Mathematics Confidence Scale Krosnick and Fabrigar (1997), as was the crux of this research, argued that scales with fewer options (three or fewer scale points) allows for more ambiguous responses on the perception or preference performing an activity. The contrary is stressed by (Krosnick & Fabrigar, 1997), who stated scales with more significant numbers become less precise and doubtful of the meaning of the specific point queried. Furthermore, Krosnick and Fabrigar expressed caution that too many responses act as a discouragement for expressing their genuine opinion. Consequently, Krosnick and Fabrigar recommend surveys with items that have four to seven points on the scale.

Lee and Paek (2014) examined the optimal number of response categories in Likert-type rating scales. In these categorical datasets, survey items that ranged between four and six points generated comparable outcomes with slight differences concerning correlations, reliability, and validity. The optimal number of response categories should be between and four and six points per Lee and Paek.

Therefore, to allow for the literature recommendations, I adjusted the study's instruments to fall within a five-point range to allow for the best sample of responses. The Engagement scale was not only revised but also randomized for each subject between pretest and posttest. The randomization was conducted by Qualtrics using a randomization counter in each section of the Engagement questionnaire. The randomizer changed the question order in each corresponding area of the Cognitive, Behavioral, and Affective engagement survey for both pre and posttest. The Learning Scale Inventory (VAK) survey was not randomized for its purpose was to provide one measure of the student's learning style. The sole purpose of LSI was to place the students into cells aligned with the preferred Learning Style (Visual, Auditory, or Kinetic).

Data Collection

The process of data collection commenced in earnest in the Spring semester of 2021. Miami Dade College sustained a level two lockdown due to the COVID-19 pandemic. According to the Centers for Disease Control, State of Florida, and college protocols, these restrictions allowed for limited access to the campus. The instruments listed below collected demographic, learning style, engagement, and assessment data. The collection period began on February 25 and concluded on April 8, 2021. Qualtrics compiled the scores for future statistical analysis.

Validity of the Tool

The instrument's validity was established through a panel of (37) experts of different specialties related to the field of the present study. Experts were asked to review the questionnaire for content clarity, relevancy, and adequacy.

Another step to ensure sample validity was to set qualification parameters on individual participants (Chandler, Mueller, and Paolacci 2014). The steps were incorporated to ensure the sample for both surveys consisted of genuine, attentive subjects who were not advancing quickly through the survey and lesson to achieve extra credit in their respective classes. First, only students who were taking math courses essential to completing their degree were allowed to participate.

Second, only subjects 100% completion rate on the process were credited by their instructor. Third, subjects were strictly prohibited from participating more than once, and this was strictly maintained through Qualtrics validation.

Furthermore, every user had a unique identifier, allowing for a further identification layer to discard any repeated attempts at the experiment. Validation mechanisms were also embedded inside the survey. Unseen to respondents, an electronic timer tracked how much time was spent in the individual treatment lesson and prevented the user from simply moving ahead without participating.

Instrument

Part I. Personal Information

The first section of the survey was a set of questions to collect information based on the subjects' demographic characteristics in terms of (1) College ID #, (2) Gender, (3) Age, (4) Educational Level, and (5) Major.

Part II. Learning Style Inventory

The Learning Style Inventory used within the study was developed by Kolb, one of the most influential and widely distributed scales to measure learning style and preference. This scale was formulated in the 1970s and has undergone revisions to improve its psychometric properties. The LSI is a self-report self-scoring instrument that measures individual choice to learning scenarios based on Visual, Auditory, and Kinetic cues (Kayes, 2005). In this study, an adapted version LSI-Likert was utilized to measure learning style. The LSI is a 24 item Likert scale with 3=often, 2=sometimes, and l=seldom. Each item in the scale represents the different learning styles in Visual, Audio, and Kinetic. The total scores were calculated to determine each individual's learning style and place them in a learning style group.

Moreover, the internal reliability of the LSI-Likert scale was relatively high (Pickworth and Shoeman, 2000). The survey had 24 items adapted to a 5-point Likert Scale being 5=Always, 4= Often, 3=Sometimes, 2=Rarely, 1=Never. Factor analysis conducted on the 24 items to validate the internal consistency and reliability of the LSI, based on the results, proved adequate. The scale received a value of .412 to .828 on factor analysis was received. Items loaded into subgroups based on Learning style; those factors had closer factorial numbers.

The Visual component of the survey loaded into values of .608 to .699. The Auditory element in the survey loaded into values of .547 to .755. The final segment, Kinetic, loaded between .547 to .766. The VAK split into visual, auditory, and kinetic categories generated the lowest accepted Cronbach's Alpha was .795, considered a valid and reliable scale to measure learning preference. I used exploratory factor analysis to measure the construct validity of the LSI. A primary criterion of eigenvalues greater than 1 was used for factor selection. It is considered that item loading over 0.30 is deemed significant, and loading over 0.40 is deemed essential, and 0.50 is considered very significant. Moreover, the LSI's content and face validity, readability, and user-friendliness were conducted on approval by a panel of experts in an informed pilot study (Kayes, 2005).

Two separate pilot studies were conducted to investigate the learning style of students on 132 subjects. The subjects also came from the population of Miami Dade College. From the first year to the fourth year, the mixed group of students was recruited from multiple campuses. The data collection process commenced by inviting students to share in the study, and only those who agree will be included in the study. The operation lasted two weeks at both schools. The adapted survey came out from those two additional pilot studies using Miami Dade College students. Furthermore, the treatments were an English curriculum instead of Mathematics, so that sample was more convenient to collect at the start of the semester. Several English professors who I had a personal relationship with volunteered to help with the pilot study to test for validity and experimental process. These were conducted early in January at the beginning of the 2021 Spring semester.

Qualtrics calculated the results of the 24 multiple-choice questionnaire and compiled the scores based on response. The score then assigned a designation to the subject based on their replies. These cluster samplings were then used to deliver the prescribed treatment, which Qualtrics randomized based on the count. The three buckets (sample cluster), the Visual, Auditory, and Kinetic, were then prompted to continue onto the pre-Engagement survey to establish a baseline of engagement.

Part III. Engagement Scale

The pre-Engagement survey had 14 items associated with Cognitive, Affective, Behavioral, and a separate output category. The CAB scale set the baseline of engagement on the course they were currently enrolled in. The survey questions prompted the subject concerning that particular course.

As stated previously, subjects/students could not participate in a pre-lecture before the treatment lesson due to COVID-19 restrictions pandemic restrictions. The restrictions imposed created a challenging environment for instruction and face to face learning. To note that most learning was completely online and at times asynchronous. However it should be noted the College does rely on this model for the majority of their online courses.

After completing the pre-engagement scale, a pretest was presented to all learners before the manipulation lesson. The pretest established a baseline for learning on the subject's knowledge of the course they were participating in. Thus, the subjects in this research were exposed to several lessons before the experiment in the professor's traditional instruction method.

Pretest

One of the professors recommended the pretest, which was generally given during the semester at this point in the course. The quiz is provided in Appendix A and was adapted from twelve questions down to ten. The reduction was due to the repetition of two questions and thus was removed. This assessment was graded on a 100 point scale with a value of ten for each correct answer. The purpose of the pretest was to set a baseline of knowledge of the subject. The study will look at the delta between the pretest and the posttest to evaluate the effect of the lesson. The matching of the lecture to learner should provide an increased Engagement and score. Lack of a match might lower or not change the score in a mismatch as the literature opines, the instruction method one student finds effective will not suit another (Pashler, 2008).

Subject Assignment Randomization

Subjects were assigned in a randomized manner based on the count. Each learner, once categorized by Learner style, received a Visual or an Auditory lecture. The randomization mechanism was programmed into the survey flow to count the subjects and assign the lesson based on that count.

Students need to be divided into groups based on Learning style from which each student can be randomly assigned to receive one of many instruction methods (Pashler, 2008). In Figure 3, the randomization scheme is how I randomized the test to each student.

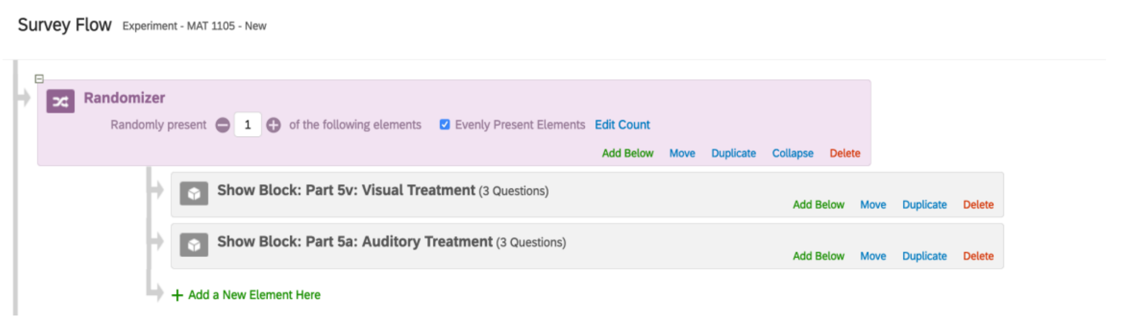

Figure 3 Randomization programming in the survey flow of Qualtrics.

Also, Qualtrics ran randomization schemes into the engagement surveys to control for click-through answering by the subject. I also built several measures into the survey to determine participation. Qualtrics handled the student's lack of involvement, and a timer was incorporated during the lesson to select the click-through rate of the subject and the time spent on the lesson. These controls allowed for more accurate checks and let the data be more concise at the time of analysis.

Treatment Lesson

A Visual treatment lecture was delivered as a video presentation by Pearson Publishing in 2012, with a preference for seen or observed things, including pictures, diagrams, demonstrations, and displays. The lesson progressed without sound and with only an emphasis on visual cues. The progression of the video provided examples to be worked on as the lesson played. The problem was broken into steps that are from a list, written directions, and instructions. These are all recommended for a Visual treatment by the literature (Linayage, et al., 2016).

The second treatment was an Auditory lecture delivered with a preference for the transfer of information through listening: the spoken word, self or others, sounds, and noises. The use of background music further enhanced the experience with a track that would fade in and out as the spoken lesson was played. No visual representation was presented at any point in this manipulation. An audio file was played with the lesson content allowing the subject to follow the lesson in an auditory experience.

Upon completing the lesson, an online summative assessment was given as a posttest to gauge the effect of the treatment on one of the dependent variables, outcome, or score. The scores of the assessments were compared to the previous score of the pretest given before the treatment, and the data were analyzed for a variance of treatment and score improvement. These scores were compared to the difference in outcome and measured for a change in one dependent variable.

The treatment lecture followed the same instructional curriculum used previously for these sections of Mathematics. The treatment lesson was based on a Pearson Education, Inc., slide show 2020, converted to a video and auditory format. The video treatment lesson was created by exporting a PowerPoint slide show into a movie file format and uploaded to YouTube. A YouTube link was generated to allow its inclusion into the Qualtrics. The Auditory lecture was converted into an audio file narrated by myself, and background music was added. The background music was downloaded from Sound Cloud and was titled “Peace” by Yasirmir Music. This particular piece was a royalty free sample. The audio file was uploaded to Qualtrics, and a link was also embedded in the experiment for ease of use. The same randomization scheme was applied to both lessons.

The manipulation was delivered on Qualtrics without any special treatment or attention save being online and virtual. The measured variables show what the manipulated variables concurrently affect besides the dependent variable of interest. An example of this can be introducing a new concept, the treatment lesson, and formative assessment, which was given as a posttest.

Posttest

The posttest was the same quiz provided in the pretest except for randomization. A randomization mechanism was employed again to scramble the question to remove any patterns recognition by the students of the previous exam. The randomization process used is also displayed in Figure 4. You will notice the crossing arrows in the right-hand corner, set to shuffle the question order. The process was more simplified as it was added into the block structure instead of the survey flow. Qualtrics would randomize the ten questions to provide each subject with a different pattern from the pretest.

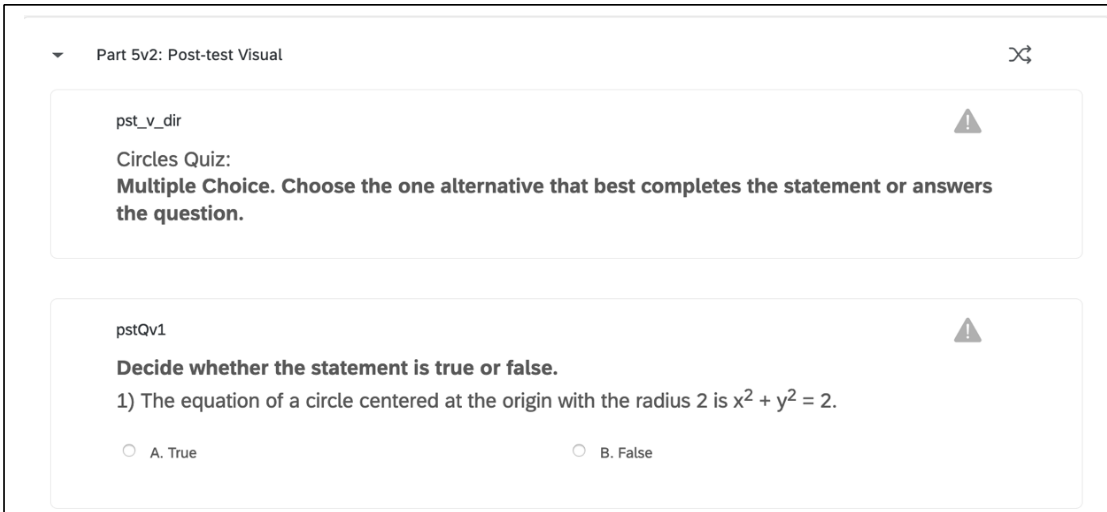

Figure 4: Block randomization of assessment questions in Qualtrics.

The assessment is also provided in Appendix A and used the same scoring method as the pretest. In addition, the posttest was conducted to establish a change in score based on the treatment lesson. Once again, the difference will provide evidence of the effect of the treatment as measured by the score.

After the lesson, another engagement survey was conducted, which was correlated and stated directly to relate to the lesson previously taken by the subject. The preface message was to orient the subject to keep the treatment lesson in mind when answering the post-engagement survey.

The information was collected by Qualtrics and compiled in their online systems. A file was exported from Qualtrics in a native SPSS native file format for analysis. The file was then cleaned to extract relevant data and allow the deletion of subjects who had not fulfilled the requirements of the study. All files suitable and exported from Qualtrics were stored on cloud storage in a password-protected account to ensure the security of the data.

Ethical Issues

Permission to conduct the study was requested from Florida International University Institutional Review Board (IRB). Once IRB permission was granted (Approval #: IRB-19-0242, Reference #: 107889), the researcher requested authorization to conduct the study in the higher education institution serving the population of interest for this study, Miami Dade College (Approval # 2019-05-24_Marakas (Piñera)-Change of Research). Upon receipt of IRB permission, the researcher contacted the chairs of the Mathematics departments at each respective campus. In addition, an email recruitment proposal was sent to every mathematics professor and all documentation and IRB approval to secure their participation. Several professors responded and provided their agreement to participate in the study. In addition, professors' and students' concerns were addressed based upon request. As explained previously, this study used well-established scales. (Gall et al. 2007) described in their research the advantages of using scales for which validity and reliability have been previously established.

Finally, statistical analyses were conducted to explore the relationship among the variables of this study. The students did not provide any personal information. Therefore, a student's identity could not be traced further based on their responses.

Operational Definitions of Variables

Dependent Variables

Students' level of engagement split into multiple factors—variates that account for three engagement levels (Behavioral, Cognitive, Affective). Building on a theory proposed by (Kahu, 2013), this section defines the dependent variables used in this study. The variables included adaptation on the subject when matched and unmatched to their preferences, the level of engagement in three distinct classes (Behavioral, Cognitive, Affective), and the relationship with learning outcomes. A case in point, each variable has a specific effect on the learner. Behavioral relates to time, effort, interaction, and participation (Fredericks, Blumenfeld & Paris, 2004). Behavior is a critical factor that allows for more concentrated effort. Cognition focuses on deep learning, self-regulation (Fredericks, Blumenfeld & Paris, 2004). The cognitive engagement level allows for association with the material. Finally, Affective engagement displays the learner's enthusiasm, interest, belonging (Fredericks, Blumenfeld & Paris, 2004). This class of engagement promotes a sense of community in the learning environment.

A change in the engagement scores will cover the dependent variable over three phases Cognitive, Affective, and Behavioral. An expected difference in these scores would explain the effect of the treatment. The delta change contrasted to the pre-engagement survey looked at the subjects' reactions to the lessons from current course enrollment instead of completing the assignment. The collection of categorical variables such as gender, age group, and educational level rounded out the other data collected.

Which factors are underlying the effect of learning style on student engagement and learning outcomes in college courses? The dependent variables subdivide into various levels of engagement. The Outcome level is a direct query to the subject in the form of a survey question. These random variables account for the students' judgment as a reaction to the treatment presented and reported.

Learner outcome based on pretest and posttest- the change in score was grounded on matching the lesson to the assessment given from the pretest as opposed to the posttest. The delta of these scores is the relative change as opposed to the absolute posttest score. The engagement and assessment results and their differences with a matched lecture or unmatched reveals the delivery adaptation's effect.

The Visual or Auditory lesson measures the deltas between pre-post results of both engagement and assessment surveys as compared by the outcome. Further support of this, Personal adaptation increases learning outcomes. (Bambacus & Sanderson 2011)

Further confirming the beneficial effect of providing students with an adaptive online course matched their preferred learning style (Bajraktarevic, Hall, & Fullick, 2003). Although stated in the literature review, it bears that personal adaptation increases learning outcomes (Bambacus & Sanderson 2011), confirmed a beneficial effect of providing students with an adaptive online course that matched their preferred learning style (Bajraktarevic, Hall, & Fullick, 2003).

Summary

The third chapter discussed the research study methodology that included the experimental design, population, sample, instruments, and the procedures and data collection. The design was the heart of this study as many factors restricted the experimental model from being carried out in a traditional fashion. Therefore, I sought to give as much clarification to the study in this chapter to allow for gap in previous studies and their criticisms. Analysis of the data collection is forthcoming in the next chapter.

CHAPTER FIVE

ANALYSIS AND RESULTS

This chapter presents the analysis and findings of the research study. Statistical Package for the Social Sciences ® version 26 was used to analyze the collected data from a Qualtrics online survey. The online survey was exported into a native SPSS format and examined for accuracy and incomplete data. In addition, an SPSS syntax file was created for verification and replication of the analysis process.

First, the data response rate is discussed to explain removing subjects who failed to complete portions of the survey or did not consent to the research. Second, a descriptive analysis of the sample used is presented to give the subject population and setting. Third, overall, the complexion for the institution is presented, with a further breakdown of demographic data. The purpose of the research was to examine the effect of factors underlying the use of adaptive delivery (Learning style) on learning Engagement and thus measure outcomes through assessment in the context of an online asynchronous mathematics lesson at an institution of higher education. Finally, the application of statistical procedures to the research question provides the results forthcoming in this chapter. The study focuses on the matching and unmatching lecture styles to customize learning to prove increased Engagement and thus outcomes.

Survey Response Rate

The study's data was collected in the spring semester of the 2021 academic year at Miami Dade College through an anonymous link provided to students by their instructors. A total of 214 students used the anonymous link to start the survey process.

Unfortunately, several factors led to the exclusion of several subjects in the survey. One of the factors was the lack of consent to participate in the survey itself. Two respondents decided not to participate after reading the study description. Also, some subjects failed to complete each of the items in the instruments (missing values), thus were unable to receive the treatment or did not take a pre-post assessment; these were not included in the study. As a result of these discrepancies, the final sample in the study consisted of 163 subjects.

Descriptive Statistics

A quantitative analysis using Descriptive Statistics was used to characterize the data obtained in the study to include the percentage distribution and frequency, means, and standard deviation, which was applied to the analysis of the respondents' demographic data and scores (Pagano, 2012).

Part one of the survey included a series of demographic questions to collect relevant information about the subjects. The demographic information collected is shown in (Table 2). Two hundred and fifteen students responded to the anonymous survey link, and one hundred and sixty-three completed the survey. Eighty-eight subjects (54%) were male, and seventy-five (46%) were female. A slightly higher number of males than females were noted. One hundred and sixteen students (71.2%) were 18 to 20 years old, followed by 23 (14%) students in the range of 21 - 25 years, and 24 (14.7%) students who were 26 and above in age range. The educational level of students was also recorded out of the 163 respondents; 90 (55.2%) were first-year, 51 (31.9%) second year, seven (4.3%) third year, and 15 (9.2%) from the fourth year.

Compared to Miami Dade College's current student demographics, which were supplied in Chapter 3, Table 1, 58% males, 42% females, placed gender within 4%, not a significant difference. Forty-one percent of students are between 18 to 20 years old (NCES IPEDS Data Center, 2019), which is not reflective of our sample. Since the course selected was introductory, it would follow a representation of subjects that would be younger than the norm. The support for this can be witnessed by third and fourth-year students, who made up only 13.5% of the sample.

Table 2: Demographic Indicators for Students

Indicator	N	%
Gender		
Male	88	54
Female	75	46
Age		
18 – 20 yrs.	116	71.2
21 – 25 yrs.	23	14.1
26 – & Above	24	14.7
Educational level		
1st year	90	55.2
2nd year	51	31.3
3rd year	7	4.3
4th year	15	9.2

Based on the Learning Style Inventory (VAK) scale employed, the subject population was divided into three groups: Visual, Auditory, and Kinetic. Sixty-eight (41.7%) were classified as Visual, 65 (39.9%) Auditory, and 30 (18.4%) Kinetic. These populations were then randomly assigned after completing a pretest to establish baseline learning measures. The treatment lessons were randomized to create an experimental design that would allow equal treatment between subjects (Kempthorne, O., 1952).

A separate Crosstabs analysis was also conducted to verify cell composition between Learner Style and Lecture Style (Visual or Auditory). The analysis was a shed 20 subjects under the frequency and percentages provided by the Descriptive statistics. The results of these demonstrate a balanced cell design which randomized subjects within one subject of each cell. Kinetic subjects which were a smaller population group also received a random assignment of either lecture style.

Fifty-seven (49.1%) subjects received a Visual lecture, 58 (50.9%) were treated to an Auditory lecture. Subjects were further randomized to match or un-match a learning style to a treatment lesson. Twenty-six (51%) Visual students were matched to a Visual treatment, 26 (50%) Auditory students were assigned to a Visual lesson, 13 Kinetic students were assigned to a Visual lesson, 25 Visual students were assigned to an Auditory treatment, 26 Auditory students were matched to an Auditory lesson, and 15 Kinetic students were given to an Auditory lesson. The descriptive indicators of these are

Table 3: Group Distribution and Cell Composition

	Visual	Auditory	Kinetic
N	57	58	28
Lecture Style	49.1%	50.9%	*
Style Match to Treatment			
No Match	26	25	13
Match	26	26	15

presented in (Table 3) in alignment with the experimental cell composition. The Kinetic students were not given a matching lesson as part of treatment.

Reliability of Scales Employed

The two scales employed in this study were a Learning Style Inventory (LSI) developed from (Kolb, 1970) and an Engagement scale from various sources, split into subcategories of Cognitive, Affective, and Behavioral subsets. In addition, an Outcome scale was included in the Engagement scale, with two additional questions was added to measure direct student perceived engagement. The engagement scales were administered pre and post-treatment to measure the change in Engagement across four categories.

To allow for the validation of instruments, a Factorial analysis (EFA) was also used to measure the value of the variables and test the hypothesized relationship between dependent variables and independent variables (Weiner, 2003). Reliability analysis was then added to calculate the instrument's reliability and all subsets of that instrument.

Exploratory factor analysis was conducted on 24 items of the LSI, using principal component extraction with a varimax rotation revealed a three-factor solution. The measure accounted for 64% percent of the variance of the Learning Style Inventory.

The initial analysis was conducted previously in two separate pilot tests. The LSI served to place the student in one of the three learning style groups to receive one of two experimental treatments. A further analysis loading the individual factors Visual, Auditory, and Kinetic provided a better match for each category.

Several well-recognized criteria for the factorability of a correlation were used. Firstly, it was observed that 23 of the 24 items correlated at least .4 with at least one other item, suggesting reasonable factorability (see Appendix A). Kinetic (KIN6) question which did cross load is not significant as the group acts as a control. The Visual and Auditory factors all loaded on appropriate dimensions. Secondly, the Kaiser-Meyer-Olkin measure of sampling adequacy was .812, above the commonly recommended value of .6, and Bartlett's test of sphericity was significant ($\chi 2$ (276) = 1634.269, $p < .001$). Finally, the commonalities were all above .3 (see Table 4), further confirming that each item shared some common variance with other items. Given these overall indicators, factor analysis was deemed to be suitable with all 24 items.

The readability and internal consistency of the LSI (VAK) were determined by conducting a Reliability analysis on each segment of the scale. The Visual subscale consisted of 8 items ($\alpha = .75$), the Auditory subscale consisted of 8 items ($\alpha = .81$), and

Table 4: Principal Extracted Components of the Learner Style Inventory

Variables	Question #	Loadings
Visual Learner Style (α= .753)		
VIS1	1	0.690
VIS2	6	0.719
VIS3	9	0.532
VIS4	12	0.535
VIS5	13	0.545
VIS6	18	0.774
VIS7	21	0.577
VIS8	24	0.601
Auditory Learner Style (α = .810)		
AUD1	2	0.531
AUD2	4	0.711
AUD3	8	0.693
AUD4	10	0.422
AUD5	14	0.486
AUD6	17	0.805
AUD7	19	0.753
AUD8	22	0.528
Kinetic Learner Style (α=.812)		
KIN1	2	0.767
KIN2	5	0.833
KIN3	7	0.610
KIN4	11	0.625
KIN5	15	0.636
KIN6	16	0.531
KIN7	20	0.696
KIN8	23	0.462

the Kinetic subscale consisted of 8 items (α = .81). All the alphas indicate the LSI was highly reliable.

Two separate Exploratory factor analyses were conducted on 12 items of the Pre-Engagement (CAB) scale, using principal component extraction with a varimax rotation revealed a three-factor solution. The measure accounted for 68% of the variance on the Engagement scale. The initial analysis was also conducted previously in two separate pilot tests where the scale was reduced from its original 35 items. The Cognitive, Affective, and Behavioral components were then analyzed for each engagement level, and the Outcome item was treated separately. In addition, the scale recorded pre and post results to measure the effectiveness of the treatment on the dependent variable. It was observed that 12 of the 12 items correlated at least .3 with at least one other item, suggesting reasonable factorability (see Appendix A). In addition, the KMO measure of sampling adequacy was .873, above the commonly recommended value of .6, and Bartlett's test of sphericity was significant ($\chi 2$ (66) = 869.81, $p < .001$). Finally, the commonalities were all above .3 (see Table 6), further confirming that each item shared some common variance with other items. Given these overall indicators, factor analysis was determined to be highly suited with all 12 items.

The readability and internal consistency of the Pre-Engagement (CAB) were determined with a Reliability analysis conducted on the scale as a whole and each segment of the scale. The entire scale consisted of 12 items (α =.86). The Cognitive subscale consisted of 4 items (α = .85), the Affective subscale consisted of 4 items (α = .84), and the Behavioral subscale consisted of 4 items (α = .72). All the alphas indicate the CAB was highly reliable.

Table 5: Principal Extracted Components for Pre Engagement in Course

Variables	Question #	Loadings
Cognitive Engagement with Lecture (α=.77)		
Pre-Engagement Cognitive	1	.801
Pre-Engagement Cognitive	2	.868
Pre-Engagement Cognitive	3	.870
Affective Engagement with Lecture (α=.83)		
Pre-Engagement Affective	1	.784
Pre-Engagement Affective	3	.841
Pre-Engagement Affective	4	.806
Behavioral Engagement with Lecture (α=.71)		
Pre-Engagement Behavioral	1	.652
Pre-Engagement Behavioral	2	.835
Pre-Engagement Behavioral	3	.745

The Post Engagement scale also noted that 12 of the 12 items correlated at least .3 with at least one other item, suggesting reasonable factorability (see Appendix A). Furthermore, the KMO measure of sampling adequacy was .855, above the commonly recommended value of .6, and Bartlett's test of sphericity was significant ($\chi 2$ (36) = 863.58, $p < .001$). Finally, the commonalities were all above .3 (see Table 7), further confirming that each item shared some common variance with other items. Given these overall indicators, factor analysis was determined to be highly suited with all 14 items.

Table 6: Principal Extracted Components for Post Engagement with Lecture

Variables	Question #	Loadings
Cognitive Engagement with Lecture (α=.84)		
Post-Engagement Cognitive	1	.889
Post-Engagement Cognitive	2	.840
Post-Engagement Cognitive	3	.862
Affective Engagement with Lecture (α=.94)		
Post-Engagement Affective	1	.881
Post-Engagement Affective	3	.854
Post-Engagement Affective	4	.856
Behavioral Engagement with Lecture (α=.79)		
Post-Engagement Behavioral	1	.703
Post-Engagement Behavioral	2	.836
Post-Engagement Behavioral	3	.831

The readability and internal consistency of the Post-Engagement (CAB) were determined with a Reliability analysis on the scale as a whole and also on each segment of the scale. The entire scale consisted of 14 items (α =.90). The Cognitive subscale consisted of 4 items (α = .84), the Affective subscale consisted of 4 items (a = .94), and the Behavioral subscale consisted of 4 items (α = .79). All the alphas conclude that the Post CAB was also highly reliable.

DATA ANALYSIS

Statistical Program for Social Sciences (SPSS) MAC 26.0 was used for data analysis, as follows: the data were normally distributed, and the verification method was selected. A p-values less than 0.05 were considered statistically significant.

Pre-Test Benchmarking

In the first step I established a benchmark value for pre-manipulation. The benchmarking allows me to learn the accuracy of my non-experimental design. The comparison of my observational results to the post treatment findings aids in calibrating for bias (LaLonde, Robert, 1986). My benchmarking was attempt to calibrate a non-statistical uncertainty or flaw in my assumption since I could not carry out a pre lesson in a face to face lecture. I could not control for pre-lectures due to pandemic restrictions.

Among the three learner groups there was a borderline significant difference in pre-test scores. The Kinetic group had a higher mean in pre-test scoring then the other groups as noted in (Table 8).

Therefore, I am using course Engagement to direct the subject frame of reference, due to previously explained limitations that were experienced due to the pandemic causing the course to be online and asynchronous. A synchronous unison lecture pre manipulation could not be created. Only a course Engagement could only focused on with the same professor.

To test for pre-existing skills a pretest was created based upon an existing quiz provided by the professor. This quiz was based on actual curriculum assessment and was shortened from 12 to 10 questions and provided in the Appendix. Each question was scored at 10 point increments for a total score of 100. This would provide a range of scores from zero to 100.

The MANOVA conducted between Learner Style and Engagement (Table 8) further verifies no effect between subjects solidifying that we do not have an inherent bias of Engagement. The effect of Learner Style on these three dependent variables, pre-engagement (Cognitive, Affective, and Behavioral). Significant differences were not found among the Learner Style $F(8, 304) = 1.438^b$, $p > .01$; Wilk's $\Lambda = 0.18$, partial $\eta 2 = .037$. These effects were tested across all dependent factors of Engagement by a MANOVA.

The repeated ANOVA results show no significant differences between learners tyles for the three engagement dimensions. By examining the means of the pre-treatment on Engagement we will note no significance difference between those levels.

Repeated ANOVA analysis was conducted to evaluate Learner Style on Cognitive engagement pretreatment. The ANOVA indicated a nonsignificant effect for Learner Style, $F(2, 160) = 1.69$, $p = .189$, partial $\eta 2=.02$. Another ANOVA was conducted to evaluate Learner Style on Affective engagement pretreatment. The ANOVA indicated a nonsignificant effect for Learner Style, $F(2, 154) = .651$, $p = . 523$, partial $\eta 2=.01$. The third ANOVA was conducted to evaluate Learner Style on Behavioral engagement pretreatment. The ANOVA indicated a nonsignificant main effect for Learner Style, $F(2, 159) = 2.01$, $p = .138$, partial $\eta 2=.03$.

Table 7: Pre-Manipulation Differences for Engagement and Test Scores

Dependent Variable	LEARNER STYLE	Mean	Std. Error	Type III Sum of Squares	F	Sig.
Course Engagement						
Pre-Cognitive	Visual	3.851	.095	1.020	1.050	.352
	Auditory	3.651	.097			
	Kinetic	3.643	.143			
Pre-Affective	Visual	3.667	.102	1.175	1.045	.354
	Auditory	3.582	.104			
	Kinetic	3.471	.153			
Pre-Behavioral	Visual	4.236	.079	1.304	1.791	.170
	Auditory	4.026	.080			
	Kinetic	4.126	.119			
Test Scores						
Pre-Test	Visual	48.462	1.993	1376.069	2.864	.060
	Auditory	50.159	1.963			
	Kinetic	56.552	2.894			

The significant higher test results for the benchmarking Kinetic group is not seen as confounding as we do not have a manipulation for them. Kinetic learners did not receive a lesson tailored to their Learning style.

Table 8: MANOVA Pre-Engagement

	Effect	Value	F	Sig.
MANOVA by LEARNER_STYLE	Pillai's Trace	.073	1.445	.177
	Wilks' Lambda	.928	1.438[b]	.180
	Hotelling's Trace	.076	1.431	.183
	Roy's Largest Root	.049	1.878[c]	.117

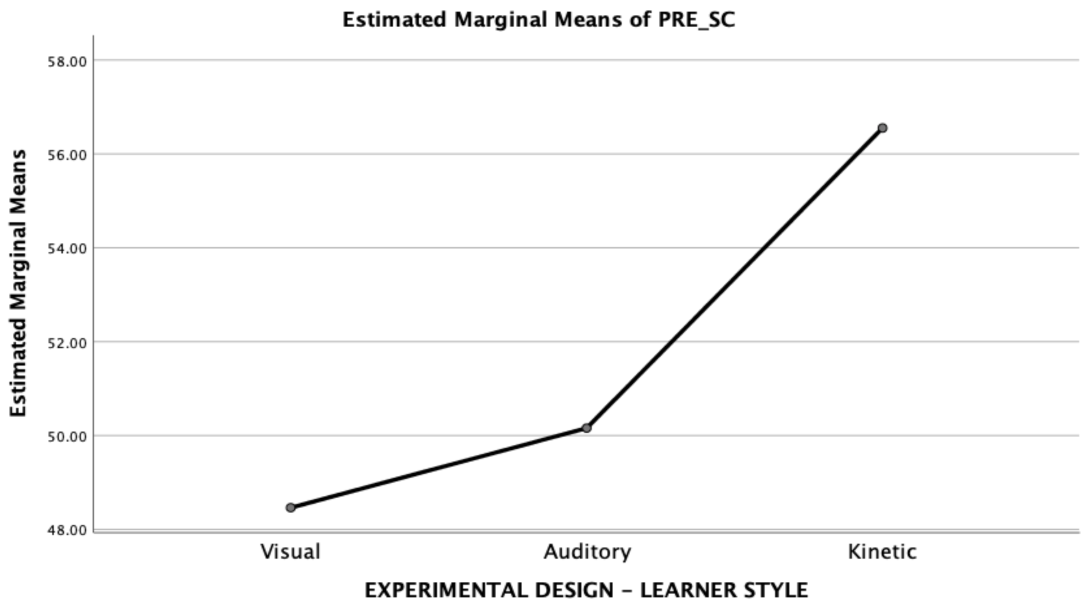

Figure 5: Profile Plot of Learner Style compared to Pre-Score.

The profile plot Figure 5 displays the difference between these Kinetic and Visual learners viewed by Pre-Scores and its slight significance.

Finally, an ANOVA was conducted to evaluate Learner Style on pre-score before treatment. The ANOVA indicated a slight significant effect for Learner Style, $F(2, 160) = 2.64$, $p = .08$, partial $\eta 2=.03$. This was due to the difference in scores mentioned earlier between Kinetic and Visual learners. To further illustrate the comparison of means a

Bonferoni analysis states the significant difference between the Visual and the Kinetic learner of -8.09 in one direction and 8.09 in another as seen in (Table 9).

Table 9: Post Hoc Test - Experimental Design Pre-Score

EXPERIMENTAL DESIGN - LEARNER STYLE

Dependent Variable	(I) EXPERIMENTAL DESIGN - LEARNER STYLE	(J) EXPERIMENTAL DESIGN - LEARNER STYLE	Mean Difference (I-J)	Std. Error	Sig.
Pre-Score	Visual	Auditory	-1.70	2.76	1.00
Bonferroni		Kinetic	-8.09	3.48	0.06
	Auditory	Visual	1.70	2.76	1.00
		Kinetic	-6.39	3.50	0.21
	Kinetic	Visual	8.09	3.48	0.06
		Auditory	6.39	3.50	0.21

Results for 3X2 Experimental Design

To test for hypotheses $H1_{abc}$ and H2, the positive impact of matching Lecture Style to Learner Style, I tested a 3X2 experimental design with MANOVA and repeated ANOVAs. The design has three learner styles (Visual, Auditory, Kinetic) and two lecture styles (Visual, Auditory). Kinetic learners did not have a matching lecture style. Analysis of Variance tests for the main effects of Learner and Lecture styles as well as their interaction.

First, I analyzed the engagement dimensions to determine main and interactive effects of learner and lecture style. My hypotheses stated that adapting a lecture to a student's preferred learning style will lead to higher engagement The MANOVA analysis showed a main effect of Learner style and an interaction effect between Learner and Lecture style. The result for the post-manipulation MANOVA is displayed in Table 10).

The MANOVA indicated a significant main effect for Learner Style, $(10, 256) = 2.380$, $p < .01$; Wilk's $\Lambda = .837$, partial $\eta 2 = .08$, a nonsignificant effect for Lecture Style, $F(5, 128) = 1.615$, $p = .06$; Wilk's $\Lambda = .941$, partial $\eta 2=.06$, and a significant interaction between Learner style and Lecture style, $F(10, 256) = 2.04$, $p = .02$; Wilk's $\Lambda = .810$, partial $\eta 2=.10$.

Table 10: Post-Manipulation MANOVA Results for Engagement

	LEARNER_STYLE			LECTURE_STYLE			LEARNER_STYLE * LECTURE_STYLE		
Effect	Value	F	Sig.	Value	F	Sig.	Value	F	Sig.
Pillai's Trace	0.163	2.294	0.014	0.059	1.615[b]	0.161	0.193	2.752	0.003
Wilks' Lambda	0.837	2.380[b]	0.010	0.941	1.615[b]	0.161	0.810	2.844[b]	0.002
Hotelling's Trace	0.194	2.464	0.008	0.063	1.615[b]	0.161	0.231	2.934	0.002
Roy's Largest Root	0.191	4.934[c]	0.000	0.063	1.615[b]	0.161	0.215	5.543[c]	0.000

	LEARNER_STYLE			LECTURE_STYLE			LEARNER_STYLE * LECTURE_STYLE		
Dependent Variable	Type III Sum of Squares	F	Sig.	Type III Sum of Squares	F	Sig.	Type III Sum of Squares	F	Sig.
Cognitive Engagement	3.262	2.555	0.082	0.468	0.733	0.394	0.914	0.716	0.491
Affective Engagement	22.089	10.054	0.000	0.003	0.002	0.961	12.492	5.686	0.004
Behavioral Engagement	0.764	0.652	0.523	0.632	1.078	0.301	2.021	1.725	0.182
Delta Score	3271.8	3.202	0.044	205.798	0.403	0.527	10231.4	10.013	0.000

Using repeated measures ANOVA the engagement and test scores were analyzed. Results are displayed in (Table 11).

Table 11: Differences in Engagement and Test Scores for 3X2 Experimental design

Variable	LEARNER STYLE	LECTURE STYLE	Mean	Std. Error	F	p
Cognitive Engagement	Visual	VISUAL	3.733	0.160	.716	.491
		AUDITORY	3.460	0.148		
	Auditory	VISUAL	3.607	0.151	.716	.491
		AUDITORY	3.690	0.151		
	Kinetic	VISUAL	3.333	0.222	.716	.491
		AUDITORY	3.156	0.206		
Affective Engagement	Visual	VISUAL	3.398	.198	5.68	.004
		AUDITORY	2.724	.191		
	Auditory	VISUAL	2.777	.195	5.68	.004
		AUDITORY	3.482	.195		
	Kinetic	VISUAL	2.173	.285	5.68	.004
		AUDITORY	2.067	.266		
Behavioral Engagement	Visual	VISUAL	3.886	.141	1.73	.182
		AUDITORY	3.397	.136		
	Auditory	VISUAL	3.545	.139	1.73	.182
		AUDITORY	3.857	.139		
	Kinetic	VISUAL	3.308	.203	1.73	.182
		AUDITORY	3.244	.189		
Delta Score	Visual	VISUAL	9.259	4.343	10.0	.00
		AUDITORY	-11.724	4.191		
	Auditory	VISUAL	-7.857	4.265	10.0	.00
		AUDITORY	6.786	4.265		
	Kinetic	VISUAL	-20.000	6.259	10.0	.00
		AUDITORY	-6.000	5.827		

Behavioral Engagement

Hypothesis 1A stated that adapting a lecture to a student's preferred learning style will lead to higher Behavioral Engagement. Results of the ANOVA indicated a nonsignificant main effect for Learner Style, $F(2, 137) = .706$, $p = .50$, partial $\eta 2=.01$, a nonsignificant effect for Lecture Style, $F(1, 137) = .899$, $p = .345$, partial $\eta 2=.00$, and a nonsignificant interaction between learner style and lecture style, $F(2, 137) = 1.49$, $p = .23$, partial $\eta 2=.00$. In Figure 6 we see the profile plot showing a subtle change of Auditory learners between lecture styles with the least difference between lectures at a .10 difference. The Visual learner represents a more significant difference at .39. The Kinetic learner which has a difference of .11 responds behaviorally better to the Visual lecture yet still is under both learners. The greatest change observed in Behavioral engagement rests with our Visual learner.

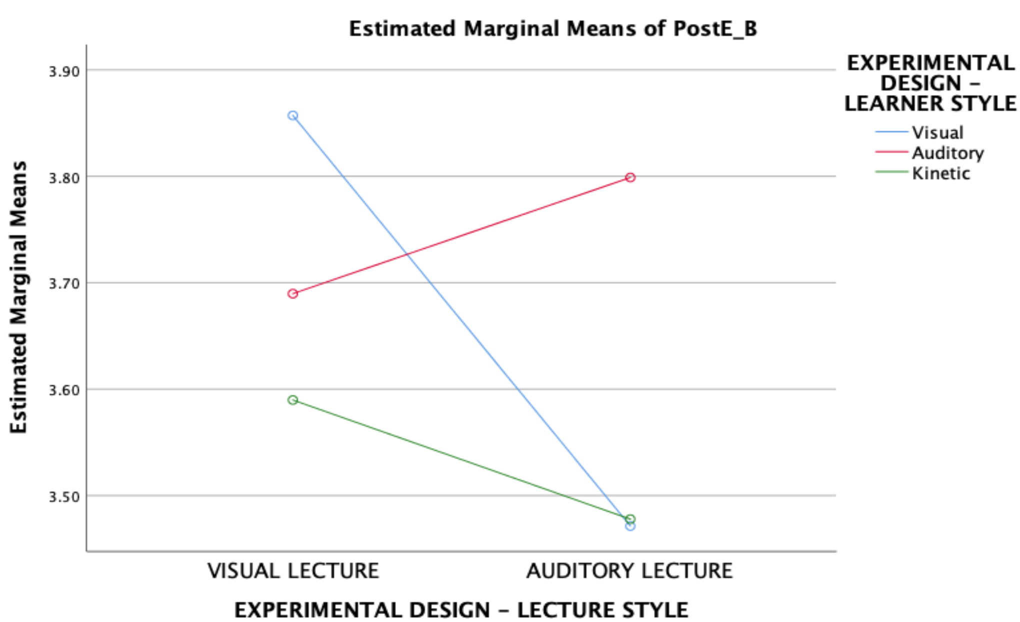

Figure 6. Profile Plot for Post Engagement Behavioral

Cognitive Engagement

Hypothesis 1B stated that adapting a lecture to a student's preferred learning style will lead to higher Cognitive Engagement.

The following hypothesis looked directly at Cognitive Engagement, which deals with deep learning and how a student self regulates in their environment. The ANOVA indicated a significant main effect for Learner Style, $F(2, 137) = 2.96$, $p = .05$, partial $\eta 2 = .04$, a nonsignificant effect for Lecture Style, $F(1, 137) = .748$, $p = .389$, partial $\eta 2 = .00$, and a nonsignificant interaction between learner style and lecture style, $F(2, 137) = 1.03$, $p = .36$, partial $\eta 2 = .02$. In this analysis, we see smaller differences between the matched and unmatched lessons. However, the Learner still had a significant impact on Engagement of $p = .05$. The gains between matched and unmatched treatment were smaller yet still apparent in the realm of Cognitive Engagement as seen in (Figure 7) below. The profile plot displays the margin of means between the three Learning style and their level of Cognitive engagement. The Visual learner loses Cognitive engagement when they receive an Auditory lecture .30 of variance between both Lecture styles.. The effect is also noted with Auditory learners when they are unmatched with their Learning style to a lesser degree at .12. The Kinetic learner still struggles with .43 variance from the Visual leaner and .58 from the Auditory leaner.

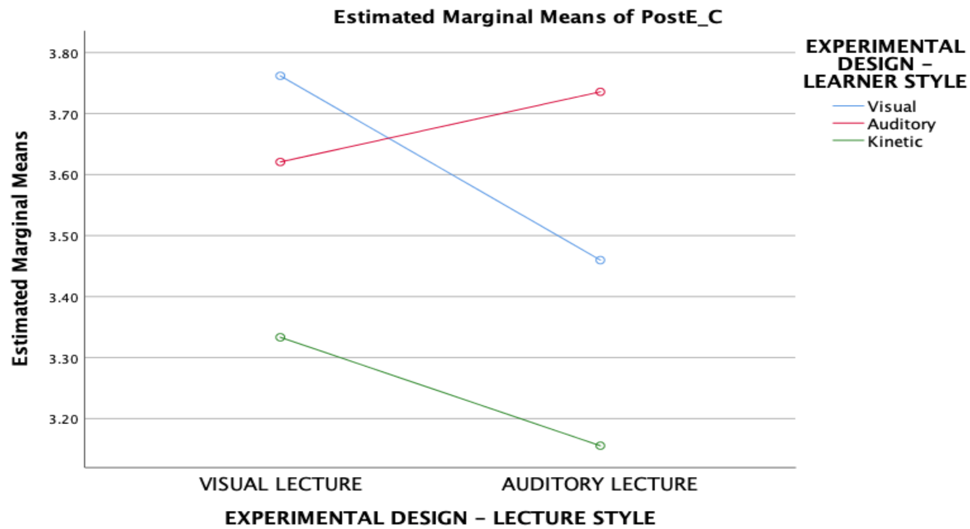

Figure 7: Profile Plot for Post Engagement Cognitive

Affective Engagement

Hypothesis 1C stated that adapting a lecture to a student's preferred learning style will lead to higher Affective Engagement.

The last hypothesis in the Engagement cluster examined Affective Engagement, which centers on interest, enthusiasm, and sense of belonging. The Learner perceives a sense of community within the learning environment. This form of Engagement is noted for longer lasting effects. Enthusiasm, interest and a sense of belonging make up this factor. An ANOVA indicated a significant main effect for Learner Style, $F(2, 132) = 10.1$, $p = .01$, partial $\eta2=.13$, a nonsignificant effect for Lecture Style, $F(1, 132) = .019$, $p = .961$, partial $\eta2=.00$, and a significant interaction between learner style and lecture style, $F(2, 132) = 5.69$, $p = .00$, partial $\eta2=.08$. Affective engagement resulted with a mixed result as Learner Style and interaction between Learner and lecture being significant. The means of Kinetic learners (2.17 Visual, 2.07 Auditory), again, were lower than the other groups adding to the effect of an unmatched lesson. Of course, Visual and Auditory learners also had at least a .63 to .72 in variance from each other in scores between matched and unmatched lectures respectively.

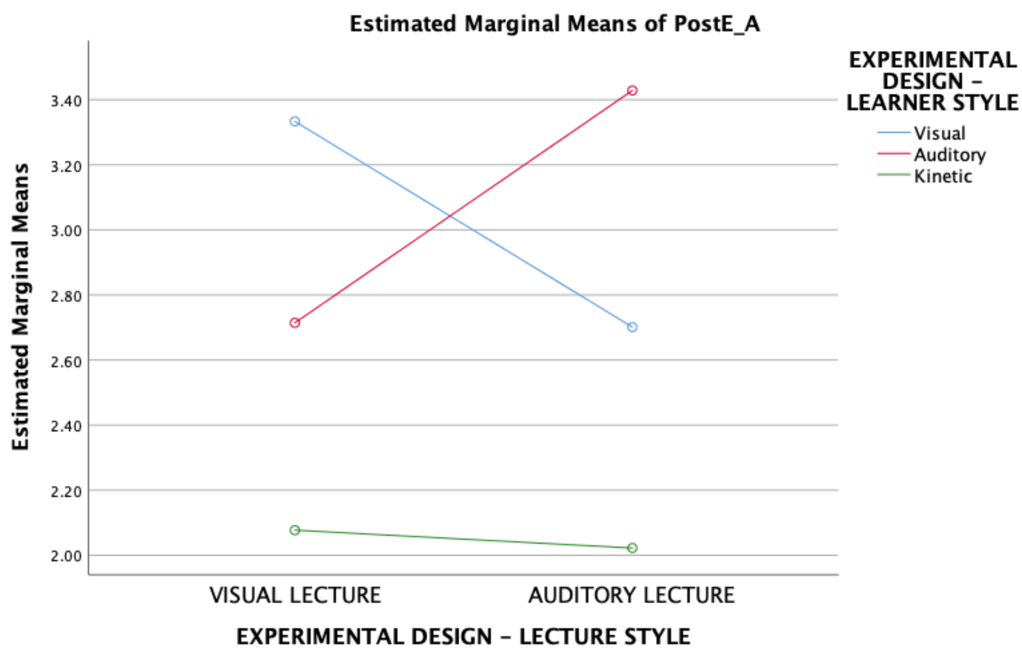

Figure 8. Profile Plot for Post Engagement Affective

Post-Manipulation Test Scores

Hypothesis 2 stated that adaptation increase outcomes. Our second hypothesis concerns the differences (delta Δ) between pre and post scores. The means result for the Δ score improvement as a function of Learner Style and treatment manipulation match are posted in (Table 10). The MANOVA indicated a nonsignificant main effect for Learner Style, $F(4, 246) = .807$, $p = .52$; Wilk's $\Lambda = .807$, partial $\eta2=.01$, a significant effect for treatment manipulation match, $F(2, 123) = 13.0$, $p = .01$; Wilk's $\Lambda = .825$, partial $\eta2=.18$, and a significant interaction between learner style and lecture style, $F(2, 123) = 3.10$, p =

.05; Wilk's Λ = .952, partial $\eta 2$=.05. The MANOVA proves the overall effect across matching treatments and the interaction between Learner and Lecture style. Visual learners are seen on top of the scoring field by a mean difference of (21.9) when matched to their comfort manipulation. Auditory learners display a mean (9.2) which shows a level of increased Outcome centered on the analysis. Kinetics further supports the claim which outcomes fall short consistently by their lack of adaptive comfort level.

An ANOVA was conducted to further support the hypothesis two one the effect of adaptation on the Δ score. The ANOVA indicated a nonsignificant main effect for Learner Style, $F(2, 137) = .271$, $p = .70$, partial $\eta 2$=.04, a nonsignificant effect for Lecture Style, $F(1, 137) =.756$, $p = .386$, partial $\eta 2$=.01, and a significant interaction between Learner style and Lecture style, $F(1, 137) = 9.28$, $p = .000$, partial $\eta 2$=.12. Let us assume that although the ANOVA disclosed nonsignificant effects for Learner and Lecture, the interaction between Learner and Lecture was significant. The analysis of the results leads us to support the hypothesis by the effect of adaptive delivery has a direct effect on Outcome scores.

Results for 2X2 Design – Match of Learner/Lecture Style by Visual or Auditory Learner

To parse out the matching effect of Lecture to Learner I removed the Kinetics group which was there for benchmarking only and applied a MANOVA to a 2x2 design. The main effects were (a) match between Lecture and Learner style (No Match/Match) and Learner style (Visual/Auditory). The MANOVA evaluated the main effects of Learner/Lecture Style Match (No Match/Match) as well as learner style plus their interaction. The results for the engagement scores and the Δ test score improvement as a function of Learner and Lecture Style (No Match/Match) on Visual and Auditory learners are posted in (Table 12).

The MANOVA indicated a significant main effect for Manipulation Match, $F(4, 93) = .93$, $p = .01$; Wilk's $\Lambda = .715$, partial $\eta 2 = .01$, a nonsignificant effect for Learner Style, $F(4, 93) = .221$, $p = .926$; Wilk's $\Lambda = .991$, partial $\eta 2 = .01$, and a nonsignificant interaction between learner style and lecture style, $F(2, 123) = 3.10$, $p = .05$; Wilk's $\Lambda = .952$, partial $\eta 2 = .05$. The MANOVA proves the overall effect across matching treatments and the interaction between Learner and Lecture style and the Visual learners are seen on top of the scoring field by a mean difference of (21.9) when matched to their comfort manipulation. Auditory learners display a mean (9.2) which shows a level of increased Outcome centered on the analysis.

The MANOVA in (Table 12) indicates also a nonsignificant effect for Learner Match in relation to Cognitive Engagement $F(4, 93) = .174$, $p = .20$; Wilk's $\Lambda = .715$, partial $\eta 2 = 1.2$, a significant effect for Learner Match in relation to Affective Engagement $F(4, 93) = 14.6$, $p = .00$; Wilk's $\Lambda = .715$, partial $\eta 2 = 1.2$, a significant effect for Learner Match in relation to Affective Engagement $F(4, 93) = 5.37$, $p = .02$; Wilk's $\Lambda = .715$, partial $\eta 2 = 1.2$, and a significant effect for Learner Match in relation to Δ Score $F(4, 93) = 31.4$, $p = .00$; Wilk's $\Lambda = .715$, partial $\eta 2 = 1.2$. The Learner style to Lecture match did not provide any significant values in either category of Engagement or Δ of Scores.

Table 12: Post-Manipulation MANOVA Results for Engagement and Δ Test Scores

	Learner/Lecture Match			LEARNER_STYLE			Match*LEARNER_STYLE		
Effect	Value	F	Sig.	Value	F	Sig.	Value	F	Sig.
Pillai's Trace	0.285	9.253[b]	0.000	0.009	.221[b]	0.926	0.025	.601[b]	0.663
Wilks' Lambda	0.715	9.253[b]	0.000	0.991	.221[b]	0.926	0.975	.601[b]	0.663
Hotelling's Trace	0.398	9.253[b]	0.000	0.009	.221[b]	0.926	0.026	.601[b]	0.663
Roy's Largest Root	0.398	9.253[b]	0.000	0.009	.221[b]	0.926	0.026	.601[b]	0.663

	Learner/Lecture Match			LEARNER_STYLE			Match*LEARNER_STYLE		
Dependent Variable	Type III Sum of Squares	F	Sig.	Type III Sum of Squares	F	Sig.	Type III Sum of Squares	F	Sig.
Cognitive Engagement	1.153	1.724	0.192	0.037	0.055	0.814	0.668	0.999	0.320
Affective Engagement	15.219	14.608	0.000	0.185	0.178	0.674	0.001	0.001	0.976
Behavioral Engagement	3.443	5.370	0.023	0.504	0.787	0.377	0.571	0.891	0.347
Δ Score	9122.7	31.362	0.000	41.55	0.143	0.706	27.205	0.094	0.760

Table 13: Differences in Engagement and Test Scores for 2X2 Match/No Match

Dependent Variable	Match of Learner Style with Lecture Style	LEARNER STYLE	Mean	Std. Error	F	P
Post Cognitive Engagement	No Match	Visual	3.413	0.164	.055	.82
		Auditory	3.615	0.160		
	Match	Visual	3.792	0.167	1.72	.192
		Auditory	3.667	0.164		
Post Affective Engagement	No Match	Visual	2.587	0.204	.178	.67
		Auditory	2.667	0.200		
	Match	Visual	3.361	0.208	14.1	.000
		Auditory	3.453	0.204		
Post Behavioral Engagement	No Match	Visual	3.373	0.160	.787	.38
		Auditory	3.667	0.157		
	Match	Visual	3.896	0.163	5.37	.023
		Auditory	3.887	0.160		
Delta Score	No Match	Visual	-6.400	3.411	.143	.71
		Auditory	-6.154	3.345		
	Match	Visual	11.667	3.481	31.4	.000
		Auditory	14.000	3.411		

Next I will offer support to adaptation of matching and unmatched lessons proves to be a key indicator of higher scores as based on the MANOVA. A one-way multivariate analysis of variance MANOVA was conducted to evaluate this effect and consolidate the Δ pre/post scores. The means result for the Δ score improvement as a function of Learner Style and Lecture style (No Match/Match) are posted in (Table 13). The MANOVA indicated a nonsignificant main effect for Learner Style, $F(4, 246) = .807$, $p = .52$; Wilk's $\Lambda = .807$, partial $\eta 2=.01$, a significant effect for treatment manipulation match, $F(2, 123) = 13.0$, $p = .01$; Wilk's $\Lambda = .825$, partial $\eta 2=.18$, and a significant interaction between learner style and lecture style, $F(2, 123) = 3.10$, $p = .05$; Wilk's $\Lambda = .952$, partial $\eta 2=.05$. The MANOVA proves the overall effect across matching treatments and the interaction between Learner and Lecture style (No Match/Match). Visual learners are seen on top of the scoring field by a mean difference of (21.9) when matched to their comfort manipulation. Auditory learners display a mean (9.2) which shows a level of increased Outcome centered on the analysis. Kinetics further supports the claim which outcomes fall short consistently by their lack of adaptive comfort level.

An additional ANOVAs was conducted on the delta score in the refinement of the analysis. The ANOVA evaluated Learner Style and Lecture Style (No Match/Match) on the Δ post score after lesson treatment. The mean result for the Δ post score improvement as a function of the Learner Style and treatment manipulation match is posted (Table 13). The ANOVA confirmed a significant effect for treatment manipulation match, $F(1, 124) = 25.7$, $p = .01$, partial $\eta 2=.12$, Importantly, both, the main effect for Learner Style, $F(2, 124) = .316$, $p = .73$, partial $\eta 2=.01$and the interaction between learner style and treatment manipulation match, $F(1, 124) = .051$, $p = .82$, partial $\eta 2=.00$ are nonsignificant. The manipulation match was significant, and the means of those matches revealed positive and negative means in the direction of scores, thus Outcomes. The profile plot in (Figure 9) below results adds further support to hypothesis 2 by the effect of treatment manipulation match based on Outcome scores.

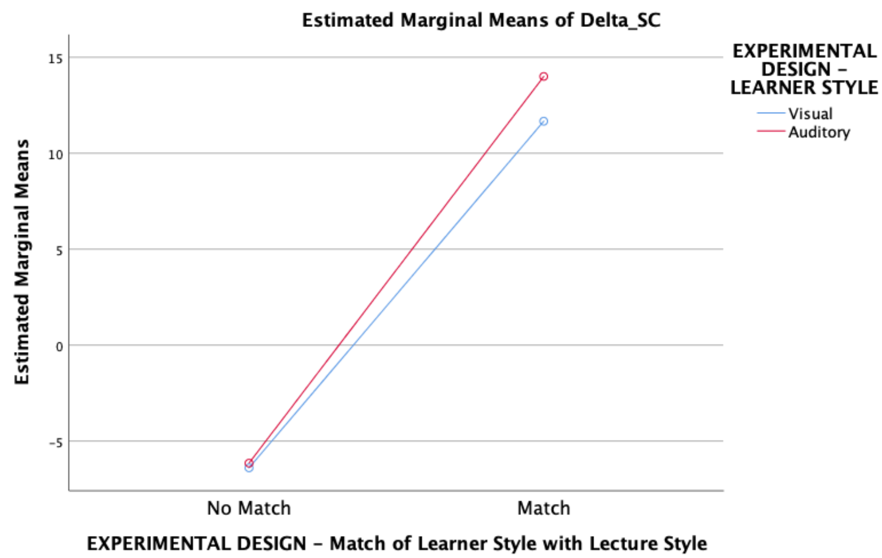

Figure 9: Profile Plot for No Match/Match Δ Pre/Post Score

Therefore we cannot support hypothesis $H1_a$. However we support $H1_b$, $H1_c$ and H2 based the previous findings.

Impact of Engagement on Test Scores

In hypothesis 3 I stated that increased Engagement of the student will lead to better outcomes. The study concludes with the last hypothesis Engagement's effect on learning outcomes. Linear regression was used to measure the impact of the three Engagement dimensions on learning outcome scores. Results of the multiple linear regression indicated and R^2 of 0.102 ($F(3, 151) = 6.80$, $p < .001$-effect between the post Engagement dimensions and the Δ pre-post test score. The individual predictors were examined further and indicated that Cognitive engagement ($t = .262$, $p = .793$) and Behavioral engagement ($t = .072$, $p = .943$) were not significant predictors on the model. However Affective engagement ($t = 3.25$, $p = .001$), was a significant predictor. Therefore, one aspect of Engagement that is communal and generates enthusiasm could prove to be a lynchpin for further analysis.

Table 14: Regression Analysis Summary for Post Engagement on the Δ of the Scores.

Variable	β	*t*	*p*
Cognitive	.025	.262	.793
Affective	.326	3.25	.001
Behavioral	.007	.072	.943

Mediation Analysis

I also investigated whether Engagement mediates the effects of matched lecture to learner style using the Hayes "process" module (Hayes, A.F., 2009) within SPSS. The path (direct effect) from Manipulation Match to Post Cognitive Engagement was positive and statistically significant (b=.3080, s.e.=.1484, p<.001). The path (direct effect) from Manipulation Match to Post Affective Engagement was positive and statistically significant (b=.9926, s.e.=.1918, p<.001). The path (direct effect) from Manipulation Match to Post Behavioral Engagement was positive and statistically significant (b=.3652, s.e.=.1388, p<.001).

The indirect effect is tested using non-parametric bootstrapping. If the null of 0 falls between the lower and upper bound of the 95% confidence interval, then the inference is that the population indirect effect is 0. If 0 falls outside the confidence interval, then the indirect effect is inferred to be non-zero. In this case the indirect effect (IE=6.025) the total is statistically significant: 95%CI=(2.457, 10.59).

The path (direct effect) from Manipulation Match to the Δ of Scores is positive and significant (b=14.23, s.e.=3.574, p=.0001), indicating that subjects having a manipulation match to their learning style are more likely to higher learning outcomes than those not matching on the measure. The direct effect of Cognitive Engagement on Δ of Scores is negative and not significant (b=1.164, s.e.=.2.593, p=.6544), indicating subjects scoring higher on Cognitive Engagement are less likely to have higher Learning on the measure. The direct effect of Affective Engagement on Δ of Scores is positive and significant (b=6.741, s.e.=2.079, p=.0015), indicating subjects scoring higher on Affective Engagement are more likely to higher Delta of Scores than other forms of

Engagement on the measure. The direct effect of Behavioral Engagement on Δ of Scores is negative and not significant (b=-2.804, s.e.=2.561, p=.2759), indicating subjects scoring higher on Behavioral Engagement are less likely to have higher Learning on the measure.

In this case the indirect effect of Cognitive Engagement on the Δ of Scores (IE=.3585) the total is statistically not significant: 95%CI=(-1.891, 2.260). In this case the indirect effect of Affective Engagement on the Δ of Scores (IE=6.691) the total is statistically significant: 95%CI=(2.452, 12.73). In this case the indirect effect of Behavioral Engagement on the Δ of Scores (IE=-1.024) the total is statistically not significant: 95%CI=(-3.609, .9843).

Mediation of effect exists in Affective Engagement mediates Lecture to Learner Style matching into improved Outcome Scores. Therefore, between results of the regression as seen in (Table 14) and Mediation analysis (Table 15 & 16) led us to support the hypothesis.

Table 15: Mediation Direct Effects

Model Cognitive						
	coeff	se	t	p	LLCI	ULCI
constant	3.4199	.0926	36.9495	.0000	3.2367	3.6031
Man_Mtch	.3080	.1484	2.0750	.0401	.0142	.6017
Model Affective						
	coeff	se	t	p	LLCI	ULCI
constant	2.4156	.1196	20.2000	.0000	2.1789	2.6523
Man_Mtch	.9926	.1918	5.1762	.0000	.6130	1.3721
Model Behavioral						
	coeff	se	t	p	LLCI	ULCI
constant	3.5260	.0866	40.7360	.0000	3.3547	3.6973
Man_Mtch	.3652	.1388	2.6310	.0096	.0905	.6399
Model Delta Scores						
	coeff	se	t	p	LLCI	ULCI
constant	-17.7796	8.7161	-2.0399	.0435	-35.0355	-.5237
Man_Mtch	14.2344	3.5747	3.9820	.0001	7.1574	21.3115
PostE_C	1.1642	2.5945	.4487	.6544	-3.9724	6.3007
PostE_A	6.7408	2.0789	3.2425	.0015	2.6251	10.8566
PostE_B	-2.8042	2.5618	-1.0946	.2759	-7.8759	2.2675

Table 16: Mediation Indirect Effects

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	6.0253	2.0881	2.4569	10.5898
PostE_C	.3585	1.0010	-1.8905	2.2602
PostE_A	6.6908	2.6363	2.4524	12.7255
PostE_B	-1.0240	1.1527	-3.6093	.9843

Hypothesis Results

In summary, effects were analyzed and the results are reflected in the following:

Hypotheses	Citation/Construct	Supported/Not Supported
H1$_a$: Adapting a lecture to the preferred learning style of a student will lead to higher behavioral engagement.	(Kahu 2013), (Fredericks, Blumenfeld & Paris's, 2004), Cognitive Theory	Not Supported
H1$_b$: Adapting a lecture to the preferred learning style of a student will lead to higher cognitive engagement.	(Kahu 2013), (Fredericks, Blumenfeld & Paris's, 2004), Cognitive Theory	Supported
H1$_c$: Adapting a lecture to the preferred learning style of a student will lead to higher effective engagement.	(Kahu 2013), (Fredericks, Blumenfeld & Paris's, 2004), Cognitive Theory	Supported
H2: Adaptation increase outcomes.	(Bambacus & Sanderson 2011), (Bajraktarevic, Hall, & Fullick, 2003). Learning Style Theory, Adaptive Delivery	Supported
H3$_a$: Increased behavioral engagement of the student will lead to better outcomes.	(Bajraktarevic, Hall, & Fullick, 2003), Adaptive Delivery	Not Supported
H3$_b$: Increased cognitive engagement of the student will lead to better outcomes.	(Bajraktarevic, Hall, & Fullick, 2003), Adaptive Delivery	Not Supported
H3$_c$: Increased cognitive engagement of the student will lead to better outcomes.	(Bajraktarevic, Hall, & Fullick, 2003), Adaptive Delivery	Supported

Summary

This chapter presented the complete findings of the study. Provided are a description of the sample's demographic characteristics used in the study and discussed the statistical procedures used to respond to the research questions. Exploratory factor analyses were conducted to assess the dimensionality of the instruments used for data collection. A MANOVA, a 2x3 ANOVA, Linear Regression, and a Hayes Model Process mediation analysis were used to confirm the empirical results. The chapter concluded with a discussion of the effect of adaptive delivery on student engagement and outcomes. The results section provided a pattern of less Engagement and score achievement for the Kinetic learners who struggled with a mis-matched lesson as they acted as a baseline group. Moreover, the matching lesson revealed significant strides by both Visual and Auditory students from a -5 point testing in an unmatched lesson to 15 point gain in a matching scenario. The results reveal an actual decline in performance from pre-test scores which further strengthens the hypothesis that matching adaptive delivery to Learning styles improves outcomes. These results were a surprise as to scores were expected to climb or remain the same with the subject pool.

CHAPTER SIX

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

This chapter postulates the restatement of the research problem, summarizes the methods used for data analysis, followed by a discussion of the findings and limitations of the study. Finally, the results accompanied by recommendations for future research round out the conclusion and the implications for future research.

Restatement of the Problem

Community colleges serve as an essential part of the higher education system by providing affordable self-improvement. In addition, these programs offer many underprepared students the foundation that enables them to move on to college-level coursework, which, based on their demographic and economic background, they were ill prepared for (Community College Research Center, 2014).

The constant onslaught by legislatures has decreased funding in the guise of return on investment for the taxpayer, shifting funding away from the public model of higher education as agents. Therefore, community colleges need to find ways to make more with less adapting to more effective models of instruction. The contingency is to act upon these external forces to adapt instruction to conform to their students' intrinsic learning styles. This study explored if adjusting the delivery method of teaching through learning style personalization could increase Engagement, thus improve learning outcomes. The focus on learning style was used to create a simplified approach to build since the literature states that matching learning style has a significant beneficial effect on scores (Bajraktarevic, Hall, & Fullick, 2003).

Moreover, several studies have also criticized learning styles as a concept that should be rejected (Husmann, 2019). However, these studies have limitations from very skewed groups (anatomy students) to improper methodology, which does not follow valid visual or auditory lessons format. Opposition research focused on meshing hypothesis and their lack of experimental method, which was a goal of this study to correct. A quasi-experiment set the basis for an accurate future experimental model by testing the deltas between pre-post measures in a randomized group of college students. The subject groups represented every major group with the subtle larger group of business students, which comprised seven percent of the total population in line with statistical averages of primary student choice at Miami Dade College.

One research question was the guide for this study: Does an increase of Engagement based on adaptive delivery help learning outcomes? A limited budget and falling completion rates should be a concern for every college administrator. For this reason, we offer a different perspective on personalized instruction more cost-effectively; an adaptation can be applied to online instruction and a broader range of students. The model of the study pinpointed its effect on personalization to achieve Engagement on three levels. Once this was achieved, assessment scores were noted to rise. The rise in scores being directly correlated to one or more engagement levels also increasing based on matching learning modality to a comfort level of the individual learner. According to the literature conducted by Radford and the National Center for Education Statistics (2011), "student participation in a distance education course was most common among undergraduates attending public 2-year colleges; 22 percent were so enrolled". Therefore, as demand for these online courses increases, their delivery should evolve to help solve the elements of their failings when they become the vehicle of introductory "bottleneck" courses. To that end, create a familiar learning environment for successful completion rates for students through better outcomes.

Review of the Methods Used

Qualtrics online was used to create a self-contained experiment. The purpose was to allow for some of the limitations imposed by the pandemic. A phase two lockdown at Miami Dade College allowed for mostly online instruction through the Fall and Spring semester. In addition, certain precautions prevented a complete experimental process from being carried out with the use of a baseline lesson. Therefore, the self-contained quasi-experiment allowed the study to be conducted under the current conditions. In total, 215 subjects participated in the study, of which 163 were used as a final sample.

Statistics Program for Social Sciences version 26 was used to analyze the collected data from a Qualtrics online survey. The online survey was exported into a native SPSS format and examined for accuracy and incomplete data. Furthermore, an SPSS syntax file was created for verification and replication of this process. Finally, the data was secured on a passworded cloud storage solution.

The data analysis required the use of Descriptive statistics through frequencies, a MANOVA, and deeper dependent variable analysis with several ANOVAs. A Linear Regression was finally used to analyze the effects of the dependent variable of Engagement as mediation effect on Outcomes.

Summary of the Results

Chapter four outlined the analysis and the results of this study which included an exploratory factor analysis of the instruments used. The relationship between the Learning Style Inventory (LSI) and the subject's personal preference for Learning fell along with three factors (visual, auditory, and kinetic). Factor one visual learning style garnered 41.6% of the subjects, within a narrow range of auditory 39.6% learners, and kinetic at 18.8% followed current historical norms.

Discussion of Findings

Building on Kahu's (2013), Framing student engagement in higher education as a theoretical approach to evaluate the research question. Kahu's theory is that students in higher education that Engagement is an important influence on achievement and Learning. This splits into three dimensions of Engagement, Cognitive, Affective, and Behavioral, as recommended by Fredericks, Blumenfeld, and Paris's (2004) comprehensive review.

The results of this study look at a simple form of Learning styles for adaptation. This simplified approach was looked at as a starting point for adaptive delivery. As the literature states, teaching across disciplines, Engagement can present problems in measuring its effect with one standard (Nelson Laird et al. 2008). The focus on mathematics and science students has led to this lack of Engagement (Ahlfeldt, Mehta, and Sellnow 2005). To start as a base to stimulate Engagement when there are contrasting opinions from tutors who see it as a Cognitive problem and students view it as Affective (Solomonides and Martin 2008).

Furthermore, by failing to take Behavioral Engagement as an aspect of students' feelings, we are missing valuable pieces to the puzzle of Engagement overall. The goal of creating a lynchpin to increasing Engagement through learning style adaptation was the fulcrum of this study. Moreover, this model found that the manipulation used increased Engagement to varying degrees and increased assessment scores. These scores being the basis for determining return on investment for taxpayers by legislatures. The better scores lead to self-confidence, which allows the student to seek completion of the course. Generally, activities are chosen, which leads to higher self-confidence (Shrauger, J., & Schohn, M. 1995).

The approach of this research was to refute current criticisms of Learning styles by expanding the subject pool of participants and using experimental processes, which would allow for a more careful measure than self-reported surveys. Further, the use of a self-contained experiment would also control for instructor bias in the methods used. Finally, engaging learners through personalization allowed for a link between comfort and higher achievement, as proven by the previous analysis chapter. Educators should consider these changes in courses as a lower-cost alternative to the "one size fits all" model we have followed for the last century. This benefits students to participate in practical learning activities and maintains positive Engagement toward learning outcomes. In particular, converting slide shows to video or complete audio experiences is a service found in many community college campuses with the proof of raised scores to benefit its funding. Cost-effectively solving reduced funding is a real-world problem for community colleges across the country. Therefore this provides a solution that can be attempted with a modest cost which has been a critique of opposition research (Pashler, H., McDaniel, M., Rohrer, D., & Bjork, R. 2008).

Debates over Learning style tend to dominate discussions of education. But these debates obscure the far more critical issue of where can Community Colleges become more effective in their instruction with adaptive delivery. The data suggest that Affective Engagement of all the factors is most collective, which is the heart of community college and their mission to educate the community.

Finally, the study finds that Learning style delivery can increase Engagement and outcomes by providing knowledge by adjustments to delivery. Approximately 60% of community college students start their college career in a developmental course then move on to college-level work (Rutschow & Schneider, 2011), which becomes a "bottleneck" to their success. We need to find a better way to engage students and help them succeed. Why not find their "comfort zone?"

Engagement and Improved Outcomes Factors Based on the Research Instrument

The significant findings of hypotheses testing revealed:

All subjects in the study began with baseline Engagement levels, and no significance was seen between Learners. Scores in the pre-test revealed that Kinetic learners achieved better scores than their Visual and Auditory counterparts. Further analysis into each factor confirmed that levels of Engagement were level concerning the course being taken by students.

1. Adapting a lecture to a student's preferred learning style will lead to higher Behavioral Engagement.

The ANOVA, which focused on Behavioral Engagement linked Learner style and Lecture style, found significance in Learner style and the interaction between both. Visual learners performed best in a matching situation by comparing means. Auditory learners were also not far behind in their engagement levels. Kinetic learners underperformed compared to the two other styles expected by their unmatched treatment lesson in all cases.

2. Adapting a lecture to a student's preferred learning style will lead to higher Cognitive Engagement.

The second ANOVA, which concentrated on Cognitive Engagement linked Learner style and Lecture style, also established significance in Learner style yet failed to find it with Lecture or the interaction of both. The Learners impact on Engagement was still significant at $p= .03$. The discrepancy is noted in the change between pre and post Engagement by lowering cognitive Engagement after the treatment. Although smaller gains were made in this engagement factor, there was still an increase.

3. Adapting a lecture to a student's preferred learning style will lead to higher Affective Engagement.

The third ANOVA, which focused on Affective Engagement, established a significant main effect between learner and the interaction of Learner and Lecture style. Kinetic learners were found once again to be lower than the other groups.

4. **Adaptation increases outcomes.**

A MANOVA to examine Learner style and Lecture style on post scores and the delta of pre-post scores did not find significance for either style. However, they did find significance in their interaction. More importantly, the MANOVA, which analyzed the Learner style and treatment manipulation match, found significance for manipulation match. The Learner style and manipulation match also proved significant. This measure substantiated an overall effect by matching treatment to Learner style, thus increasing scores. Kinetic learners further illustrated the impact of lack of comfort with the lesson by reduced assessment scores post manipulation.

5. **Increased Engagement of the student will lead to better outcomes.**

The last analysis on the data used two Linear regressions to define the moderating effect of Engagement on Outcomes in this study. The first regression found there was no significance on post scores by Engagement factors overall. However, individual elements do not affect all moderate outcomes. The second regression analysis did find a significant communal between post-treatment engagement and the delta of post scores. Affective Engagement being the most influential, which expresses a sense of community learning. The effect of this singular factor bears further study.

Implications for Future Research

Community colleges historically are the closest entity to public education on a more significant academic scale. The community college allows a pathway to higher education for primarily underserved communities. These institutions, by their mandate, take all students regardless of scores or previous academic performance. Community colleges as almost exclusively funded by tuition, fees, and the reminder tax dollars. Therefore, adopting course delivery to improve Engagement allows students to complete courses that are historical “bottlenecks.” Mathematics courses become indicators of student completion of their college education (NCES, 2015; Ross, Kena, Rathbun, KewalRamani, Zhang, Kristapovich, Manning, & National Center Education Statistics, 2012; Villarreal, & Cabrera, 2012). Effective instructional strategies can be developed with a deeper understanding of the relationships between students’ Engagement regarding the personalization in their course work. Creating a standard modality as a pathway to instruction will engage the student on several levels. In turn, the level of engagement increases self-confidence in course materials to allow for better learning outcomes, as proven by higher scores. The gaps in research require further study of how personalization allows for measurable gains. Thes proven improvement in student Engagement and assessment outcomes gives us a basis to further explore a solution for public higher education which is currently under fire.

Recommendations for Future Research

Recommendations for future studies on adaptive delivery learning strategies include qualitative and observational components to more clearly ascertain a broader array of Behavioral, Cognitive, and motivational outcomes and, perhaps, explain the mechanisms by which personalization affects student learning.

Furthermore, this study does not provide adequate data for long-term information retention. Objective data was obtained in this study using a standardized assessment; as we increase the complexity of personalization, we should shift to more straightforward questions and broader learning objectives.

Moreover, more research is needed to explore the relationship between the dimensions of Engagement. Each element should be examined as it ties to the learner's emotions, precisely the role of emotion response by the student to his or her immediate learning environment. The narrowing of the scope of this study to community colleges allowed for the broadening of your baseline student; this, in turn, tamped the criticism by this researcher against the use of specific student populations in previous studies. This research helped prove that we have to move beyond the scope of quantitative analysis. A qualitative study that would be longitudinal by nature would allow the capture of the diversity of experience and the dynamic process, which is student engagement. Qualitative research in developmental course programs can help determine why students fail or withdraw from these "bottleneck" courses and what community colleges can do to reverse the impacts of non-completion.

Lastly, motivation, as previously discussed, relates to the successful completion of computer-based Learning; therefore, we need to access not just personalization but also the cues which allow for the delineation of students who are better served by face-to-face instruction. With a lack of self-motivation in students in community colleges and the majority of students being underprepared, developmental college courses that rely solely on self-paced Learning seem self-defeating. Therefore, we need to take a closer look at Affective Engagement to unlock the sense of belonging and community. It would bear additional research to examine how motivation and Affective Engagement go hand in hand.

CHAPTER SEVEN

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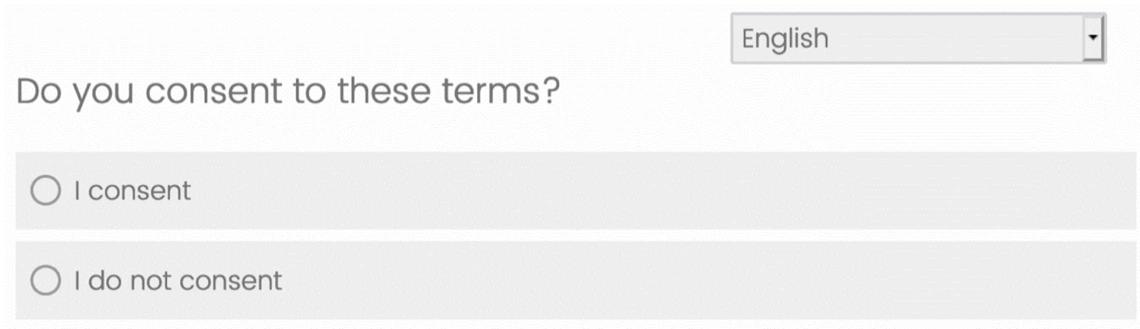
APPENDIX A

CONSENT


English

Do you consent to these terms?

I consent

I do not consent

ADULT CONSENT TO PARTICIPATE IN A RESEARCH STUDY

Why Adaptive Delivery Will Help More Effective Cognitive Engagement of Math

SUMMARY INFORMATION

Things you should know about this study:

- **Purpose:** The purpose of the study is to measure the improvement in math scores by an electronically adapted lesson.
- **Procedures**: If you choose to participate, you will be asked to take a survey to determine your learning style, and cognitive engagement. Your regular scheduled lesson will be the experiment you will participate in. There will be a survey when the class changes style and at the end followed by a regular summative assessment.
- **Duration:** This will take about 10 -15 minutes for each survey. Your class will be determined by your instructor.
- **Risks**: The main risk or discomfort from this research is discovering your learning style.

- **Benefits:** The main advantage to you from this research is the benefits of finding out your particular learning style.
- **Alternatives:** There are no known alternatives available to you other than not taking part in this study.
- **Participation:** Taking part in this research project is voluntary.

Please carefully read the entire document before agreeing to participate.

PURPOSE OF THE STUDY

The purpose of this study is to determine if the adaptive delivery of a math lesson is more effective in Learning.

NUMBER OF STUDY PARTICIPANTS

If you decide to be in this study, you will be one of 150 people in this research study.

DURATION OF THE STUDY

Your participation will involve 10-15 minutes for the surveys. Your class participation is determined by your instructor.

PROCEDURES

If you agree to be in the study, we will ask you to do the following things:

- You will be asked to fill out a self-assessment learning style questionnaire of 25 questions.
- This will allow you to be grouped into clusters by learning style

- You will be asked to fill out an additional cognitive assessment survey of 12 questions.
- The experiment will be conducted during the regularly scheduled classes.

RISKS AND/OR DISCOMFORTS

The study has the following possible risks to you: You will discover your learning style, which could set a classification in your mind.

BENEFITS

The study has the following possible benefits to you:

Discover your learning style and apply it to future study or learning practices.

Improvement in your comprehension of mathematics based on your style of Learning.

ALTERNATIVES

There are no known alternatives available to you other than not taking part in this study.

CONFIDENTIALITY

The records of this study will be kept private and will be protected to the fullest extent provided by law. In any sort of report, we might publish, we will not include any information that will make it possible to identify you. Research records will be stored securely, and only the researcher team will have access to the documents. However, your records may be inspected by authorized University or other agents who will also keep the information confidential.

All participants will be assigned a random number for identification; this number does not identify the subject.

The number will link the subject to the results of the questionnaire, and learning style cluster result. A secondary identifier will be Gender as it relates to the survey.

USE OF YOUR INFORMATION

Identifiers about you might be removed from the identifiable private information and that, after such removal, the information could be used for future research studies or distributed to another investigator for future research studies without additional informed consent from you or your legally authorized representative.

COMPENSATION & COSTS

You will receive payment based on Amazon's fee schedule for your participation. Lack of participation, non-participation, or early withdrawal will end the study. There are no costs to you for participating in this study

RIGHT TO DECLINE OR WITHDRAW

Your participation in this study is voluntary. You are free to participate in the study or withdraw your consent at any time during the study. You will not lose any benefits if you decide not to participate or if you quit the study early. The investigator reserves the right to remove you without your consent at such time that he/she feels it is in the best interest.

RESEARCHER CONTACT INFORMATION

If you have any questions about the purpose, procedures, or any other issues relating to this research study, you may contact Juan M. Piñera at Florida International University, 201-606-3596, jpine080@fiu.edu.

IRB CONTACT INFORMATION

If you would like to talk with someone about your rights of being a subject in this research study or about ethical issues with this research study, you may contact the FIU Office of Research Integrity by phone at 305-348-2494 or by email at ori@fiu.edu.

PARTICIPANT AGREEMENT

I have read the information in this consent form and agree to participate in this study. I have had a chance to ask any questions I have about this study, and they have been answered for me. I understand that I will be given a copy of this form for my records.

Part 1: Personal Information:

Directions: Please select the box that corresponds to your personal information.

1. Gender ( ) male ( ) female

2. Age ( ) 18-20 yrs. ( )21-25 yrs. ( )26 and above

3. Educational level ( ) 1st year ( ) 2nd year ( ) 3rd year ( ) 4th yea

Part 2: Learning Style Scales

This questionnaire was designed to help you find out your preferred way of Learning.

There are no wrong or right answers. (1, Strongly Agree; 2, Moderately Agree; 3, Somewhat Agree; 4, Somewhat Disagree; 5, Moderately Disagree; 6, Strongly Disagree)

Scoring:

6, Strongly Agree;

5, Moderately Agree;

4, Somewhat Agree;

3, Somewhat Disagree;

2, Moderately Disagree;

1, Strongly Disagree

Most of the time, I …

1. …prefer to study alone.
2. …enjoy competing.
3. …create a mental picture of what I study.
4. …prefer to study with other students.
5. …compete to get the highest grade.
6. …create a mental picture of what I see.
7. …learn better when someone represents information in a pictorial (e.g., picture, flowchart) way.
8. …learn practical tasks better than theoretical ones.
9. …learn better when I study with other students.
10. …compete with other students.

11. …create a mental picture of what I read.

12. …learn better when someone uses visual aids (e.g., whiteboard, PowerPoint) to represent a subject.

13. …learn better when I am involved in a task.

14. …focus more on the details of a subject.

15. …consider the details of a subject more than its whole.

16. …learn better when I watch an educational program.

17. …learn better when I watch a demonstration.

18. …create a mental picture of what I hear.

19. …remember the details of a subject.

20. …learn better when I study alone.

21. …remember specific details of subjects.

22. …learn better when studying practical, job-related, subjects.

SURVEY

English

Please enter your Miami Dade College ID #.

Select your Gender

- ◯ Male
- ◯ Female

Select your Age group

- ◯ 18 - 20 yrs.
- ◯ 21 - 25 yrs.
- ◯ 26 - & Above

Select your educational level

- ◯ 1st year
- ◯ 2nd Year
- ◯ 3rd year
- ◯ 4th year

Please state your major, if unknown state this.

VAK Survey

VAK Most of the time, I …

Never (1) Rarely (2) Sometimes (3) Often (4) Always (5)

1. …prefer to see information written on a chalkboard and supplemented by visual aids and assigned readings. (VAK_1)
2. …can remember best about a subject by listening to a lecture that includes information, explanations and discussions. (VAK_2)
3. …prefer to use posters, models, or actual practice and other activities in class. (VAK_3)
4. …require explanations of diagrams, graphs, or visual directions. (VAK_4)
5. …enjoy working with my hands or making things. (VAK_5)
6. …like to write things down or to take notes for visual review. (VAK_6)
7. …can remember best by writing things down. (VAK_7)
8. …can tell if sounds match when presented with pairs of sounds. (VAK_8)
9. …am skillful with and enjoy developing and making graphs and charts. (VAK_9)
10. …do best in academic subjects by listening to lectures and tapes. (VAK_10)
11. …play with coins or keys in my pocket. (VAK_11)
12. …can easily understand and follow directions on a map. (VAK_12)
13. …can understand a news article better by reading about it in a newspaper than by

listening to a report about it on the radio. (VAK_13)

14. …learn to spell better by repeating words out loud than by writing the words on paper. (VAK_14)

15. …chew gum, smoke or snack while studying. (VAK_15)

16. …learn the spelling of words by "finger spelling" them. (VAK_16)

17. …would rather listen to a good lecture or speech than read about the same material in a textbook. (VAK_17)

18. …I think the best way to remember something is to picture it in your head. (VAK_18)

19. …prefer listening to the news on the radio rather than reading the paper. (VAK_19)

20. …grip objects in my hands during learning periods. (VAK_20)

21. …am good at working and solving jigsaw puzzles and mazes. (VAK_21)

22. …follow oral directions better than written ones. (VAK_22)

23. ...feel very comfortable touching others, hugging, handshaking, etc. (VAK_23)

24. ...prefer obtaining information about an interesting subject by reading about it. (VAK_24)

Pre Engagement Cognitive

Please think of the lessons in this course when you answer the following question:

When engaging in the lessons for this COURSE...

Never (1) Rarely (2) Sometimes (3) Often (4) Always (5)

1. I try to associate the lessons in this course with what I learn in other courses about the same or similar things. (E_PrC_1)

2. I try to see the similarities and differences between things I am learning in this course

and things I know already. (E_PrC_2)

3. I try to match what I already know with things I am trying to learn for this course. (E_PrC_3)

Pre Engagement Affective

Please think of the lessons in this course when you answer the following question:

When engaging in the lessons for this COURSE...

Strongly disagree (1) Somewhat disagree (2) Neither agree nor disagree (3) Somewhat agree (4) Strongly agree (5)

4. What I learn in this course is important for me. (E_PrC_4

5. I believe the lessons in this course are beneficial to me. (E_PrA_1)

6. I take the lessons in this course seriously. (E_PrA_2

7. I think I gain more in the lessons for this course than in other courses. (E_PrA_3

8. The lessons makes me very interested in learning. (E_PrA_4)

9. I carefully pay attention to the lessons in this course. (E_PrB_1)

Pre Engagement Behavioral

Please think of the lessons in this course when you answer the following question:

When engaging in the lessons for this COURSE...

Never (1) Sometimes (2) About half the time (3) Most of the time (4) Always (5)

10. I try hard to do well in the lessons for this course. (E_PrB_2

11. I spent a lot of time and effort to learn the lessons in this course. (E_PrB_3)

12. I can easily complete the steps for this lesson. (E_PrB_4)

Pre Engagement Output

E_PrO Please think of the lessons in this course when you answer the following question: When engaging in the lessons for this COURSE...

Strongly disagree (1) Somewhat disagree (2) Neither agree nor disagree (3)Somewhat agree (4) Strongly agree (5)

13. This course is the most meaningful. (1)

14. This course engages me the most. (2)

Post Engagement Survey

The difference between pre and post Engagement surveys were the prompts supplied before the survey.

For the LESSON you just completed, please answer the following question: When engaging in the lessons for this COURSE...

VAK Learning Styles Explanation

The VAK learning styles model suggests that most people can be divided into three preferred learning styles. These three styles are as follows (and there is no right or wrong learning style):

- Someone with a **Visual** learning style has a preference for seen or observed things, including pictures, diagrams, demonstrations, displays, handouts, films, and flipcharts. These people will use phrases such as 'show me,' 'let's have a look at that,' and will be best able to perform a new task after reading the instructions or watching someone else do it first. These are the people who will work from lists and written directions and instructions.

- Someone with an **Auditory** learning style has a preference for the transfer of information through listening: to the spoken word, of self or others, of sounds and noises. These people will use phrases such as 'tell me,' 'let's talk it over,' and will be best able to perform a new task after listening to instructions from an expert. These are the people who are happy being given spoken instructions over the telephone and can remember all the words to songs that they hear!
- Someone with a **Kinesthetic** learning style prefers physical experience - touching, feeling, holding, doing, practical hands-on experiences. These people will use phrases such as 'let me try,' 'how do you feel?' and will be best able to perform a new task by going ahead and trying it out, learning as they go. These are the people who like to experiment, hands-on, and never look at the instructions first!

People commonly have a main preferred learning style, but this will be part of a blend of all three. Some people have an extreme preference; other people have a more even mixture of two or less commonly, three styles.

When you know your preferred learning style(s), you understand the type of learning that best suits you. This enables you to choose the types of learning that work best for you.

There is no right or wrong learning style. The point is that there are types of Learning that are right for your preferred learner.

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all three. Some people have an extreme preference; other people have a more even mixture of two or less commonly, three styles.

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Please note that this is not a scientifically validated testing instrument – it is a free assessment tool designed to give a broad indication of preferred learning style(s).

Acknowledgments to Victoria Chislett for developing this assessment.

Terms of the Study

• Auditory- Felder and Silverman (1988,) an auditory learner, follow the modality where learners learn more from what they hear.

• Information Processing- Is the change in the learner's mental performance. Online Learning focuses on the aspect of information processing, which is influenced by human-computer interaction and animated presentations (Zhang, Zhang, Yanqing, Zetian, and Yanwei, 2010).

In this research proposal, information processing will be measured employing an information processing subscale by the Learning Style Scale (LSS) developed by Abdollahimohammad and Jaafar (2014). It is represented in Part II of the questionnaire on items 15-22 in the survey.

• Instructional Preference – determines how students obtain, sort, store, and use the information. An insight into how individuals gather and process information base on the knowledge they acquired (Cox, 2008). This paper will be measured using the instructional preference subscale by the Learning Style Scale (LSS) developed by Abdollahimohammad and Jaafar (2014). It is represented in Part II of the questionnaire on items 1-9 in the survey.

• Learning Style- by definition, is employed in the process of Learning, and preference may differ based on their personality and cognitive (McLoughlin, 1999). Learning style will be measured by the Learning Style Scale (LSS) developed by Abdollahimohammad and Jaafar (2014) with subscales Instructional preference, social interaction, and information processing. It is represented in Part II of the questionnaire on items 1-22 in the survey.

• Personality Style – is the pattern of an individual that governs behavior, emotion, and logical thought (Arockiam and Selvaraj, 2013). In this research project, social interaction is examined on how learners share their information among other learners in and out of the classroom (Bartomeus, 2003). The focus is the network created based on environment and support structure (Langley, 2007). This research project will be measured utilizing a social interaction subscale by the Learning Style Scale (LSS) developed by Abdollahimohammad and Jaafar (2014). It is represented in Part II of the questionnaire on items 10-14 in the survey.

• Tactile or Kinesthetic – This is a learning style in which the modality of the student is to learn from their environment where they can touch or be physically involved with the process (Kratzig and Arbuthnott, 2006).

• Visual - Vincent and Ross (2001) classify visual learners as using a modality where their visual sense is the focus of knowledge absorption. A visual learner must see to learn or absorb knowledge.

Part 3: Learning Self-Efficacy Scale (Engagement Measure)

Instrument Type: Inventory/Questionnaire

Test Format: Responses to the 33 items are all provided on Likert scales.

Source: Lam, Shui-fong, Jimerson, Shane, Wong, Bernard P. H., Kikas, Eve, Shin, Hyeonsook, Veiga, Feliciano H., Hatzichristou, Chryse, Polychroni, Fotini, Cefai, Carmel, Negovan, Valeria, Stanculescu, Elena, Yang, Hongfei, Liu, Yi, Basnett, Julie, Duck, Robert, Farrell, Peter, Nelson, Brett, & Zollneritsch, Josef. (2014). Understanding and measuring student engagement in school: The results of an international study from 12 countries. School Psychology
Quarterly, Vol 29(2), 213-232. doi: https://dx.doi.org/10.1037/spq0000057

Student Engagement in School Measure

Cognitive Engagement

Item:

When learning things for school in this semester, how often do you do the following?

1. When I study, I try to understand the material better by relating it

to things I already know. (Samuelstuen & Bråten 2007)

2. When I study, I figure out how the information might be useful in the real world. (Samuelstuen & Bråten 2007)

3. When learning new information, I try to put the ideas in my own words. (Greene et al. 2004)

4. When I study, I try to connect what I am learning with my own experiences. (Wolters, 2004)

5. I make up my own examples to help me understand the important concepts I learn from school. (Wolters, 2004)

6. When learning things for school, I try to see how they fit together with other things I already know. (Dowson & McInerney, 2004)

7. When learning things for school, I often try to associate them with what I learnt in other classes about the same or similar things. (Dowson & McInerney, 2004)

8. I try to see the similarities and differences between things I am learning for school and things I know already. (Dowson & McInerney, 2004)

9. I try to understand how the things I learn in school fit together with each other. (Dowson & McInerney, 2004)

10. I try to match what I already know with things I am trying to learn for school. (Dowson & McInerney, 2004)

11. I try to think through topics and decide what I'm supposed to learn from them, rather than studying topics by just reading them over. (Elliot et al., 1999)

12. When studying, I try to combine different pieces of information
from course material in new ways. (Greene & Miller, 1996)

The Likert scale for the cognitive engagement subscale is the following: 1 (never), 2 (rarely), 3 (sometimes), 4 (often), and 5 (always).

VITA

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PUBLICATIONS AND PRESENTATIONS

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