

Accounting Students' Preferred Learning Techniques and Complex Data Analysis: An Odds Ratio Investigation

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Abstract

The study investigates connections between students' preferred learning techniques (PLT) and the odds of increasing performance on testing incidents as they are exposed to complex accounting topics. It was conducted as an in-class experiment using three testing incidents activity-based costing (ABC), standard costing and variance analysis (SCVA), and a mock exam for simulating complex accounting data. The results indicate the odds are not great that visual learners are more likely than other learners to process complex data more effectively. Rather, the odds are that kinesthetic learners are most likely to analyze and process complex data effectively. The Odds ratio also indicates that while each of the PLT group improved their performance from the SCVA test to the Mock-MC test, this improvement was weaker than that of the Unidentified group. This implies faculty should use various assignments to help students develop skills needed to analyze and make sense of data, rather than focus on individual preferred learning techniques or modalities. Additionally, if we know students' learning style(s) early in their academic careers, we can better prepare them for successful accounting careers.

Key words: Complex Data Analytics, Data Analytics, Student's Cognition, Learning Techniques, Odds Ratio Statistics

Introduction and Purpose

Overview of the Study

The New CPA exam, which became effective in 2024, requires students to have an adequate background in data analytics. Therefore, the AICPA and NASBA recently announced a CPA Evolution Model (NASBA, n.d.; AICPA, n.d.) to help accounting departments modify their curriculum and prepare students for the incorporation of technology and data analytics in their learning repertoire. Regardless of their preferred or identified learning techniques, it is imperative that graduating students think critically, analytically, and can effectively process complex data used for decision-making. Complex data is often used interchangeably with big data, an old concept, espoused in the business world as a noun describing large data sets requiring sound analysis. It also acts as a verb for advanced predictive analytics used to abstract value from data. (Gandomi, & Haider, 2015; Sharma, 2019). The nuances of big data are expressed in four Vs: volume, velocity, variety, and veracity (Henry & Venkatraman, 2015; Zhang et al., 2015).

Regardless of the interpretations of these terminologies, complex data analysis in the information age is indicative of the evolving capabilities of organizations, utilizing technology, artificial intelligence (AI), and others to obtain, process, and use specific and streamlined information to predict customers' or clients' needs, behaviors, and preferences. The findings of these analyses are used to determine business value because results can be used to enhance greater operational efficiencies in complex projects, supply-chains, risk management, and cost reduction (Chen et al., 2015; Mayer-Schönberger, & Cukier, 2013; Sisense Team, n.d.; Whyte et al., 2016).

The methods of complex data analytics have the potential to cause a change in standards, which allows economic activities to be tracked and evaluated more quickly and efficiently. This change may be deemed to be threatening to

some professionals, yet it offers opportunities for accounting and auditing regulatory organizations to implement amendments to accounting standards in response to this issue. It also has profound implications for the accounting profession, broadly defined, and for internal and external accounting, attestation, and consulting procedures and measurement processes using new forms of transaction evidence. Accountants, particularly CPAs, can utilize their extensive knowledge of corporations' operations and related data, together with their knowledge of finance, to transform their analytical insights into competitive advantages (Haverson, 2014). This, in turn, creates value for clients and firms (Capriotti, 2014; Griffin & Wright, 2015; Lin, 2014; Vasarhelyi et al., 2015). In 2009, economists with the Bureau of Labor Statistics, Lacey and Wright, noted the U.S. Department of Labor predictions that by 2018, there would be over four million job opportunities in the data analytics field. Hence, to be competitive when they begin seeking employment as accountants, students must be prepared to integrate elements of data analysis into their cognitive learning techniques and modalities, specifically to take advantage of opportunities in the field (Meyer, 2016).

In 2012, a Brookings report entitled “Big Data for Education: Data Mining, Data Analytics, and Web Dashboards” referred to an Acuity Diagnostic Assessment tool developed by Darrell West. This tool assists teachers in assessing how students solve problems and assess data, while providing guidance on preferred learning techniques, thus focusing their instruction on those preferences. West asserts that “schools must understand the value of a data-driven approach to education” and that having performance systems will contribute to informed decision-making (pg. 10). The intersection of data analytics approach to education has been widely studied in higher education in general and in the education of psychology (Li and Jiang, 2021; Lodge & Corrin, 2017; West, 2012). But it has not been widely studied in the accounting classroom and has not gained much attention in accounting literature.

Accordingly, this study aims to understand the **odds** of students' ability to understand, process, and analyze complex data, and if those odds increased relative to their preferred learning techniques, as they are exposed to intricate accounting topics, throughout the semester. Odds Ratios are simply defined as “the probability of an event occurring divided by the probability of that event not occurring” (Field, 2013, p. 319). This method of data analysis is particularly useful and intuitive to understand variances when predictor variables are categorical. The overarching question guiding this study is: Do learning techniques increase the likelihood of students' ability to analyze simulated complex data as reflected on testing incidents throughout the semester as they are exposed to intricate accounting topics? Answering this question is of tremendous importance given the digitalization and skill sets that the accounting profession requires of graduates who enter the profession. Accounting educators must be poised to aid students in preparing for their careers. They should be concerned about the impact of students' learning techniques on analytical abilities and the likelihood of increasing their performance as they are exposed to complex accounting concepts. The thesis here states that when faculty know and focus on the learning style(s) of students early in their careers, they can better prepare them for success, by honing the styles that best match the related skills development.

Thus, the research relies on a combination of three major concepts to form the theoretical framework (1) an understanding of complex data analytics in accounting; (2) cognitive learning techniques (LT) and modalities of higher education students. See for example, Dr. Jeffery Barsch, 1996, Riechmann & Grasha, 1974, and Stephenson 2020. The third conceptual framework relies on the last two or the four Vs of big data, variety (many) and veracity (large). These two categorizations help users understand the analytical interpretation of the complexity of data analytics (Capriotti, 2014; Vasarhelyi et al., 2015). Moreover, the explosion of AI has allowed for variety and veracity of data to be analyzed more efficiently and timely.

The testing incidences used to simulate complex data for this study are activity-based costing (ABC) and standard costing variance analysis (SCVA) concepts. ABC and SCVA are two of the most complex analytical concepts, which students must learn in managerial and cost accounting courses (Lucas, 1997; Nassiripour & Xu, 2004). Moreover, scholarly research in accounting has always compared ABC to the traditional means of Job and Process Costing systems. The fact is ABC costing involves several steps, is more complex to analyze and understand, and takes more time in translating the data, yet is more accurate than Job and Process Costing. (Towai, et al., 2018). Subsequent sections of the paper outline the conceptual framework and literature review, methodology, results, discussion, conclusions, and implications of the study.

Conceptual Framework and Literature

The conceptual framework for this article is essentially dependent on a discussion of the theories on learning styles, and the link of these theories to education, to needs of the accounting profession broadly defined, and specifically to the needs of CPAs. An evaluation of existing literature on complex data analytics reveals that only a few studies, for example West (2012), have made a direct correlation between complex data analysis and preferred learning techniques. Thus, this intersection or correlation is yet to be explored in meaningful ways. Therefore, this study is important in its contribution to understanding this phenomenon as follows: It helps faculty understand the need to teach and expose accounting students to complex data and analytics, regardless of their learning styles and or techniques. It has implications for the use of various data analysis related assignments to help students develop the necessary analytical skills required to make data-driven decisions. This is precisely what accountants are required to do every day in their vocations. Learning style, and linkage of learning theory to education is important in framing the theoretical framework for this study. Moreover, the link to the accounting profession and specifically the skills required by CPA is paramount and is addressed below. The literature about these concepts is still developing, but this review highlights some of the extant studies, which indicate a relationship between students learning techniques and modalities and their performance when faced with the challenge of analyzing complex data. Scholars, practitioners, and proponents of the CPA Evolution and the recently implemented new version of the CPA Exam, are emphasizing the need for changes in accounting curriculum that will help encourage students to garner the collection, processing, and data analytics skills necessary to prepare for their careers. Major accounting firms have highlighted the influence of these analytical concepts on the procedures and practices for organizing, summarizing, and reporting economic activities and on recording accounting transactions. One such conceptual focus is value creation in accounting and auditing (Feiqi et al., 2022; Nissim, 2022).

Lv et al. (2019) and others indicate that complex economic problems can be handled in many industries by using big data technology, which is adaptable to analyzing economic transactions used in decision-making (Alsunaidi et al., 2021; Fényes, Németh & Gáspár, 2022; Oboke et al., 2019; Wiech et al., 2019). Lutfi et al. (2022) suggest that emerging economies regard data analytics as having enormous significance despite the barriers that prevent its adoption. It is also necessary to unfold the implications of the advancement of financial and managerial accounting procedures, which reflect the underpinning of complex data analytics. Gandomi and Haider (2015) observed that using related big data concepts, methods, and analytics require a broader definition that “captures its unique characteristics other than size” (pg. 1). See also Sharma, 2023. These authors included definitions from practitioners and academics, thus substantiating the rationale for focusing the literature for this study on a blending of the theories of learning styles with the context of variety, and veracity of complex data analytics.

Learning Styles And The Profession

Extant literature related to supporting and opposing views on cognitive preferred learning styles became popular in the 1970s. A range of competing and contested theories including several seminal works, account for differences in individuals' knowledge acquisition and in how they learn (Cobb, 2001; King, 2011; Swanson, 1995; Willingham, Hughes, & Dobolyi, 2015). Studies indicate that learning style is contextual and based on cognition, and that learning styles can be grounded in the application, modality, or context of the learning situation. Furthermore, they indicate that learning styles are based on the individual's typical modality of solving problems or making decisions, or on perceiving and remembering information (Cassidy 2004; Curry 1983; King 2011; Stephenson, 2019; Swanson 1995).

The cognitive approach to learning styles has been favored as an explanation for how people learn in settings such as colleges, where knowledge is complex and the process of thinking critically is as important as recalling facts. There is precedence for this link of learning styles to college teaching and skills acquisitions. For example, in 1988, a seminal study by Felder and Silverman designed a learning inventory for use in understanding engineering students' learning styles. The objective was to increase instructor awareness of learning styles and improve their course designs. Additionally, Curry (1983) conducted a meta-analysis of 46 studies of various concepts of learning styles in general education, and a second analysis of 16 additional studies in the professional field of education. These studies showed that when positive results of learning styles are found, they generally indicate that students' learning can be

improved by adapting various instructional modalities as much as possible to each student's learning style or preference.

Types of Cognitive Learning Styles and Techniques

Over the years, various models and theories have emerged to capture the diversity of learning styles, each has its own uniqueness and perspective. Among these seminal and other studies are Kolb's (1984) Experiential Learning Theory and Kolb (2013), which posits that individuals engage in a continuous cycle of experiencing, reflecting, thinking, and acting. While Honey and Mumford's (1992) Learning Styles Theory categorizes learners into four groups of learners, rather than personal individual characteristics or styles. These include activists, reflectors, theorists, and pragmatists. They assert that these categories are based on students' learning preferences. Additionally, there is the visual learning, auditory learning, read/write learning, and kinesthetic learning (VARK) model, developed by Neil Fleming in 1995.

Felder and Silverman (1988) study of engineering students concluded that they have one or more learning style preferences within four dimensions: sensing/intuitive, visual, active, and sequential. Another seminal study by Barbe, Swassing, and Milone (1979), identified three learning styles, which they referred to as learning modalities. These modalities include visualizing, auditory, and kinesthetic (VAK). They argued that the most frequent modality strengths lie in visual learning or a mix of visual and one other modality, concluding that learning can be based on one modality, or a combination. Fleming (1995) expanded the concept of VAK modalities posed by Barbe, Swassing, and Milone adding a read/write component. He favored the term learning styles rather than modalities and categorized them as, visual learning, auditory learning, read/write learning, and kinesthetic learning (VARK). Fleming asserted students could use the model to identify their preferred learning style and maximize their learning by focusing on that which was most beneficial to them. An explanation of each style includes Visual learners who prefer learning through visual aids that represent ideas without using words, including graphs, charts, diagrams, or symbols. Auditory learners who learn best through listening (e.g. lectures, discussions, or tapes). Tactile/kinesthetic learners prefer to learn via experience, such as moving, touching, or doing (e.g. active exploration of the world, science projects, or experiments (Flemming 1995; Leite, Svinicki, & Shi 2010).

Additionally, the concept of learning techniques is often used interchangeably with learning styles, modalities, or contexts. These have also been described as sets of behaviors and attitudes related to the learning context (Brown, 2003; Coffield et al., 2004; King, 2011; Swanson, 1995; Willingham et al., 2015). Thus, learning styles and techniques are some of the most studied topics in the field of education and in psychology of education and research, and the related conceptual literature in these areas has been well established. These studies discuss the range of competing and contested theories, which aim to account for differences in individuals' knowledge acquisition. Accordingly, the studies referenced above, and their results have generated relevant modifications in teaching-learning processes (Cassidy, 2004; Willingham, Hughes, & Dobolyi, 2015). There are also several theoretical models, which explain the characterization and development of learning techniques from different points of view, some share concepts, while others differ completely.

For example, Dr. Jeffery Barsch (1996) developed a learning inventory to test sensory receptors which affect learning. He agreed with other researchers and experts that learning techniques fall into four basic categories visual, auditory, tactile, and kinesthetic learners. In that study, he suggested that students' cognitive development leads to these different learning techniques. Barbe et al. (1979) proffered three learning modalities, which they identified as visualizing, auditory, and kinesthetic. The authors concluded that the strengths of learning modality can be based on one independent modality, or a combination of modalities. Fleming (1995) also suggested multiple modalities of learning and expanded the concept of the visual, auditory, and kinesthetic modalities of learning by adding read/write. He also renamed the variables in the model to visual, auditory, read/write, and kinesthetic. See also Leite et al., (2010). Riechmann and Grasha (1974) developed a modality relative to students' cognitive learning techniques known as the Grasha-Reichmann learning style scale. It focuses on students' interactions amongst their peers, instructors, and learning in general. Other studies have shown that learning techniques can be grounded in the application, or context of the learning situation, and on the individual's modality of solving problems, making decisions, and remembering information (Cassidy, 2004; Curry, 1983; King, 2011; Swanson, 1995).

The literature shows that the concepts of learning techniques have been widely studied and proffered in education, yet have been seriously criticized and debated by psychologists, educators, neuroscientists, and other practitioners (Dantasa, & Cunha, 2022). The major debate and arguments are against the validity of students' learning due to orientations of the brain. Some argue that the notion of learning modalities is a myth, fad, or senseless (Coffield et al., 2004; Greenfield, n.d.; Willingham et al., 2015). Hattie and Yates (2014) indicated it is naïve to determine that students can be classified as visual, whereas others can be auditory learners, or have other learning techniques within the same classroom. Notwithstanding the criticisms learning style theories have received from some researchers, the research on learning techniques has greatly influenced education and learning in general. Moreover, there is no known scientific validity to this criticism or to making any such stipulations based on neurology or behavioral performance, because students often note they do have a preferred learning style (Klein, 2003; Swanson, 1995; Vasquez, 2009).

For example, Stephenson (2019) designed a learning techniques assessment modalities preferences diagnostics (LAMP-D) framework after conducting a study on cognitive learning techniques, modalities, and assessment preferences. The student survey results were analyzed using structural equation modeling. The framework included assessments preferences as the dependent variables and their correlations to the learning modalities (the mediating variables) and the four learning techniques as the independent variables. The LAMP-D framework suggests that while criticisms of learning styles may be valid, students do have preferred learning styles, which are often correlated to the learning modalities and contexts. The study found that learners' preference for multiple choice response assessments is not significantly affected by any learning style, even when mediated by learning context modality. It also shows that visual learners' preference for quantitative problem-based assessments is most positively and statistically significantly affected by contextual learning modalities. Furthermore, tactile, and kinesthetic learners' preference for quantitative problem-based assessments is also both positively correlated with, and significantly affected by, the learning modalities. It shows, conversely, auditory learners' preference for quantitative problem-based assessments is both negatively correlated with, and significantly inversely affected by, contextual learning modalities.

Ware (2008) suggested our brains can represent abstract information visually, which makes it possible for us to recognize relationships and detect meaningful patterns in data. When words and numbers are not sufficient, pictures of data are often necessary to understand relationships and patterns. This is particularly true due to the many complex issues that we face today. Data sense makers must understand the potential of visual thinking and know when and how to convey information visually in ways that enable our brains to see, compare, and comprehend meaningful patterns and relationships, that is to learn! Several studies indicate a general population percentage distribution for learning techniques or preferences. Although the results of these studies are not conclusive, estimates of the range of percentage distributions within the general population have been made in Figure 1. Most of the general population learns visually, 60–65%; while on the opposite extreme, only approximately 5% are tactile (read/write learners). The auditory (10–30%) and kinesthetic categories (5–50%) are most inconsistent, resulting in the most significant ranges in percentages (Buşan, 2014; Mindtools, 2009; Sebor, 2008; University of Illinois Extension, 2009). These percentage distributions will never add to 100% due to varying thoughts, especially when learning techniques are combined, or instances where students identify with more than one style of learning. The University of Illinois study indicated that 40% of secondary students are visual learners; only 10% are auditory learners, while 50% are kinesthetic. Buşan's (2014) study of medical students indicated that 14% of them have a predominant kinesthetic style, but the distribution changes when learning techniques are combined.

Learning Styles Effect on Students' Success

Only a few studies indicate a direct correlation between learning techniques and various professional students' ability to analyze complex data. West (2012) noted that some students solve problems in a systematic manner and analyze materials in a linear manner, while others prefer visual or graphical presentation and integrating information in a non-linear manner. Amalec et al. (2019) in their study of learning style using big data, concluded that learning style preferences of college students enable teachers to properly guide the teaching-learning activities by selecting the best strategies, thus contributing to raise the quality of education (Sarkar et al., 2021). Felder and Silverman's (2008) study of engineering students also make that link to their learning styles one of the variables driving their

success. Furthermore, Romanelli, Byrd, & Ryan (2009) indicates that despite debates surrounding learning styles, they have the potential to advance application and best practice within the realm of professional-based education. Li and Jiang (2021) research suggest that the trend in learning style in education has an impact on teacher psychology and educational development. Teachers must explicitly or implicitly contend with five basic concerns, which are expressed in five questions: (1) How can I help students acquire and retain knowledge? (2) What can I do to enhance the ability of students to concentrate in class? (3) How can I help students to think critically? (4) What will help me motivate my students? And (5) How can I help them become self-directed learners? (Grasha, 1996 & 2002 p. 208). While teachers who ask themselves such questions are critically reflective practitioners, the concept of students' learning style and preference(s) as related to students' success and preparation for career advancement remain somewhat elusive.

Specifically related to accounting education, is Duff's (2004) analysis of accounting students' cognitive learning styles. The study contrasted different models of operational learning style inventories in accounting students. He analyzed various learning style instruments and seminal works, including David Kolb's (1984), to determine which most effectively identified whether cognitive or preferred learning styles are linked to students' quest for learning. Duff subsequently proposed five suggestions for educators, which can be used to further the cognitive learning styles assessments of accounting students to help them learn. These and other models offer educators a framework to better understand how students approach learning. This knowledge of learning style can be used to assist them in the adaptation of instructional approaches. The authors referenced above also assert that understanding learning techniques is essential to educational attainment and is crucial to personalizing and tailoring instructional presentation in the most effective manner.

Complex Data Analytics and Accounting Education

CPAs and accounting graduates will need to confront the nuances and challenges of these emerging techniques and the prevalence of using complex data analysis in accounting, auditing, and consultation careers (Watson, 2022). Consequently, exceptional statistical knowledge, insights into algorithms, knowledge of social sciences, and other disciplines are underlying qualifications for understanding and analyzing data referenced in economic transactions. Specifically, accountants will need to understand the why and how economic transactions fit together, not just the dollars and cents (Meyer, 2016; Sommer, 2015b). Transactions such as recording, identifying, and tracking inventory activities prior to receiving or delivering those goods, and customer related activities such as identifying calls before acting on servicing those customers are a few examples of the way big data analytics are used in identifying economic activity (O'Leary, 2013). Therefore, it is advantageous for accounting graduates, academicians, practitioners, and researchers to learn about the substantial benefits of complex data analytics and conversely its potential hurdles and difficulties. Not only accounting students and graduates, but all business students could benefit from a renewed focus on data analytics. As these views continue to grow in importance in every business discipline, students will need exposure to a variety of data sets, accounting technologies, and security and privacy matters, to enhance their future career development (Vasarhelyi et al., 2015).

Accordingly, business schools must design programs which are adaptable to the emergence of the complex data analytics world. This could be by promoting content, assignments, and learning modalities which support simulated complex data sources and advanced data analytics (Henry & Venkatraman, 2015; Sommer, 2015a). Dr. Mitchell Wenger, Assistant Professor of accounting at the University of Mississippi suggested, with the massive amounts of data that clients are generating, "the profession sees the need for future CPAs to have a strong background in the techniques and tools required to sift through and evaluate that data effectively" (Meyer, 2016, p. 1).

Educators must prepare to minimize the gap created by the advancement of data analytics by focusing their curriculum on the demands of the current marketplace (Lodge & Corrin, 2017; Ferguson, 2014). Students must be exposed to simulations which will help them learn how to organize, analyze, and report results from large data sets which are used in decision-making and for competing in a global economy. Additionally, integrating such learning objectives in the curriculum keeps the learning relevant and prepares students for challenges they will encounter during their careers, while working with complex data. Ferguson (2014) and Sarkar, et al., (2021) indicate data analytics is applicable to variety of industries, from finance to healthcare, and is used to improve efficiency, reduce

costs, and identify new business opportunities. Therefore, the more complex data students are exposed to, the more they will be prepared to garner:

- Effective critical and problem-solving skills and ability
- Outstanding interactive and cooperation skills needed to work effectively in a team setting
- Familiarity with techniques required to understand technology in analysis

The Futures Company Project (2013) noted that most schools required that early in the curriculum students take one course on computing and technology, basic data analysis, and one or two courses in statistics. But it suggests that revising these courses to be more data analytics focused could provide all business students with a base level of analytics skills. These proposed changes offer opportunities for programmers to innovate in both curriculum design and delivery. PricewaterhouseCoopers (2015) also indicates that accounting faculty should collaborate with faculty who possess expertise in information systems, statistics, and computing to deliver new curricula.

Prior to 2014, only a few undergraduate business programs, such as Ohio State, implemented innovative undergraduate data analytics programs. The curriculum was based on the recognition that the impact of big data concepts is interwoven across all disciplines from medicine to the arts (Barmer, 2014; Box-Steffensmeir et al., 2014). Subsequently other universities adopted complex data prospectuses in graduate programs including Drexel, Southern New Hampshire, and Arizona State (Henry & Venkatraman, 2015).

According to the ICAEW (2019) complex data will influence the conception and modification of future accounting standards and procedures, while ensuring the accounting profession continues to provide valuable information to users in our evolving, dynamic, and global economy. Additionally, the Association to Advance Collegiate Schools of Business (AACSB), the international accreditation body for business schools, directed there need to improve importance on analytic skills. They specifically mandated that those skills outlined in their Standard 5 be integrated into the accounting curriculum, (Sarkar et al., 2021; Schmidt, 2020). Regardless of the above suggestions and what is done at the institutional or program levels, faculty must devise ways to infuse analytical exercises into their courses to help students develop those proficiencies in addition to their core accounting knowledge. This is the premise on which this study is based.

Methodology

Frizzo-Barker et al. (2016) suggested that scholarship and investigations in complex data are still being developed. The study of this phenomenon in terms of theoretical grounding, methodological diversity, and empirically oriented work is in a fragmented, early-stage area of research. In a contemporary context, this study contributes to the challenges associated with the limited research available to improve our understanding of implementing complex concepts and data analysis into the accounting curriculum.

This study was conducted using a classroom experimental design. It was the second phase of a major ongoing study on students' leaning techniques and learning modalities, coupled with assessment preferences (Cobb, 2001) in accounting classes. The results of the first phase of the study established that students' learning techniques and modalities are correlated with their assessment preferences. This phase expanded the study to understand and establish if there is a learning trajectory (Cobb & Gravemeijer, 2014) or process for students developing skills for analyzing complex data, from a cognitive viewpoint (Lobato, 2003).

Research Questions and Hypotheses

The main questions and the hypotheses guiding this study were developed based on references to extant literature, on dominant or cognitive learning techniques and or preferences and the need to adapt various course assessments to such learning techniques (Stephenson, 2020; Busan, 2014). This is influenced by the nuances in literature about big data analytics, particularly the veracity and variety concepts, rather than the hype of big data as only volume and velocity (Gandom & Haider, 2015). Basically, the conceptual framework (highlighted in Figure 2) shows how learning techniques relate to complex data analysis, and the odds are of students' performance increasing in tests incidences based on their learning techniques.

Research Questions:

1. Do students' preferred learning techniques increase or decrease their skills of analyzing and deciphering simulated complex accounting data sets?
2. Do students' ability to examine and make sense of simulated complex accounting data sets increase their odds of performing better in course assessments, which simulates complex accounting data?

Hypotheses:

- H₀** Students' preferred learning techniques have no effect on their abilities to analyze complex data.
- H₁** Students who self-identify as visual learners will find it **less** difficult to analyze assignments representing complex data sets such as quantitative problem-based assignments, which do not include multiple choice responses. The Odds are they will perform the strongest on each test.
- H₂** Students who self-identify as audio learners will find it **more** difficult to analyze assignments representing complex data sets such as quantitative problem-based assignments, which do not include multiple choice responses. The Odds are they will perform the weakest on each test.
- H₃** Students who self-identify as tactile learners will find it **less** difficult to analyze assignments representing complex data sets such as quantitative problem-based assignments, which do not include multiple choice responses. The Odds are they will perform typically (average) each test.
- H₄** Students who self-identify as kinesthetic learners will find it **less** difficult to analyze assignments representing complex data sets such as quantitative problem-based assignments, which do not include multiple choice responses. The Odds are they will perform typically (average) each test.

Experimental Design

Experimental design research is widely used in education to understand students' learning and learning outcomes (Brown, 1992; Cobb, 2001; Lobato, 2003). Cobb and Gravemeijer (2014), in their analysis of experimental designs in education, noted that methodological research, which uses experimental designs in the classroom is the most common form of research supporting students' learning and the learning practices of teachers. Research is often conducted to develop future or grounded theories in the context of learning. This is done specifically to identify initial trends and correlations between variables and observed relationships which represent the trajectory of learning processes. For example, Cobb et al (2003) asserted in his study, "Design experiments are pragmatic as well as theoretical in orientation in that the study of function—both of the design and of the resulting ecology of learning—is at the heart of the methodology" (p. 9).

This study was conducted in two managerial accounting classes at a major university. The two classes had a total of One hundred and forty-three students. However, the study participants are represented by one hundred and thirty-seven (N=137; 96%) who participated in all three testing incidences and earned a grade. The internal review board approved the purpose and method of the overall study and participants. Students were not paid for their participation; they received the normal credits for in-class attendance and work. Prior to the study and prior to them doing the three tests, I engaged them in a discussion about the concepts and categories of learning techniques, which were based on the literature. They acknowledged that they fully comprehended the concepts and that they each knew their preferred learning technique if they had one. The *treatment* group comprised 68% (n = 93) who chose a (visual, auditory, tactile, or kinesthetic) preferred learning technique. The *unidentified* group comprised 32% (n = 44) of whom were uncertain or did not identify with the dominant or preferred learning technique.

The Experimental Incidents

All accounting and business majors must take managerial accounting before being admitted to the college of business; will be exposed to ABC Costing and SCVA. These two concepts provide some of the most complex aspects of managerial accounting curriculum when compared to traditional methods and are compatible with the current business environment (Hicks, 2002; Lucas, 1997; Nassiripour & Xu, 2004, Wilkinson, 2013). Moreover, in managerial accounting literature, SCVA is often used to understand various quantitative modeling in a manufacturing setting (Alami & ElMaraghy, 2020; Myrelid & Olhager, 2019; Zhuang & Chang, 2017). The author believed these concepts provided good prototypes for simulating complex data because in an actual organization,

these methods of analyzing costs usually require the use of advanced information technology (Towati et al., 2018; Horngren, et al., 2015).

Students' performances were measured in three testing incidents, utilizing concepts from the ABC and SCVA chapters of the managerial accounting text, immediately after those chapters were presented in class. Students in the treatment group were given questions along with the dominant learning techniques (visual, auditory, tactile, and kinesthetic) outlined on green assignment sheets. They were instructed to rank their preferred learning techniques using a numeric value of 1-4; with 1 being the most and 4 being the least dominant learning techniques. Students in the unidentified group were given the same exercises and questions, but without the dominant learning techniques, on white assignment sheets (see Appendices 1 and 2).

The study is based on the two last Vs of complex data, veracity, and variety, and it was important to make the testing incidents both open questions and multiple-choice formats, replicating validity and variety of the assessments. This was to ascertain that each test represented a different level of complexity. Discerning the veracity (authenticity) and the variety (diversity) of the data are the skills required of accountants when analyzing complex data. This furthers an understanding of students' ability to think critically and to analyze complex data, when portrayed in a variety of methods. In the first test incident, the questions were based on ABC. In the second test incident, the questions were based on SCVA. In each of these two testing incidents there were a total of six questions each. There were three quantitative-based exercises with questions and sub-questions—some questions had multiple parts (simulating variety). No answers were provided; students were asked to answer them.

The third testing incident occurred one week after the second testing incident. In addition, the students in the treatment group were directed to rank their preferred learning techniques using a numeric value of 1-4; with 1 being the most dominant and 4 being the least preferred learning techniques. Students in the undefined group were given these same exercises and questions, but without the dominant learning techniques, on a white assignment sheet (Appendix 3). Students were given the same assignments and exercises, presented in a multiple-choice format (MC) as a component of their mock (pre-exam). However, the pseudo names of the companies used in the two prior testing incidences were changed to mask the fact they were being tested on the same quantitative exercises. The objective of restructuring the third testing incidence was to know if students could recognize the same data in different formats, also a data analytics skill.

Data Analysis

The data set is 411 (137*3) assignments submitted by participating students who completed all three testing incidences. The assignments were graded, and a percentage correct value was assigned to each. IBM's Statistical Package for Social Sciences, version 22, was used to analyze the data from different perspectives and for comparison. Participants were assigned to learning techniques (LS) groups based on their self-reported preferred LS, while those in the unidentified group were assigned a dummy value for this variable. Continuous test scores represented the outcome, or response variable of interest, while learning style represented the explanatory, or predictor variable.

Descriptive statistics were calculated and used to evaluate the efficacy of the data. The average and standard deviations were calculated for each group and each test; no outliers were identified. Data for the sequential measurement incidents were analyzed using multivariate analysis of variance (MANOVA), as well as individual one-way ANOVAs, exploring correlations between performances and learning style, both between and within group effects. These analyses were followed by the calculation of the **Odds Ratio Statistics (ORS)** to determine the likelihood of weak or strong performance within and between LS groups on each of the three testing incidents. It is also used to assess the significance of change over time in the students' ability to analyze complex data, as they learned more during the semester. ORS are particularly effective and intuitive to understand variances when predictor variables are categorized. ORS is defined as "the probability of an event occurring divided by the probability of that event not occurring" (Field, 2013, p. 319).

Results and Discussion

Findings and discussions are based on the concepts and hypotheses developed for this study. The learning techniques distributions of the participants are—visual learners 40%; auditory learners 4%; tactile learners 8%, and kinesthetic learners 17%. These results are comparable to previous findings such as the 2009 University of Illinois Extension Study, which stated that learners are 40% visual, 10% auditory, and 50% kinesthetic. Dr. Jeffery Barsch (1996) and others agree students have dominant learning styles, which when situated in context allows them to experience different modalities of solving problems (Cassidy, 2004; King, 2011).

Table 1 summarizes the students' learning techniques performance, descriptive statistics, and changes in test scores, by LS group for all three testing incidents. The size of the standard deviations, relative to the means, indicate a high degree of variance in scores. The results show three groups of learners: unidentified, visual, and tactile experienced a drop in performance between the ABC test and SCVA (more complex concept than ABC) test. However, they managed to recover their initial scores on the Mock-MC test, when the answer choices were available. The auditory group scored the lowest on the first two tests, then experienced a significant improvement in performance, scoring relatively equal to other groups on the Mock-MC test. The kinesthetic group commenced strong, held even on the second test, and outperformed all other groups on the third test. Figure 3 helps to augment these results. Tables 2 and 3 demonstrate errors, significance, and confidence measures tests; they provide information on the validity of the outcomes and data analysis. Table 2 presents the results of the repeated measures ANOVA, which are both informative and encouraging.

The major finding for LS group differences revealed that performance was not significantly affected by group membership, $F(1.9, 253.6) = 2.2$, $p = 0.1$. Nevertheless, examining the variance within LS groups, comparing the second test to the first, and the third to the second, we observe some considerable results. Comparing performance on the SCVA test to the ABC test showed meaningful results with $F(1, 132) = 4.2$, $p = 0.4$. Comparing the Mock-MC test to the SCVA test showed that the results were slightly higher, with $F(1, 132) = 3.2$, $p = 0.7$. The overall differences between LS groups were less evident and may be influenced by the differences in group sizes; this produced $F(4, 132) = 0.908$, $p = 0.4$. Dissecting the differences between groups in greater detail, comparing each LS to the unidentified (control) group produced the results in Table 3, which shows confidence in the significance of the findings.

Odd Ratio Statistics

Tables 4 to 8 highlight the Odd Ratio Statistics (ORS) of the change in test performance with each testing incidence by LS groups. Unlike simple distributions, odds ratios are not proportional to 100 percent. A weak score indicates no correct answers; typical (average) indicates some correct answers; strong indicates all correct answers. Weak and strong would be at the extremes, but typical would be the center of the bell curve. The change in odds can be interpreted as the change in response, based on the predictor, test performance. Therefore, for this study that would be a change in performance among the ABC, SCVA, and Mock tests. The odds ratios allowed comparisons across three testing incidents by LS, and comparisons across LS groups on each test.

Table 4 shows the participants' mean distribution of test results by learning style (Table 1), the number of students in each group, and the odds of them performing weak, typical, or strong. The ORS contrasts the original test scores in Table 1 and confirms the likelihood that the unidentified and visual groups performed weaker on the SCVA test and stronger on the ABC test. The auditory group performed weakest on ABC and typically on Mock. Tactile group performed weakest on the SCVA and typical on the Mock. The Kinesthetic group performed weakly on both ABC and SCVA and typically on the Mock Exam.

Within and Between LS Group Comparisons

Table 5 highlights the more interesting results of the ORS for each test, by LS group. It confirms the odds of each group's performance on each test. The odds were that auditory learners were 1.5 times more likely to have a weak score on the ABC test than a typical or strong score; their average score was the lowest for this test. While the odds of visual learners performing weakly on the SCVA test, was high, at 1.6 times more likely than either a typical or a strong score; their average test score was the lowest for this test. The probability was that all LS groups were more

likely to have a typical score than either a weak or strong score on the Mock test. The unidentified, tactile, and kinesthetic groups had the highest odds ratios for a typical score, 2.2, 1.8, and 2.8 times respectively.

Table 6 presents result within groups comparing the SCVA to ABC, and the Mock-MC to SCVA tests. It shows the odds of the changes in performance as students progressed from ABC test to SCVA tests and then to the Mock test. The most interesting results are found in the 'Typical' column comparing the Mock-MC test to the SCVA test. The odds were that all groups were more likely to earn a typical score on the Mock on the SCVA test. The strongest improvements were demonstrated by the Kinesthetic and Unidentified groups who were 2.8 and 2.2 times more likely to score typical results on this test compared to the SCVA test.

Table 7 shows the results of ORS comparisons between LS groups and the unidentified group on the three tests. The odds show that the auditory and tactile groups were 2.7 and 2.2 times more likely to perform weakly vs. the Unidentified group on the ABC. For the SCVA test the odds were that every identified LS group was more likely to perform stronger when compared to the unidentified group. For the Mock test, the odds were that three of the four LS groups were more than likely to score weaker (visual learners 1.5, auditory 2.4, and tactile learners 2.1) than the unidentified group. Looking at the highlighted cell in Table 8, the change in ORS indicates when comparing the change in performance on Mock Test to SCVA Test, an auditory learner was 9 times more likely to score a weak performance than the unidentified group.

Discussions

The following discussions are presented considering the hypotheses developed and results presented above. As a point of reference, the results showing several *P* values above conventional thresholds suggest there are limitations to the above conclusions. Furthermore, the effect sizes and confidence intervals should be considered complementary metrics to the conclusions drawn. The statistics and odds ratio indicate that visual learners were **no** more likely than other learners to process complex data more effectively. Rather, the study finds the kinesthetic group performed equally well on both simulated data testing incidences.

Therefore, as discussed below, H1 was not supported, while H4 was supported. Likewise, interesting conclusions are suggested by comparing Tables 6 and 7. For instance, while each LS group improved their performance from the SCVA test to the Mock-MC test (showing the highest odds of a typical score), their improvement on the Mock-MC test was weaker than the unidentified group, where each group was 1.0 to 2.4 times more likely to earn a weak score. This indicates faculty should use various types of simulated complex data assignments and exercises to help students develop skills needed to analyze complex data, rather than focus on preferred learning techniques.

- H1: Students who self-identify as visual learners will find it **less** difficult to analyze assignments representing complex data such as quantitative problem-based assignments, which do not include multiple choice responses.

This hypothesis was not supported. Odds ratios indicate a visual learner was 1.6 times more likely to have a weak score than either a typical or strong score on SCVA test 2. The odds were maintained in that visual learners performed the weakest on both the ABC (27) and SCVA (34) respectively; those students earned no correct answers on either of these two tests. On the Mock-MC test 33 visual learners performed typically, that is, earning some correct answers (Tables 2 and 3). The descriptive characteristics (Table 1) reveal ($\bar{x} = 40.16$; $s = 42.58$) for the ABC test 1; ($\bar{x} = 29.16$; $s = 40.96$) for the SCVA test 2, and ($\bar{x} = 31.71$; $s = 33.75$) for the mock-MC test. Further, compared to the unidentified group, the visual learners produced a contrast estimate of 0.99, with a 95% confidence interval of -9.522 to 11.498, and $p = 0.8$.

- H2: Students who self-identify as audio learners will find it **more** difficult to analyze assignments representing complex data such as quantitative problem-based assignments, which do not include multiple choice responses.

This hypothesis was delineated by odds ratio. The odds ratios indicated an audio learner was 1.5 times more likely to have a weak score than either a typical or strong score on the ABC test. These odds were maintained in that auditory learners performed the weakest on both the ABC and SCVA. That is, 3 and 2, respectively, of the 5 students who identified as audio learners did not get any correct answers on either of these two tests. The odds ratio revealed that an auditory learner would be 1.5 times more likely to have a typical score on the Mock-MC test. In fact, three auditory learners performed typically on the Mock-MC test, that is, they got some correct answers (Tables 2 and 3). Further, table 1 reveal ($\bar{x} = 13.40$; $s = 21.74$) for the ABC test; ($\bar{x} = 13.60$; $s = 17.73$) for the SCVA test, and ($\bar{x} = 33.20$; $s = 35.24$) for the Mock-MC test. When compared to the unidentified group, the audio learners produced a contrast estimate of -12.6, with a 95% confidence interval of -36.9 to 11.7, $p = 0.3$. A small percentage of auditory learners may have impacted the results although they provide support for this hypothesis; auditory students performed the best on the multiple-choice response test 3.

- H3: Students who self-identify as tactile learners will find it **less** difficult to analyze assignments representing complex data such as quantitative problem-based assignments, which do not include multiple choice responses.

These results indicate there is some support for this hypothesis, although the odds were greater for weaker performance. The odds ratios indicated that a tactile learner was 1.2 and 1.8 times more likely to have a weak score than either a typical or strong score on the ABC test and the SCVA test. The odds were maintained; these learners performed the weakest on both the ABC and SCVA testing incidents. That is, 6 and 7 of the 11 students who identified as tactile learners respectively earned no correct answers on either of these two tests. The odds ratio also revealed that a tactile learner would be 1.8 times more likely to have a typical score on the Mock-MC test. Seven tactile learners performed typically on the Mock-MC test, that is, they got some correct answers here (see Tables 2 and 3). Further, the descriptive characteristics (table 1) reveal ($\bar{x} = 34.82$; $s = 43.07$) for the ABC test 1; ($\bar{x} = 15.16$; $s = 30.22$) for the SCVA test 2, and ($\bar{x} = 33.20$; $s = 35.24$) for the Mock-MC test. When compared to the unidentified group, the tactile learner produced a contrast estimate of -7.5, with a 95% confidence interval of -24.9 to 9.9, $p = 0.4$. The small sample size ($n = 11$) of tactile learners could have impacted these results.

- H4: Students who self-identify as kinesthetic learners will find it **less** difficult to analyze assignments representing complex data such as quantitative problem-based assignments, which do not include multiple choice responses.

The results indicate some support for this hypothesis; Kinesthetic students performed almost equally on the ABC test 1 and SCVA test 2. The odds ratios indicated a kinesthetic learner was 0.8 times more likely to have a typical score than either a weak or strong score on both the ABC test and the SCVA test. The odds were maintained, coincidentally, of the 23 students who identified as kinesthetic learners 10 and 10 (respectively) performed typically on both ABC and SCVA. The odds ratio also revealed these learners would be 2.8 times more likely to have a typical score on the Mock-MC test. Seventeen kinesthetic performed typically on the Mock-MC test, they earned some correct answers (Tables 2 and 3). Further, the descriptive characteristics (table 1) reveal ($\bar{x} = 38.39$; $s = 38.06$) for the ABC test 1; ($\bar{x} = 38.39$; $s = 38.42$) for the SCVA test 2, and ($\bar{x} = 41.35$; $s = 29.25$) for the Mock-MC test. When compared to the unidentified group, the tactile learner produced a contrast estimate of 6.7, with a 95% confidence interval of -6.7 to 20.0, $p = 0.3$.

Rationale of Learning Techniques vs. Odds Ratio Results

Learning is based on the students' reaction in the classroom rather than on the instructor. Consequently, possible reasons for the above results are that visual learners may look at data, but do not interact with it deeply and from a critical lens. Analyzing data often requires more than seeing it, analysis requires thought, calculations, reflection, practice, etc. (Ulfiana, et al.2019). Visual learners usually prefer visual data aids such as pictures, charts, etc. which are not typically used in instructions in an accounting course.

Auditory learners are often referred to as aural learners; they prefer to learn via listening. By interacting through listening to lectures, discussions, or even simply talking aloud to themselves, these learners retain information about concepts more easily (Anu, 2023; Ela Ulfiana et al., 2019). Kaylar & Kaylar (2017) in their study of language

learners suggest auditory learners should study in groups, talk things out, read aloud, tape record the lectures for (post class learning) and engage in small study groups, rather than taking lecture notes in writing. These suggestions, while very important, can only be effective when done. Most accounting courses do not have the capacity for students to do so in a typical class. Moreover, in an exam, the instructor most likely will not allow students to read questions out loud, nor have visual aids for visual learners. Therefore, this could explain why the odds of visual and auditory learners performing well on complex assessments will likely decrease.

Kinesthetic and tactile learners need to engage by feeling touching, reading, and writing. Tactile preferred learning emphasizes text-based input and output. They interact with materials presented such as manuals, reports, essays, or assignments. Kinesthetic learning is hands-on, focused primarily on trial and error as an avenue to learning. They learn best with puzzles, games, roleplay, demonstrations, taking breaks between activities and memorizing lines while walking around. They must be continuously and actively exploring. The kinesthetic approach to learning is based on critically mastering concepts through content, which are delivered in didactic presentations, small group case-based discussion, and self-directed learning (Anu, 2023; Hernandez, et al., 2020; Stephenson, 2020). In a typical accounting classroom, instructors will usually use PowerPoints to teach concepts, they often use case studies, and small group discussions. Therefore, these learners tend to be self-directed. It is not surprising that the odds are greater of them performing stronger on a complex simulated test than the visual or auditory learner.

Conclusion and Implications

The study was conducted in two managerial accounting courses; N=137 students participated in the three testing incidences (quantitative ABC-1, SCVA-2, and multiple-choice) used in the experimental design. The tests were graded, and the results were analyzed using repeated measures ANOVA, other statistical analyses, and Odds ratio analysis. The results indicate and agree with studies such as Busan (2014) and Stephenson (2020) that most students identify as visual learners, followed by auditory or kinesthetic learners in the general population. The results show the odds are great that accounting students who self-identify as visual and auditory learners will find it more difficult to analyze complex data. The odds are in favor of students who identify as kinesthetic to have less difficulty analyzing complex data. Interestingly, the results are not as convincing for those who identify as tactile learners; they suggest tactile learners are somewhat likely to find it less difficult to analyze complex data. While each LS group improved their own performance from the SCVA test to the Mock-MC test (showing the highest odds of a typical score), their improvement on the Mock-MC test was weaker than the unidentified group, where each group was 1.0 to 2.4 times more likely to earn a weak score than the unidentified group.

The odds ratios in this study indicate an agreement with Buşan's (2014) findings that medical students who self-identify as kinesthetic learners usually want to learn in environments where they can use their skills to understand simulations about patient care, which requires much cognitive reasoning. It also concurs with The University of Illinois Extension (2009) study indicating that students identifying as kinesthetic learners, want to learn using various simulations, experiments, teamwork, etc. Moreover, these findings draw a parallel with those of Stephenson (2019) LAMP-D where she found that visual, tactile, and kinesthetic learners' preference for quantitative problem-based assessments is positively, statistically, and significantly affected by contextual learning modalities.

The odds ratios also indicate an agreement with the Accountancy Futures Academy Project Report entitled, *Big Data Its Power and Perils* (2013), sponsored by the Association of Chartered Certified Accountants and the Institute of Management Accountant. It noted that faculty should infuse quantitative assessments and assignments which simulate critical thinking about analyzing complex data into their courses and include exams which test and help to develop the analytical abilities of students. This is imperative regardless of student's preferred learning techniques (The Futures Company Project, 2013).

Implications and Limitations

This study is important in its contribution to our understanding of accounting students' preferred learning techniques and the odds of them improving their performance on tests as they are exposed to more complex accounting data throughout the semester. It also contributes to the limited extant literature regarding the correlations of these concepts, whether students learning techniques impact their ability to acquire the skills needed to analyze simulated

complex data. The challenges and changes which complex data analysis brings to the accounting profession of practice emphasizes why it is critical for accounting students to garner the ability to analyze complex data.

One limitation noted is that statistical significance and confidence intervals, as normally denoted by .05 *P* values, were not optimal in most of the results. Another limitation is the size of some of the groups and the fact that the learning techniques were self-reported. Nevertheless, it is a starting point and a rationale for more studies about complex data and analytical assessments in accounting course design. Contrarily, Rosnow and Rosenthal (1989) suggested there is overreliance on dichotomous significance-testing decisions. They note that, “defining the results of research in terms of significance levels alone fails to tell the whole story of a research” (p. 1278). They suggest that some fields, particularly the social sciences, do not need to measure the validity of effects by .05 *p* values. Although the measures of significance for this study did not meet the strict .05 standard for experimental sciences, we must keep in mind the fact that this behavioral analysis was conducted using self-identified learning techniques. Moreover, the social nature of the project indicates that this level of significance for individual effects is potentially occurring over the course of the three tests, which may have produced significant differences if a larger sample size was used. Therefore, the contribution of this study for the accounting programs should be the focus on curriculum, which includes assessments and activities, simulating complex data, regardless of students preferred learning techniques and or learning modalities.

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Appendices

Appendix 1 Figures & Tables

Figure 1. *Distribution of Learning Techniques Within the General Population*

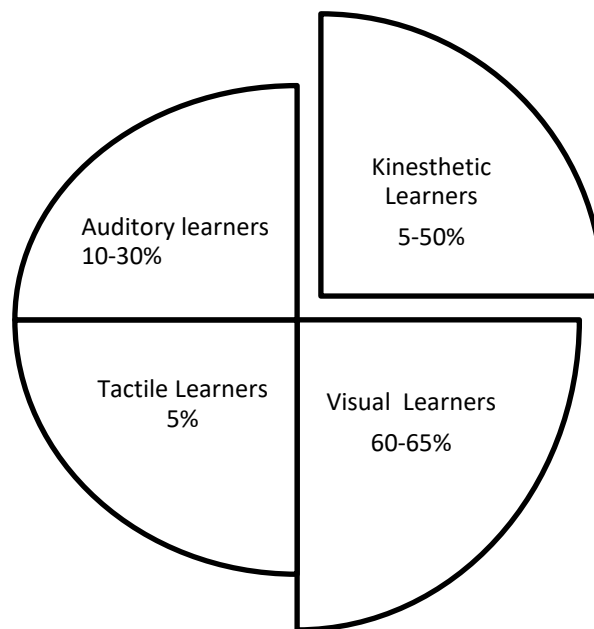


Figure 2. Conceptual Framework

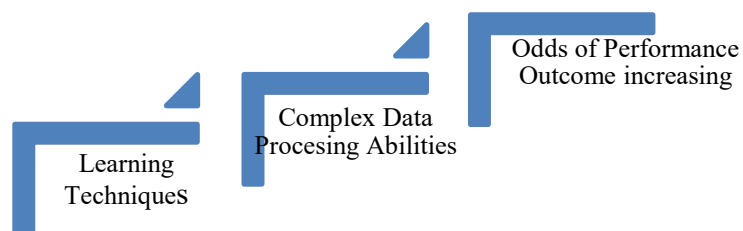


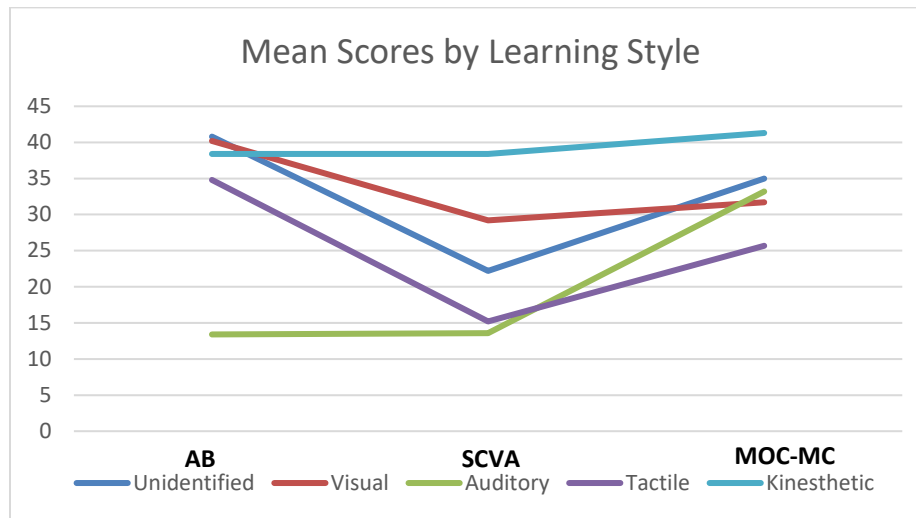
Figure 3. *Changes in Test Score Performance by Group.*

Table 1. *Descriptive Characteristics by Group Test Scores*

Tests	Learning Style	Mean	SD	N
ABC	Unidentified	40.89	38.78	42
	Visual	40.16	42.58	56
	Auditory	13.40	21.74	5
	Tactile	34.82	43.07	11
	Kinesthetic	38.39	38.06	23
	Overall	38.68	39.98	137
SCVA 2	Unidentified	22.19	28.65	42
	Visual	29.16	40.96	56
	Auditory	13.60	17.73	5
	Tactile	15.18	30.22	11
	Kinesthetic	38.39	38.42	23
	Overall	26.88	35.92	137
Mock-MC	Unidentified	35.00	32.21	42
	Visual	31.71	33.75	56
	Auditory	33.20	35.24	5
	Tactile	25.73	28.18	11
	Kinesthetic	41.35	29.25	23
	Overall	33.91	32.00	137

Table 2. *Repeated Measures ANOVA*

Tests	<i>F</i>	<i>p</i>
Within LS group Main Effect	2.2	0.1
SCVA compared to ABC	4.162	0.043
Mock-MC compared to SCVA	3.176	0.077

Table 3. *Individual Learning Techniques Compared to Unidentified Group*

Group Contrast	Estimated Hypothesized Value	Standard Error	<i>p</i>	95% Confidence Lower	95% Confidence Upper
Visual Learners vs Unidentified	.988	5.313	0.8	-9.522	11.498
Auditory Learners vs Unidentified	-12.624	12.314	0.3	-36.983	11.735
Tactile Learners vs Unidentified	-7.448	8.816	0.4	-24.888	9.992
Kinesthetic Learners vs Unidentified	6.686	6.752	0.3	-6.67	20.043

Table 4. *Distribution of Test Results by Learning Style Including Mean Exam Percentage*

Learning Style	ABC			SCVA			Mock-MC		
	Weak	Mean% Typical	Strong	Weak	Mean% Typical	Strong	Weak	Mean% Typical	Strong
Unidentified		40.89%			22.19%			35.00%	
	15	21	6	20	20	2	9	29	4
Visual		40.16%			29.16%			31.71%	
	27	17	12	34	13	9	16	33	7
Auditory		13.40%			13.60%			33.20%	
	3	2	0	2	2	1	2	3	0
Tactile		34.82%			15.18%			25.73%	
	6	3	2	7	3	1	4	7	0
Kinesthetic		38.39%			38.39%			41.35%	
	9	10	4	9	10	4	5	17	1

Table 5. *Odds Distribution of Test Results by Learning Style*

Learning Style	ABC			SCVA			Mock-MC		
	Weak	Typical	Strong	Weak	Typical	Strong	Weak	Typical	Strong
Unidentified	0.6	1.0	0.2	0.9	0.9	0.1	0.3	2.2	0.1
Visual	0.9	0.4	0.3	1.6	0.3	0.2	0.4	1.4	0.1
Auditory	1.5	0.7	0.0	0.7	0.7	0.3	0.7	1.5	0.0
Tactile	1.2	0.4	0.2	1.8	0.4	0.1	0.6	1.8	0.0
Kinesthetic	0.6	0.8	0.2	0.6	0.8	0.2	0.3	2.8	0.1

Table 6. *Change in Odds Ratios, Comparing SCVA Test to ABC Test, & Mock Test to SCVA Test*

Learning Style	SCVA Compared to ABC			Mock-MC Compared to SCVA		
	Weak	Typical	Strong	Weak	Typical	Strong
Unidentified	1.6	0.9	0.3	0.3	2.2	0.1
Visual	1.7	0.7	0.7	0.4	1.4	0.1
Auditory	0.4	1.0	*	0.7	1.5	0.0
Tactile	0.5	1.0	0.5	0.6	1.8	0.0
Kinesthetic	1.0	1.0	1.0	0.3	2.8	0.1

Note: * indicates computation was not possible because the divisor was zero.

Table 7. *Odds Ratios for Individual Learning Techniques Compared to the Unidentified Group*

Each Learning Style vs Unidentified	ABC			SCVA			Mock-MC		
	Weak	Typical	Strong	Weak	Typical	Strong	Weak	Typical	Strong
Visual	1.7	0.4	1.6	1.7	0.3	3.8	1.5	0.6	1.4
Auditory	2.7	0.7	0.0	0.7	0.7	5.0	2.4	0.7	0.0
Tactile	2.2	0.4	1.3	1.9	0.4	2.0	2.1	0.8	0.0
Kinesthetic	1.1	0.8	1.3	0.7	0.9	4.2	1.0	1.3	0.4

Table 8. *Change in Odds Ratios, Comparing Each Learning Style to the Unidentified Group, and Performance on SCVA Test Compared to ABC Test, and Mock Test to SCVA Test.*

Each Learning Style vs Unidentified	SCVA Compared to AC			Mock-MC Compared to SCVA		
	Weak	Typical	Strong	Weak	Typical	Strong
Visual	1.0	0.8	2.3	1.5	0.8	0.6
Auditory	0.3	1.1	*	9.0	0.6	0.0
Tactile	0.9	1.1	1.5	2.4	0.7	0.0
Kinesthetic	0.6	1.1	3.3	1.7	1.1	0.1

Appendix 2: Experimental Test: Activity Based Costing

Treatment Group: The purpose of this research has been explained, and my participation is voluntary. I have the right to stop participating at any time without penalty. I understand that the research has no known risks, and I will not be identified. By completing these assignment(s) I agree to participate in this research project.

Signed by: _____

Use 1, 2, 3, or 4 to indicate your dominant or established learning style in order of 1 being most dominant, 4 being least dominant.

Established Learning style¹: Visual _____; Audio _____; Tactile (manipulation) _____; Kinesthetic (whole –body, problem solving, experiment, etc.) _____

Formative Questions²

1. Carpo Company uses activity-based costing to determine the costs of its two products: A and B. The estimated total cost and expected activity for one of the company's three activity cost pools are as follows.
- 2.

<u>Estimated Cost</u>	<u>Expected Activity</u>	
	<u>Product A</u>	<u>Product B</u>
\$28,000	400	300

Part (a) What is the activity rate under the activity-based costing system for this activity?

Part (b) How much total cost is expected to be individually assigned to Products A and B for this activity?

2. Forrer Company has two products: A and B. The annual production and sales level of Product A is 18,188 units. The annual production and sales level of Product B is 31,652 units. The company uses activity-based costing and has prepared the following analysis showing the estimated total cost and expected activity in units for each of its three activity cost pools.

<u>Activity Cost Pool</u>	<u>Estimated Cost</u>	<u>Expected Activity</u>	
		<u>Product A</u>	<u>Product B</u>
Activity 1	\$ 80,000	200	800
Activity 2	360,000	600	5,400
Activity 3	58,400	1,000	500

Part (a) What is the total overhead cost allocated to Product B under activity-based costing (rounded to dollars and cents)?

Part (b) What is the overhead cost per unit of Product B under activity-based costing (rounded to dollars and cents)?

3. Forrer Company has two products: A and B. The annual production and sales level of Product A is 18,188 units. The annual production and sales level of Product B is 31,652 units. The company uses activity-based costing and has prepared the following analysis showing the estimated total cost and expected activity in units for each of its three activity cost pools. (Note that the information provided above is the same as that provided

¹ The unidentified group completes the same tests. However, the (treatment) learning techniques are removed.

² All exercises from each chapter were excerpted from course materials for Noreen, Brewer, and Garrison (2014). *Managerial Accounting*. McGraw-Hill.

for the previous question.)

<u>Activity</u> <u>Cost Pool</u>	Estimated <u>Cost</u>	<u>Expected Activity</u>	
		<u>Product A</u>	<u>Product B</u>
Activity 1	\$ 80,000	200	800
Activity 2	360,000	600	5,400
Activity 3	58,400	1,000	500

The following information is also available:

Sales price per unit	\$100.00
Direct material per unit	20.00
Direct labor per unit	10.00

Compute the total profit margin for Product B using activity-based costing.

Appendix 3: Experimental Test: Standard Costing and Variance Analysis

Treatment Group: The purpose of this research has been explained, and my participation is voluntary. I have the right to stop participating at any time without penalty. I understand that the research has no known risks, and I will not be identified. By completing these assignment(s) I agree to participate in this research project.

Signed by:

Use 1, 2, 3, or 4 to indicate your dominant or established learning style in order of 1 being most dominant, 4 being least dominant.

Established Learning style: Visual ____; Audio ____; Tactile (manipulation) ____; Kinesthetic (whole –body, problem solving, experiment, etc.) ____

Formative Questions

1. McCort Company employs a standard cost system in which direct materials inventory is carried at standard cost. The company has established the following standards for the prime costs of one unit of product:

	Standard <u>Quantity</u>	Standard <u>Price</u>	Standard <u>Cost</u>
Direct materials	12.0 pounds	\$14.00/pound	168.00
Direct labor	2.6 hours	\$44.00/hour	\$114.40

During April, the company purchased 330,000 pounds of direct material at a total cost of \$4,686,000. The total factory wages for June were \$3,200,000, of which 90% was for direct labor. The company manufactured 25,000 units of product during April using 302,000 pounds of direct material and 64,000 direct labor hours.

Part (a) What is the direct material quantity variance for April?

Part (b) What is the price variance for the direct material acquired by the company during April?

Part (c) What is the direct labor efficiency variance for April?

Part (d) What is the direct labor rate variance for April?

3. Expedient Company maintains warehouses that stock items carried by its e-retailer clients. When one of Expedient's clients receives an order from an online customer, the order is forwarded to Expedient. The item is then pulled from the warehouse, packed, and shipped to the customer. Expedient uses a predetermined variable overhead rate based on direct labor-hours. According to the company's records, 0.04 direct labor hours are required to fulfill an order for one item and the variable overhead rate is \$3.25 per direct labor hour. During December, Expedient shipped 120,000 orders using 4,600 direct labor-hours. The company incurred a total of \$14,720 in variable overhead costs.

Part (a) What is the variable overhead rate variance during December?

Part (b) What is the variable overhead efficiency variance during December and for March?

Appendix 4: Experimental Test Mock-Exam (pre-exam)

Treatment Group: The purpose of this research has been explained, and my participation is voluntary. I have the right to stop participating at any time without penalty. I understand that the research has no known risks, and I will not be identified. By completing these assignment(s) I agree to participate in this research project.

Signed by: _____

Use 1, 2, 3, or 4 to indicate your dominant or established learning style in order of 1 being most dominant, 4 being least dominant.

Established Learning style: Visual ____; Audio ____; Tactile (manipulation) ____; Kinesthetic (whole –body, problem solving, experiment, etc.) ____

Multiple Choice Responses

ABC Costing

Pisghat Company has two products: D and E. The annual production and sales level of Product A is 18,188 units. The annual production and sales level of Product B is 31,652 units. The company uses activity-based costing and has prepared the following analysis showing the estimated total cost and expected activity in units for each of its three activity cost pools.

<u>Activity Cost Pool</u>	<u>Estimated Cost</u>	<u>Expected Activity</u>	
		<u>Product D</u>	<u>Product E</u>
Activity 1	\$80,000	200	800
Activity 2	360,000	600	5,400
Activity 3	58,400	1,000	500

2. What is the total overhead cost allocated to Product D under activity-based costing (rounded to dollars and cents)?

- A. \$407,267
- B. \$407,876
- C. \$407,467
- D. \$407,976

4. What is the overhead cost per unit of Product E under activity-based costing (rounded to dollars and cents)?

- A. \$12.87
- B. \$11.28
- C. \$22.00
- D. \$21.27

Standard Costing and Variance Analysis

Mickey Company uses a standard cost system in which direct materials inventory is carried at standard cost. The company has established the following standards unit costs for the prime costs of product X:

<u>Standard Quantity</u>	<u>Standard Price</u>	<u>Standard Cost</u>
------------------------------	---------------------------	--------------------------

Direct materials	12.0 pounds	\$14.00/pound	168.00
Direct labor	2.6 hours	\$44.00/hour	\$114.40

During April, the company purchased 330,000 pounds of direct material at a total cost of \$4,686,000. The total factory wages for June were \$3,200,000, of which 90% was for direct labor. The company manufactured 25,000 units of product during April using 302,000 pounds of direct material and 64,000 direct labor hours.

5. What is the direct material quantity variance for April?

- A. \$28,000 (F)
- B. \$28,000 (U)
- C. \$32,000 (U)
- D. \$32,000 (F)

6. What is the price variance for the direct material acquired by the company during April?

- A. \$66,000 (F)
- B. \$62,000 (U)
- C. \$66,000 (U)
- D. \$62,000 (F)

7. What is the direct labor efficiency variance for April?

- A. \$44,000 (U)
- B. \$42,000 (U)
- C. \$42,000 (F)
- D. \$44,000 (F)

7. What is the direct labor rate variance for April?

- A. \$64,000 (F)
- B. \$64,000 (U)
- C. \$46,000 (U)
- D. \$46,000 (F)