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Use of an Intelligent Tutoring System and Academic Performance in an Online College Course for Pre-Nursing Students

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Walden University
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Abstract

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Mark P. Schmidt

MA, Wright State University, 2003

BS, Purdue University, 1993

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

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Abstract

The efficacy of intelligent tutoring systems (ITS) for undergraduate college level courses was not well established and specifically, the Pearson Dynamic Study Modules (PDSM) program had not been investigated locally. The purpose of this quantitative study was to determine whether the use of an ITS designed with a cognitive learning approach; the PDSM, would enhance pre-nursing student academic performance. The multiple attribute decision making and the human plausible reasoning theories grounded the study. A non-experimental quantitative research design was used to determine whether there was a difference in the assessment scores of pre-nursing students in a college level anatomy and physiology course based on their use of the PDSM while controlling for prior GPA. A multiple analysis of covariance test was used to compare the archival scores of pre-nursing students (*N* = 99) from twelve online sections of an anatomy and physiology course from a small Midwestern college where the PDSM program was an available study aid for the students. This study looked at the cumulated use of the ITS over the course of a full 16-week semester and confirming conclusions from similar studies, found that there was no causal relationship between the use of the PDSM and the students' assessment scores when controlling for prior GPA. Recommendations for future studies include a focus on individual chapters and the amount of intelligent tutor use within the chapter itself to determine if there is any effect on individual chapter assessment scores. Positive social change is facilitated for undergraduate nursing students when research-derived study strategies are identified for inclusion or exclusion to enhance students' academic performance.

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Dedication

I would like to dedicate this dissertation to my mother and father, Phillip and Elaine Schmidt, who showed me the power and value of education from the very start. Their tireless support and amazing work ethic continue to this day and will always be an inspiration in my life.

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At the completion of this dissertation, I would like to acknowledge my wife and family without whose support I would not have been able to complete this monumental task. Marisue, Xavier, Alexandria and Lydia I am so thankful for all of your support and acceptance of the time I had to commit to this degree. I also want to thank my dissertation committee for their countless revisions and support throughout the process. I would like to thank Dr. Lapin and Dr. Lane for their tireless work on this study. I would especially like to thank Dr. Carla Lane who was much more than my dissertation chair. She directed and coached me with compassion, friendship, and an occasional metaphorical kick in the pants to get back to work when needed. I could not have made it to the finish line without the unrelenting support of all those around me. Thank you one and all.

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Chapter 1: Introduction to the Study

The topic of this study was the efficacy of intelligent tutor systems (ITS) for a college level online anatomy and physiology course. The advancement of artificial intelligence (AI) in the educational sector has provided many opportunities for advancements in educational technology and pedagogical adaptions, especially in the online environment (Guan et al., 2020). However, the penetration rate and acceptance of ITS has remained relatively low in the 50 years since it was first developed (Almasri et al., 2019). Instructors have cited a lack of apparent advantage, compatibility, and perceived trust as contributing determinants in their willingness to adopt and implement AI strategies and specifically ITS in their curriculum (S. Wang et al., 2020). A 2016 meta analytic study (Kulik & Fletcher, 2016) showed that in the last 30 years, less than 50 quantitative studies had been completed on ITS, and more than two thirds of those studies related to one specific ITS, the Cognitive Tutor System.

Through this study I addressed this gap in research by looking at the efficacy of one specific ITS program called dynamic study modules, used in an undergraduate online anatomy and physiology course. I did so by evaluating the change in assessment scores relative to the students' use of the dynamic study modules over the course or a full semester, an aspect of ITS evaluation that had been absent in scholarly research up to this point (Almasri et al., 2019; Cavanagh et al., 2019; Lim et al., 2019). A systematic and formulaic intelligent tutoring system might be one key to positive social change in that it would provide personalized remediation for each student, increasing foundational knowledge and overall scores as well as individual self-efficacy. This could lead to increased completion rates in the courses being studied, allowing for faster completion of the nursing curriculum. This can ultimately address the nursing shortage particularly prevalent in rural and underserved areas (Thill, 2019).

This chapter briefly summarizes the current research that relates to ITS development and design as well as the gap in knowledge that had been identified. It also details the problem statement for the study as well as its' purpose and the research question. The theoretical framework is also introduced along with the nature of the study. This chapter includes definitions of the independent and dependent variables as well as the assumptions of the study and the scope and delimitations that define the boundary of the current work and concludes with a brief discussion of the significance of the study and a summary.

Background

According to U.S. Department of Education data, the number of college students taking at least one online class increased from 37% to 51.8% between the fall of 2019 and the fall of 2020 (Singh & Thurman, 2019). This rise in online class participation was calculated with pre-COVID numbers and will be markedly higher for the COVID pandemic period once that data become fully available and cross-referenced with pre- and post-pandemic statistics (Onyema et al., 2020).

Fully online, and in most cases asynchronous, students have a more difficult time connecting with tutoring services provided by the school, instructor, or outside institutions and there is a need for real time remediation within most school and academic platforms (Archambault et al., 2022; Bodily et al., 2019; Carlana & La Ferrara, 2021).

ITS systems provide one possible method of assistance to these remote students, in that they are available at any time, work with a wide variety of content and are adaptable to most academic delivery platforms (Beer et al., 2022; Ferri et al., 2020; X. Li et al., 2022). A review of literature on ITS, in college level students, shows that effects of ITS programs on the academic achievement of students is still not fully understood (Almasri, Ahmed, Al-Masri, et al., 2019; Guo et al., 2021; Slavin, 2019). In a meta-analysis of findings from 50 controlled evaluations of intelligent computer tutoring systems from over the past 30 years, Kulik and Fletcher (2016) found the median effect of ITS was to raise test scores 0.66 standard deviations over conventional levels. This review also exposed the fact that quantitative assessment of ITS programs has been limited, in both number and scope, as more than two thirds of these studies directly related to one ITS program.

Previous studies have not adequately addressed the effectiveness of current ITS programs to remediate individual college level students and provide quantitative statistics on the impact of ITS use over the course or a full 16-week semester (Dang et al., 2017; Guan et al., 2020; Huda et al., 2018; Jaiswal et al., 2017; Resnick & Johnson, 2020). This study was designed to provide data within this area of research deficit by providing data on the effects of ITS use within an online college level anatomy and physiology course over a 16-week semester. The study evaluated the statistical difference of students' individual chapter test scores, as well as midterm and final test scores, based on their overall use of the dynamic study module program, while controlling for the student's prior GPA.

Problem Statement

The problem addressed in this study was that the efficacy of ITS for undergraduate college level courses was not well established (Guan et al., 2020; Kumar & Ahuja, 2020; Yuce et al., 2019; Zawacki-Richter et al., 2019). Previous studies had not adequately addressed the effectiveness of current ITS programs to remediate individual college level students and discern between basic knowledge acquisition and impactful understanding of the overall concepts in a fully online class (Dang et al., 2017; Guan et al., 2020; Huda et al., 2018; Jaiswal et al., 2017; Resnick & Johnson, 2020). More specifically, the efficacy of the Pearson Dynamic Study Modules program had not been investigated (Williamson, 2017). Pearson's Dynamic Study Modules followed the latest model of ITS design, using proprietary analytics based on the cognitive science of learning, with modules designed to function as an online personalized tutor for each individual learner (Williamson, 2017). In this study, I looked at changes in learning outcomes for students using different levels of ITS in a college level, online anatomy and physiology course. Most of the students in this research group were pre-nursing students, and there was a shortage of nursing students and nurses, particularly in rural and lower socioeconomic areas of the country. This study provided statistical evidence about the efficacy of an ITS program to remediate undergraduate college students within a fully online anatomy and physiology course over the span of one semester.

Purpose of the Study

The purpose of this quantitative study was to answer the question of whether the use of an ITS, specifically Person's Dynamic Study Modules, alters knowledge acquisition in a fully online undergraduate college level anatomy and physiology course. To do this, I determined whether there were changes in academic achievement for students based on different levels of dynamic study modules utilization in a college level, online anatomy and physiology course. I compared assessment scores for students in five different categorical groups based on their self-selected use of the ITS being studied, the dynamic study module. The dependent variable in this study was the students' test scores, and the independent variable was the amount of use of the dynamic study module. A covariate, GPA, was also used to allow for a truer comparison between the groups.

The data for this study were archival and was accumulated from 12 sections of a first semester anatomy and physiology course taught completely online between the fall of 2018 and the spring of 2020. The study group consisted of students from those sections that completed the course and used the dynamic study modules program to varying degrees. The majority of the students in this research group were pre-nursing students and the study showed the effectiveness of the Pearson DSM's on altering knowledge acquisition over time, based grades of the assessments within the course, on a student-by-student basis while controlling for the student's prior GPA. The study was nonexperimental in nature because the students self-selected into each of the study groups based on their participation and use of the program being evaluated. The research question used in this study was designed to determine the overall change in academic performance, if any, experienced by students using the ITS to varying degrees.

Research Question and Hypotheses

Research Question 1: How does the level of ITS utilization in a first semester online anatomy and physiology course differentiate academic achievement, as measured by assessment scores over the course of a 16-week semester, when controlling for GPA?

$H_0$1: The level of ITS utilization in a first semester online anatomy and physiology course does not alter academic achievement when controlling for GPA?

H_a1: The level of ITS utilization in a first semester online anatomy and physiology course increases academic achievement when controlling for GPA?

The independent variables for this study were 12 chapter assessment scores as well as one midterm and one final assessment for the course. The possible score range for the chapter assessments was 0–25 points, and midterm and final assessment score ranges were 0–150 points. I considered the 14 assessments as a whole to see how many of them showed correlation with ITS use. The dependent variable in this study was the amount of ITS use.

Theoretical Foundation

This study was guided by the cognitivism learning theory and how it relates to the process of assimilating and expanding the learner's knowledge base into their existing schemas. Cognitivism asserts that instruction should be organized sequenced and presented in a manner that is understandable and meaningful to the learner while emphasizing retention and recall through the use of quality teaching practices (Piaget, 1976). These were the fundamental tenets of current ITS design, which helped me to study whether an ITS program using this design structure could significantly alter the learning gains of students in a college level online anatomy and physiology course. Student modeling based on a cognitive theory approach strives to interpret human behavior during the learning process, by applying cognitive learning theories to the evaluation of the student, in an attempt to understand the learners process of thinking and understanding (Dermeval et al., 2018a). In a cognitivist approach the teacher, or in this case the ITS, will ask the learner questions to refine their thought process identify wrong ideas, concepts or faulty assumptions and at the same time solidify correct information and ideas (Sotiropoulos et al., 2019). Other specific attributes of the cognitivist approach that are utilized by the ITS in the study were active engagement of the learner in meta cognitive tasks such as self-planning, task and step organization, as well as a sequential revision of mastered content during the learning process (Resnick & Johnson, 2020).

While cognitivism is the guiding theoretical framework for this study, two of the more specific areas of cognitive theory that were used in this paper are the multiple attribute decision making (MADM) theory and the human plausible reasoning (HPR) theory (Alkhatlan & Kalita, 2018). The MADM theory is based on the principle of making preference decisions such as prioritization, choice selection, and assessment of specific criteria, over other available options, that are generally characterized by multiple, usually conflicting, attributes (Jankowski, 2016). The second specific cognitive theory that was used to understand and identify specific aspects of the ITS was the human plausible reasoning theory. This theory uses four types of expressions to qualify the knowledge base of the learner and was helpful in better understanding and explaining potential differences observed between the control and experimental groups. Both theories are more fully explained in Chapter 2.

Nature of the Study

I chose a nonexperimental quantitative design using a multiple analysis of covariance (MANCOVA) test because the variables to be analyzed consisted of more than three independent groups with each group having more than three dependent measures consisting of a continuous test score with a covariate (Gopalan et al., 2020). There were 14 individual assessment scores that were considered as part of the dependent variables measured as continuous test scores that were comprised of the participants' (a) 12 individual chapter test scores, (b) the midterm test scores, and (c) the final exam test score. For this study there were four groups of online anatomy and physiology students selected from classes taken between the fall of 2018 through the spring 2020. There was one control group and three experimental groups composed of students who elected to use the ITS to varying degrees.

The ITS was composed of 46 individual dynamic study modules. Students who completed between 0 and 10 modules were considered to have *no significant use* and served as the control group. The three experimental groups were composed of students who completed between 11 and 20 modules and were placed in a *nominal use* group, students who completed 21 to 30 modules were placed in a *moderate use* group, and students who completed 31 to 48 modules were placed in a *saturated use* group. These variables were considered within the scope of a first semester college anatomy and physiology online course at a small Midwestern community college and none of the variables were manipulated by the researcher. I compared the amount of ITS use and its effect on individual student scores on each of the assessments to test for correlation. The study considered correlation on more than 50% of the assessments to validate the alternative hypothesis and less than 50% correlation on the fourteen assessments to validate the null hypothesis of the study. The covariate of prior GPA allowed for a truer comparison between the experimental and control groups when evaluating differences in academic achievement on the selected assessments. All data being evaluated in this study were archival~~.~~

Definitions

To fully understand the parameters of the study, it is important to be familiar with the major terms and definitions used by technicians and developers of artificial intelligence within online courses and more specifically ITSs. The first area of differentiation that must be applied is between computer assisted instruction (CAI) and ITSs like the one being evaluated in this study. CAI was first described in the 1970s by Carbonell asserting that this new mode of instructional aid could be endowed with enhanced capabilities by incorporating artificial intelligence (AI) techniques to overcome the current limitations (Alkhatlan & Kalita, 2018).

The umbrella of computer aided instruction is quite large, encompassing areas form minimally impactful additions, such as a few weblinks or YouTube videos being incorporated into a curriculum, to a fully online courses that are dependent on multimedia and web interactions and include both didactic learning as well as dynamic real-time interaction on the part of the AI program (Nolin, 2019). In the specifics of this area of design and study most authors agree that CAI generally lacks the ability to monitor the learner's progress and provide individualized steps for intervention that are focused and immediately applicable to the student's area of educational deficit. This study focused on a narrower aspect of AI as instructional aids, specifically ITS and what impact that had on the learning outcomes of individual nursing students in an undergraduate sophomore level anatomy class and the ability of the ITS to provide personalized remediation. ITSs differ from CAI in that the intervention of the program is specially tailored to each learner and creates, or tries to replicate, a one on one interaction that a learner might have with a personal tutor (Akyuz, 2020).

Further, the following is a list of terms that may not be familiar to the reader followed by a definition and/or explanation of that term.

Adaptive intelligence tutoring system: A learning system that can personalize an individual students' learning experiences and facilitate learning of knowledge on a specific subset of academic content (Phillips et al., 2020).

Affective learning intelligent tutoring system: A computerized learning approach that can detect the affective state of the learner to increase cognitive performance and enhance cognition and performance on a specific set of content or educational goals (Kukulska-Hulme, 2019).

Constraint Based Modeling (CBM): A mathematical approach in which the outcome of each decision is constrained by a minimum and maximum range of limits (Karaci, 2019).

Intelligent learning environment (ILE): Refers to a category of educational software in which the learner is placed into a problem-solving situation and is inherently different from traditional courseware based sequence in that the learner is presented with a dynamic and personalized sequence of questions, answers and feedback to facilitate knowledge acquisition (Mavrikis & Holmes, 2019).

Knowledge tracing: The task of modelling student knowledge over time that helps to predict how students will perform on future interactions. Improvement on this task means that resources can be suggested to students based on their individual needs and content that is predicted to be too easy or too hard can be skipped or delayed (Pandey & Karypis, 2019).

Learning factors analysis: A form of student modeling which is used to predict whether a student can correctly answer a computerized tutor's questions relying on prespecified series of metrics (Kumar Basak et al., 2018).

MEBN theory (MTheory): Implicitly represents a joint probability distribution over possibly unbounded numbers of hypotheses, and uses Bayesian learning to refine a knowledge base as observations accrue (Stankus et al., 2020).

Performance factors analysis: Predicts student performance based on item difficulty and student historical performances within a predetermined content set (Alkhatlan & Kalita, 2018).

Assumptions

There were several inherent assumptions within this study. First, I assumed that all students within the research groups fit the age, ethnicity, and overall demographics identified as average by the academic institution hosting the online courses. Because the A&P course is standardized for online delivery, I also assumed that all students received the same instruction, other than those identified in the experimental groups relating to the varying degree of dynamic study module use (Abdullah, 2018). Another assumption was that all assessments of each student, in each research group, were equivalent regardless of the randomization of test questions that occurred on each individual test. This assumption, if accurate, would increase the overall validity of the study, as each student was deemed to be evaluated equally (Z. Li & Chen, 2019). It was also assumed that the testing environments for each student were roughly equivalent. Even though the tests were completed in a home environment that was inherently different from student to student, these differences were assumed to be standardized over the duration of the semester and by the number of individual participants in each group, adding further validity to the study (Guo et al., 2021; Hou & Aryadoust, 2021).

The data used for this study were archived tests results which formed the primary source of overall grades for the course completed by the student and resulted in their final grade for the overall course. Therefore, the data were assumed to be accurate and valid. I also assumed that the student registered for the course was the one that took the assessments and was the one that chose to use or not use the dynamic study modules as a study aid. Because the assessments and course were completed in an online, unproctored environment, these assumptions were key to the validity and completion of the study (Clancey & Hoffman, 2021; X. Hu et al., 2018).

Scope and Delimitations

Scope

The scope of this study was the differences in students' assessments scores from three semesters of an online anatomy and physiology course where students voluntarily used to an ITS program to varying degrees. The test scores of four research groups were analyzed for differences in overall performance relative to the amount of use of the dynamic study modules program. This program has been in place within the online course since the Fall of 2017, but only the scores from the most recent semesters available, fall of 2018 through spring of 2020 were used. The reason for the selection of this time period was that it was the most recent available data and provided the largest data set possible without contributing additional cofounding factors. The selection of this group also excluded possible differences or aberrations caused by a transition into the online format by students due to the COVID pandemic. Students in online sections after the spring of 2020 might have preferred the traditional format of the course. They might not be as well suited for the online environment, but had no choice of selection due to a complete absence of the traditional format of the course; therefore, differences in scores might exist due to these factors rather than those being evaluated in this study (Adnan & Anwar, 2020; Shim & Lee, 2020; Tang et al., 2020). Future studies might compare results from the COVID effected time-period to see if any differences in overall performance could be noted using the data from this study as a control.

Delimitations

This study was delimited to the Bio 2121 Anatomy and Physiology first semester course, and the participants' data that were used were only from those students who fully completed the course and received a letter grade. The fully online sections for two identified instructors from the fall of 2018 through the spring of 2020 were used. The study was confined to archived data from 12 chapter tests as well as one midterm and one final exam score for each student from the anatomy and physiology course. These scores were sorted into research groups based on archived data of the student's self-selected participation and use of the dynamic study modules program. The data were archived at the Pearson Benjamin Cummings, Mastering A&P web site, which could be accessed through a weblink within the online course shell.

Cognitivism was chosen as the theoretical framework of the study as it is a good fit for the research problem and overall purpose of the study. Cognitivism asserts that instruction should be organized, sequenced and presented in a manner that is understandable and meaningful to the learner while emphasizing retention and recall through the use of quality teaching practices (Piaget, 1976). These are the fundamental tenants and root design structure of the dynamic study modules used in this study. The effects of this ITS program with a cognitivist approach on learning, knowledge acquisition, and retention were the focus of the study. Two of the more specific areas of cognitive theory that were used in this study were the MADM theory and the HPR theory (Alkhatlan & Kalita, 2018). These theories provided a background and understanding for the design of the dynamic study modules and how that relates to the overall field of ITS research from its inception in the 1970s to today.

Limitations

A limitation of this study was the fact that the research groups were not randomly assigned. The subjects within the study self-selected their research group by the number of dynamic study modules they completed. Additionally, the research groups were defined in an ex-post facto, after participation process to create the levels of the independent variable. The lack of randomization effects the external validity of the study. Two strategies were used to mitigate this limitation and add validity to the study. First was the inclusion of the covariate of prior GPA. Second was the exclusion of any student that did not fully complete all the assigned units within the course and received a final grade based on their test scores. The combination of these strategies allowed for discrimination between students who completed all the content and assessments within the course and received a final grade of F, which were retained in the sample, and those who did not complete the course content but did not withdraw and also received a failing grade. The archived data included three semesters and two different instructors; this did add some variability to the study. However, this was offset by the increased sample size which augmented the statistical power of the study (Aikens et al., 2020).

Another area of concern for external validity was the use of a nonexperimental design, which by convention lacks the randomization of a true scientific experiment (Gopalan et al., 2020). This lack or randomization could also lead to threats in the study’s generalizability, but according to Aikens et al. (2020), well-designed nonrandom studies, with a high degree of statistical power, can be generalized for similar settings. When evaluating data from online courses completed at offsite locations for this and similar environments, factors like the type of ITS used, location, distractions within the environment, time during the day when assessments were completed, and overall testing environment differences can threaten the construct validity of the study (Hou & Aryadoust, 2021; Vetter & Schober, 2018). However, these threats to validity and generalizability were mitigated because these factors were relatively consistent for all participants and the archived data were collected over several semesters.

A bias that is also inherent within this study is that I worked at the same institution where these courses were being taught. This bias and ethical issue were minimized because I had no direct contact with the students or instructors within these sections once the semester began and there was no interaction or direction given by me to these individuals that would in any way impact the data or results of this study. More detailed discussion of these limitations, biases, and threats to both internal and external validity are provided in Chapter 3.

Significance

This research may be valuable to both instructors who would use and designers who would develop ITSs because recent historical analysis and metanalytic studies showed that in the last 30 years, less than 50 quantitative studies had been completed on ITS, and more than two thirds of those studies related to one specific intelligent tutoring program (Alkhatlan & Kalita, 2018; Almasri, et al., 2019; Guan et al., 2020; Kulik & Fletcher, 2016b). Previous studies have not adequately addressed the effectiveness of ITS to remediate individual students or discern between basic knowledge acquisition and impactful understanding of the overall concepts in a fully online class (Almasri, et al., 2019; Dang et al., 2017; Guan et al., 2020; Jaiswal et al., 2017). This study was able to provide statistical evidence relating to the efficacy of an ITS to remediate undergraduate college students within a fully online anatomy and physiology course.

At the time of this study a little over 50% of current higher education students at public institutions took at least one online course (Carlana & La Ferrara, 2021). Though the online model of education is well proven, the national average for student to teacher ratios in higher education at the time of this study were sixteen to one (Seaman et al., 2018) and the need for on-demand individualized attention and remediation within the online environment could be instrumental in facilitating better outcomes in learning, retention, and proficiency (Nakata et al., 2017; Saultz & Fusarelli, 2017; Sottilare et al., 2017). A systematic and formulaic intelligent tutoring system might be one key to positive social change in that it would provide personalized remediation for each student, increasing foundational knowledge and overall scores as well as individual self-efficacy. This enhanced acquisition of knowledge could lead to increased completion rates in the courses being studied, allowing for faster completion of the nursing curriculum and ultimately helping to address the overall nursing shortage particularly prevalent in rural and underserved areas (Thill, 2019).

Summary

This chapter described the topic of the study as an evaluation on a current ITS program and its effects on knowledge acquisition and retention within a first semester online college anatomy and physiology course. It provided a brief overview of the current research on ITS and identified the gap in literature relating to efficacy of ITS programs within fully on online college courses. The chapter also identified that the purpose of this nonexperimental study was to determine whether the use of the dynamic study modules program effected either the chapter-by-chapter assessments scores of learners or had any effect on midterm or final assessment scores for these same students over the duration of a one semester course while controlling for the learners' prior GPA. The study was guided by cognitivism and more specifically the HPR and MADM theories, which closely align with the overall design of the dynamic study modules used in this study.

The chapter also discussed limitations and threats to validity, such as the fact that I work at the same institution where the classes for this study were being taught. The chapter then detailed how these threats would be mitigated and what measures were taken to increase the overall legitimacy and generalizability of the study. This chapter also described the significance of the current study and its potential to help determine if ITS programs could benefit students in a first-year anatomy and physiology course. The study used a nonexperimental design and archival data to answer this question.

The next chapter provides an overview of the research that was current at the time of this study on the topic of ITSs and their impact on fully online courses. It also lists the search terms and databases used for the background research on this topic. The chapter also describes in detail the theoretical foundations of the study as well as the conceptual framework. Finally, there is an extensive discussion of ITS and the difference of design, integration, and implementation.

Chapter 2: Literature Review

The advancement in educational technologies has enabled online education to proliferate (Eudy & Brooks, 2022; Phillips et al., 2020), as it continued to attract learners because of its flexibility and support for various learning styles (Alawani & Singh, 2017) and this has been an effective format for many learners due to the ease of access and flexibility of engagement with the courses (Repko et al., 2019). As more learners engaged with online education, the support of different learning styles, and the learning needs of individual learners has become more important (El-Bishouty et al., 2019). With this rapid growth of educational technology, computer based learning has become increasingly integrated with artificial intelligence techniques in order to develop more personalized educational systems (Mousavinasab et al., 2018). To that end, publishers and course developers have used ITSs to fill the gaps left by insufficient numbers of human online tutors and educational resources that are tailored to the needs of the individual student (Sottilare et al., 2018).

The efficacy of ITS for undergraduate college level courses has not been well established (Csapó & Molnár, 2019; Forum, 2016; Huda et al., 2018; Kulik & Fletcher, 2016; Slavin, 2019; Truong, 2016). A 2016 meta analytic study showed that at the time of this study, fewer than 50 quantitative studies had been completed on ITS (Kulik & Fletcher, 2016), and more than two thirds of those studies related to one specific ITS, the Cognitive Tutor System. This study used an ITS created by the Amplifier Group, who developed the DSM program for Pearson publishing in use with their advanced anatomy and physiology curriculum. The efficacy of the of this particular ITS had not been explored or recorded in research data at the onset of this study (Williamson, 2017). Pearson's Dynamic Study Modules followed the latest model of ITS design, using proprietary analytics based on the cognitive science of learning, with modules designed to function as an online personalized tutor for each individual learner (Williamson, 2017). This research studied changes in learning outcomes for students using different levels of ITS in a college level online anatomy and physiology course.

The majority of studies that relate to educational technology show that there is no significant difference for courses that incorporate educational technology over those taught traditionally (Huda et al., 2019). This is in part due to the fact that technology additions facilitate the delivery of educational instruction to the learner; it is the content within the delivery mechanism that helps move the educational component for the learner (Donnelly, 2017; Whinston, 2020). However, previous studies have not fully addressed the effectiveness of current ITS programs to remediate individual college level students and discern between basic knowledge acquisition and impactful understanding of the overall concepts in a fully online class (Dang et al., 2017; ElAtia et al., 2016; Huda et al., 2018; Jaiswal et al., 2017; Slavin, 2019). At the time of this study most studies about intelligent tutoring systems focused on small areas of assessment rather than the overall changes that might be measured over the course of several units or a complete course over an entire semester.

The purpose of this study was not to analyze the actual design of the ITS in question, but rather ascertain if the use of an ITS such as the one examined in this study, has any effect on individual unit assessments of knowledge, over the course of a 16-week semester, for the students identified in the study. The study considered correlation on more than 50% of the assessments to validate the alternative hypothesis and less than 50% correlation on the 14 assessments to validate the null hypothesis of the study. This study provides statistical evidence about the efficacy of ITS programs to remediate undergraduate college students within a fully online anatomy and physiology course. This study provided data illustrating the differences in learning that exist between student's assessment scores over the course of an entire 16 week semester, an aspect of ITS evaluation that has not been previously explored in current research (Csapó & Molnár, 2019; Slavin, 2019).

This chapter details the literature search strategies as well as theoretical foundations of the study. The chapter also discusses the conceptual framework of the study and provides an in-depth literature review related to the key variables and concepts of this study, such as how previous researchers had addressed the efficacy of current ITS designs and programs. This chapter provides the reader with a foundation for understanding the three primary designs of ITS programs and their current strengths and weakness and how the dynamic study modules explored in this study fit within the context of current research. The literature review also exposes the weakness of current studies in that their duration of overall analysis only looks at the effects of ITS use for small segments of material rather than the effects over the course of an entire semester of use. The end of the chapter is a summary.

Literature Search Strategies

While doing research for this topic the following keywords and phrases were used: *intelligent tutor Systems, CAI computer aided instruction, Knowledge tracing, Learning factors analysis, Performance factors analysis, Constraint Based Modeling (CBM) ITS, multi-entity Bayesian networks (MEBN), notion of fragments and MEBN theory (MTheory), Adaptive E-Learning Systems, Adaptive intelligence tutoring system, Affective learning intelligent tutoring system, intelligent tutoring system classroom study*, *intelligent learning system, intelligent tutoring system bayesian network, cost implications of intelligent tutoring system, Multiple Attribute Decision Making (MADM) theory Intelligent Tutor systems*, and *Intelligent Learning Environment (ILE).* The following research databases were utilized: ResearchGate, Education Resources Information Center (ERIC), ProQuest, OhioLink, Education Research Complete (EBSCO), ScienceDirect, Google Scholar, and PubMed. Current research from the past 5 years were scanned for studies directly relating to ITS in college related courses and how they would directly relate to the dynamic study modules being studied. An overall review of foundational studies from the 1970s through the 2000s were used as the foundational basis for the overall understanding of ITS from its inception to current use.

Theoretical Foundation

Learning Theory

This study was guided by the cognitivism learning theory and how it relates to the process of assimilating and expanding the learner's knowledge base into their existing schemas. Cognitivism asserts that instruction should be organized, sequenced and presented in a manner that is understandable and meaningful to the learner while emphasizing retention and recall through the use of quality teaching practices (Piaget, 1976). These are the fundamental tenets of current ITS design, allowing me to ascertain if an ITS program using this design structure could significantly alter the learning gains of students in a college level online anatomy and physiology course.

Student modeling based on a cognitive theory approach strives to interpret human behavior during the learning process by applying cognitive learning theories to the evaluation of the student in an attempt to understand the learners process of thinking and understanding (Dermeval et al., 2018a). In a cognitivist approach the teacher, or in this case the ITS, will ask the learner questions to refine their thought process identify wrong ideas, concepts or faulty assumptions and at the same time solidify correct information and ideas (Sotiropoulos et al., 2019). Other specific attributes of the cognitivist approach that are utilized by the ITS in the study are active engagement of the learner in meta cognitive tasks such as self-planning, task and step organization, as well as a sequential revision of mastered content during the learning process (Resnick & Johnson, 2020).

Cognitive Theories

Though cognitivism is the guiding theoretical framework for this study, two of the more specific areas of cognitive theory that were used in this paper are the multiple attribute decision making (MADM) theory and the human plausible reasoning (HPR) theory (Alkhatlan & Kalita, 2018). The MADM theory is based on the principle of making preference decisions, such as prioritization, choice selection, and assessment of specific criteria, over other available options that are generally characterized by multiple, usually conflicting, attributes (Jankowski, 2016). By considering and combining the most effective criteria the content can be personalized for the individual learner with specific learning objects identified and selected that will maximize the effectiveness and efficiency of the tutoring process, enriching the user experience and the teaching process (Luna-Urquizo, 2019). The dynamic study modules that were used in this study presented the learner with a short assessment based on the specific information being learned for each lesson, usually comprising about one fourth and chapter of the selected textbook for the course, and the tasks and assessments varied from unit to unit. The student also had to specify within their answer the confidence they have in each specific choice. This allowed for engagement on the part of the learner and value assessment on the part of the tutoring module within the ITS (Luna-Urquizo, 2019). The tutoring module then engaged the learner with specific content based on their identified needs and the parameters established pedagogically within the module.

The second specific cognitive theory that was used to understand and identify specific aspects of the ITS was the human plausible reasoning theory. This theory is much different than classical syllogistic argumentation methods of Aristotelian two-valued logic (Drake, 2018), in HPR the interrelated nature of the knowledge base being studied is taken into consideration (Collins & Burstein, 1991). The human plausible reasoning theory was outlined by Collins and Burstein in 1991 and uses four types of expressions to qualify the knowledge base of the learner. The first are simple statements consisting of descriptors, applied to an argument that is connected to a referent. The second expression applies to one of four relations: a similarity or dissimilarity, a generalization, or a specialization. The last two expression are called mutual implications and mutual dependencies (Collins & Burstein, 1991). By using the four expressions in concert, the tutoring module of the ITS may make value judgments, much as a real human tutor might. The specificity of the program and the ability of the tutoring module to make plausible inferences and recommendations is dependent upon the level of coding within the knowledge module. The finer the degrees of conditional similarities and typicality as well as frequency of association and conditional likelihoods the more accurate the ITS can be in making pedagogically sound qualifications of the learner current knowledge state (Kumar & Ahuja, 2020). For example, if a student is being assessed on information in Chapter 5 of the text and the computer identifies deficiencies in the learner's understanding of how cellular channels and ion pumps work at a molecular level, the tutoring program can infer that that the student is still not fully aware of how diffusion works at a molecular level. Even though this concept was covered in Chapter 3, the program will still suggest study material from the core concepts from Chapter 3 on diffusion while also providing remediation on the specific content from Chapter 5.

Literature Review Related to Key Variables and Concepts

Effectiveness of ITS Versus Human Tutor

Human tutors have been present in education since antiquity, and a plethora of studies have shown that human tutoring can have a positive effect on fidelity and knowledge acquisition (Hartley, 1977; VanLehn, 2011, 2016; Virvou et al., 2020). The actual effectiveness of the human tutoring sessions is dependent on several variables such as the knowledge base of the tutor, their skill in assessment of the learner, their pedagogical background, and their ability to facilitate knowledge gain on the part of the learner. Other variables can be associated with the learners, such as their willingness to engage in the process, their previous experience with similar material, how many tutoring sessions they attend, and their overall academic acumen (Malik et al., 2019; VanLehn, 2011). Learning gains did seem to vary by curricula, but the biggest factor that determines the learning gains seen in the studies seems to be the knowledge level and training of the tutor (VanLehn, 2011). A systematic review in 2019 confirmed similar findings from the 2011 study by VanLehn that noted the positive effective of tutoring ranged from no effect to three standard deviations difference and directly varied in relation to the level of specific content knowledge mastered by the tutor (Zawacki-Richter et al., 2019). Many of these variables remain true of assessments of ITS and their effectiveness. For example, Kulick and Fletcher (2016) reported a median overall effect of ITS tutoring in their 2016 metanalytic study as .6 standard deviations. The sheer number of variables as well as the complexity of human to human and human to machine interactions make it difficult to directly compare learning gains from ITS programs against those of human tutors as data and comparisons were limited.

Definition of ITS Versus Computer Assisted Instruction

Computer assisted instruction (CAI) was first described in the 1970s by Carbonell asserting that this new mode of instructional aid could be endowed with enhanced capabilities by incorporating artificial intelligence (AI) techniques to overcome the current limitations (Alkhatlan & Kalita, 2018). The umbrella of computer aided instruction is quite large, encompassing areas form minimally impactful additions, such as a few weblinks or YouTube videos being incorporated into a curriculum, to a fully online courses that are dependent on multimedia and web interaction throughout, for both didactic learning as well as dynamic Realtime interaction on the part of the AI program (Nolin, 2019). In the specifics of this area of design and study, most authors suggest that CAI generally lacks the ability to monitor the learner's progress and provide steps for intervention in real-time (Alkhatlan & Kalita, 2018). For the purpose of this study, I focused on a narrower aspect of AI as instructional aids, specifically ITS and what impact that had on the learning outcomes of individual nursing students in an undergraduate sophomore level anatomy class.

The goal and design of an ITS is to provide targeted one-to-one foundational instruction to an online learner that would be analogous to that of a practiced human tutor with specific knowledge of the subject in question (Almasri et al., 2019). ITS is a subfield of artificial intelligence and consists of four interacting components (Almasri et al., 2019; Nwana, 1991; Zawacki-Richter et al., 2019). The four components are

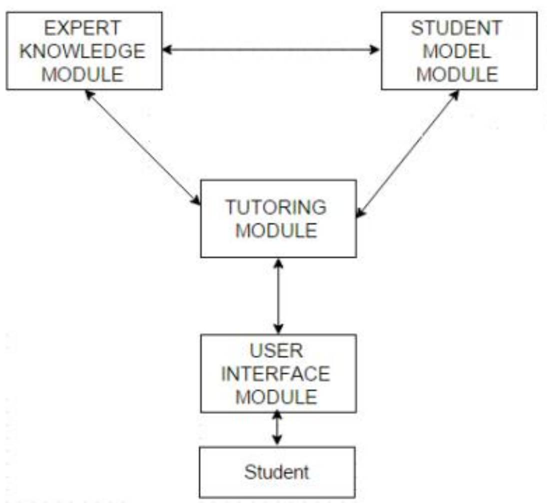
1. The student model that embodies the student's current knowledge base at the start of a tutoring session.
2. The pedagogical module is tailored to the student's needs based on their current educational state and comprises the appropriate instructional interventions relative to those needs.
3. The knowledge module contains the master template of knowledge that should be known about the subject for the amount of material being assessed.

4. The user interface module permits the dialogue between the ITS and the user. (Alkhatlan & Kalita, 2018; Mousavinasab et al., 2018)

In most current ITS programs there is usually an emphasis on the knowledge module as the primary module in the educational process. However, there are many approaches and some do stress other aspects of the four-module system as outlined in Figure 1 (Zawacki-Richter et al., 2019).

Figure 1

Traditional Architecture of ITS

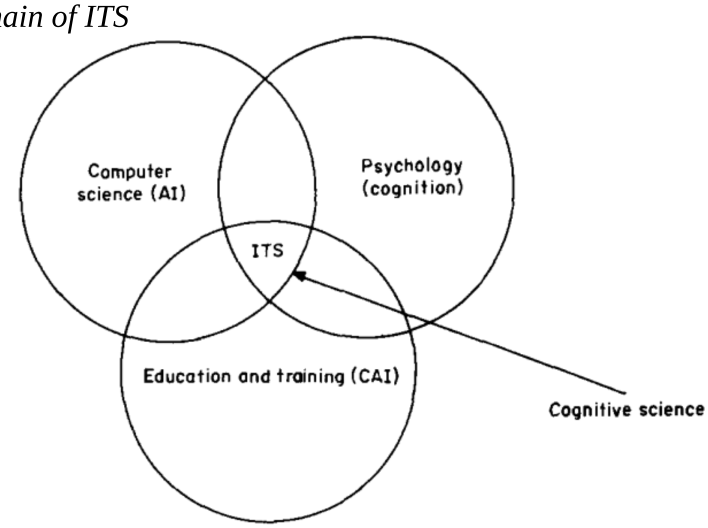


The intervention provided by the ITS can come in several forms. The system may direct the user to various activities through the user interface, in the form of hints/suggestions, Socratic dialogs, as well as feedback from the system on right and wrong answers. The system may also provide suggestions for possible material to review from the expert knowledge catalog based on parameters defined within the tutoring module (Alawani & Singh, 2017; Dermeval et al., 2018b; Kumar & Ahuja, 2020; Yang & Zhang, 2019).

The SCHOLAR tutor system was the earliest ITS and was created and introduced by Carbonell (1970; see also Carbonell & Collins, 1974). This program system was developed for reviewing the student's knowledge in the geography of South America (Mousavinasab et al., 2018). ITS research and design spans three different disciplines, computer science, psychology, and education and training (Bodily et al., 2019; Dermeval et al., 2018b). As a result, there are major differences in the goals, terminology, theoretical frameworks, and ideologies of the ITS designers and researchers. It is rare to find any two ITSs based on the same architecture (Alkhatlan & Kalita, 2018). A developer that is forming a new ITS will inherently use one or more of these areas rather than others based on their strengths and the ultimate design and functionality that is required. Figure 2 details how the different areas of computer science, psychology, and educational training overlap to form the cognitive science of ITS creation.

Figure 2

Domain of ITS



Architecture of ITS

ITS development stands on the reasoning that many studies have shown the effectiveness of one-on-one human tutoring. With the new and ever evolving capabilities of computers and programs with artificial intelligence capabilities, the possibility of more human like interactions are possible between the program and the learner. This is encouraging for learners in the online and remote formats who have far outnumbered the instructors availability and time to interact with each one of the individuals in a meaningful way (Carbonell, 1970; Dermeval et al., 2018a; Kumar & Ahuja, 2020; Sottilare et al., 2018; Yang & Zhang, 2019).

Although it is true that no two systems are exactly alike, and all ITS systems very greatly, they do share common behaviors in the way that they function to identify deficiencies in and learners knowledge base and work with the learner to correct these gaps or fallacies in knowledge (Almasri et al., 2019). As an example, most ITSs have an inner and outer loop structure (Tien, 2019; van der Bent et al., 2019). The outer loop functions to decide what task the learner will do next, a decision that is based on the functions of the inner loop. The inner loop monitors the student’s solution steps based on the problems that are presented by the outer loop and then provides the appropriate pedagogical intervention based on the assessments of knowledge and reviews of the content within the expert knowledge module (Nwana & Coxhead, 1989; van der Bent et al., 2019). The next section of the paper describes the four modules or components in more detail.

The Expert Knowledge Module

The design or structure of most expert knowledge modules can be segmented into three primary formats or models; the cognitive model, constraint-based model and the expert model (Dermeval et al., 2018a). As described, there is no set design for ITS development so based on the training and expertise of the developer, one format is chosen over others.

The cognitive model is a more traditional approach and was used in some of the earliest ITSs (Szulc, 2019). Cognitive tutoring systems use a cognitive approach to learning and provide immediate feedback to the learner, they are commonly used in fields such as computer programing, science-based curriculums, algebra, physics, geometry and is the fundamental design of the ITS for this study (Yang & Zhang, 2019). The cognitive based ITS has been proven to be very effective in many studies and the goal of this approach is to provide a detailed and precise description on the relevant knowledge in a task domain including principles and strategies for problem-solving (Alkhatlan & Kalita, 2018; Sottilare et al., 2018, 2018; Szulc, 2019). Generally, the approach of the cognitive model is to take the student through a step by step path that may be different for each learner, but will ultimately lead to the final correct answer and an accumulation of knowledge in a logical path from beginning to end (Kumar & Ahuja, 2020). In these models the learners were shown not only the correct answer, but also common mistakes that might happen at various points along the learning pathway. These alternate negative solutions are kept in what is commonly referred to as a “bug library” and is separate from, but compliment to, the expert knowledge (Nwana & Coxhead, 1989). Many cognitive tutors are built on the ACT-R theory of cognition and learning with the underlying principle being to distinguish between implicit and explicit knowledge (Alkhatlan & Kalita, 2018). Under this definition procedural knowledge is considered implicit and chunks of linking knowledge is considered explicit (Mousavinasab et al., 2018).

The Cognitive Knowledge Model

The cognitive model format is often accompanied by knowledge tracing, where the students' progress on tasks and assessments is measured against the expert knowledge module as well as the subset of the buggy module (Abu Elreesh & Abu-Naser, 2019). This system of measurement within the ITS program is called Cognitive Mastery Learning and is one of the most common methods for estimating the probability that a student knows, or has mastered, the selected skill or content base for a particular knowledge set (Zawacki-Richter et al., 2019). Learning factor analysis and performance factor analysis (Yuce et al., 2019) have also been used as a form of educational data mining to further improve and facilitate the ability of the ITS to potentiate knowledge acquisition on the part of the learner (Z. Wang et al., 2020).

Despite the fact that the cognitive tutor format has been proven effective (Alawani & Singh, 2017; Kumar & Ahuja, 2020; Szulc, 2019; Yang & Zhang, 2019) this form of ITS has not been widely adopted in the educational or corporate format due to the high cost of development and time that it takes to build a fully functional ITS using all of the components described above (Mousavinasab et al., 2018). Current research and development are focusing on Cognitive Tutor Authoring Tools (CTAT) which would allow for the creation of full ITSs without the intensive programing that is currently required. Under this new format or paradigm, broad examples of learning tracts would be established that could be applied to similar curriculum or processes without the need for detailed paths to be created for each instance the learner might encounter (Alkhatlan & Kalita, 2018). At the time of this study this new subsystem was being called Example-Tracing Tutors (van der Bent et al., 2019).

The Constraint Based Model

The second common type of ITS program is defined as a Constraint Based Model (CBM). This type of ITS was first developed by Stellan Ohlsson in 1994 (Ohlsson, 1994; Schrills & Franke, 2020) to overcome some of the limitations noted with knowledge level tracing (Mitrovic & Ohlsson, 2016). Ohlsson developed the CBM to help facilitate learning in financial accounting. This format has since been used for a variety of subjects and curriculum and is simplified from the cognitive model in that there is a common model representing the student's knowledge, the instructional domain and higher-level skills in one unit rather than a model for each (Schrills & Franke, 2020). ITSs designed using the CBM are based on Ohlsson's theory of learning which uses unique errors on the part of the learner, and measure those results against a set of constraints that may not be violated during the problem solving process (van der Bent et al., 2019). This forms a temporary set of rules that serve as the master knowledge set for the ITS to use in evaluation of the students' progress (Alkhatlan & Kalita, 2018).

The form of constraint is an ordered pair of both a relevance condition (Cr) and a satisfaction condition (Cs) where both must be true for the student's answer to be considered correct (Alkhatlan & Kalita, 2018; Mitrovic & Ohlsson, 2016). Therefore, if either of the conditions is violated the ITS program then offers hints, help, or remediation for the specific content set that is being studied.

The CBM model helped overcome some of the limitations noted in the cognitive model tracing tutors in that the CBM allowed for more creativity on the part of the student and their proposed solutions (Karaci et al., 2018). In the case of model tracing the "correct" answers are limited to those stored in the master module and the students answers and solutions cannot deviate from the prescribed solution path. Whereas with the CBM the student's solution is counted as correct if it does not violate the domain principles as defined by the Cs and Cr variables (Karaci, 2019). By allowing for more variability the CBM is also able to function in learning areas that contain "ill-defined tasks", ones in which there are problems or changeless whose solution correctness cannot be verified automatically (Bian et al., 2019; Costley, 2019; W.-C. Li et al., 2020).

The Expert Based Model

Lastly there are many ITSs that use the expert approach and is so named as these systems try to mimic the ability of an expert in the field, to make decisions and solve problems, with the advancement and aid of the student in mind (Malik et al., 2019). The systems can use many forms of algorithmic design such as neural-networks, decision trees, rule-based problem sets, and case-based reasoning (Alkhatlan & Kalita, 2018). The advantage of this type of system is that the knowledge domain can be much broader than the two systems previously discussed allowing for more real time interaction on the part of the learner than is possible with constraint based or cognitive models (Sottilare et al., 2018).

These systems work best in well-defined, non -Socratic areas, such as mathematics, physics, computer literacy, object-oriented design and teaching infectious disease diagnosis (Carbonell, 1970; Kumar & Ahuja, 2020; Malik et al., 2019; Yang & Zhang, 2019). Ideally the expert system will provide two modalities, one to generate the expert solutions, one to compare these with the learner's solutions, and then provide appropriate feedback and interventions (Schrills & Franke, 2020). As with the previous models, the expert system does have its limitations, such as cost and design constraints, as developing an ITS that is capable of reliable interaction at both the expert and student level is very difficult (Almasri et al., 2019; Karaci, 2019; Mitrovic & Ohlsson, 1999; Schrills & Franke, 2020).

The Student Module

For any ITS program to function it must have some representation of the learner or user with whom it is interacting. The student module represents the knowledge base of the learner. Under best case conditions the module can track this as a dynamic state that will change over the progress of the session and throughout the tenure of the student within the program, allowing the ITS to make inferences about the students skills and performance (Resnick & Johnson, 2020). As the student progresses through the ITS there were subsets of student knowledge that represent mastery of skills and skills that are still in development (Almasri et al., 2019). This is a critical component, as each student were different and while repetition of learned skills is important, a successful program will oscillate between reinforcement of mastered skills and challenge of unmastered material (Zawacki-Richter et al., 2019).

The challenge for ITS is that the student module is dynamic and constantly in flux and must evolve as the student progresses through the material. The student module must also integrate well with the tutoring module to measure if applied interventions and suggested study materials have a positive impact on student knowledge acquisition (Schrills & Franke, 2020). As with the expert module there are implicit and explicit loops that are constantly monitored and compared to assess mastery of defined skills (Karaci, 2019).

Inherent in the development of the student module are established student characteristics, both static and dynamic, that must be incorporated into each system for fully functional program (Bodily et al., 2019). Static characteristics are things like; name, student ID number, email address, age, and mother tongue, while dynamic characteristics are measured interactions with the ITS itself and would essentially change with each interaction within the tutoring session. The challenge in designing a good student module lies in capturing the dynamic student information in a useful and informative way so that the tutoring module has actionable data. Preferably the system is able to store this information between visits from the student, so that each interaction builds on, and reinforces, knowledge that has been mastered and is in the process of being mastered (Resnick & Johnson, 2020).

Nwana (1991) described six different uses of student modules and his distinctions have remained current today (Malik et al., 2019). In the corrective model the student's deficits are identified and correct information is immediately offered, in an attempt, to remove “bugs” from the students’ knowledge base. In the elaborative model the system probes for gaps or deficits in the students’ knowledge and offers hints suggestions and information to fill these identified gaps. The strategic model continually adapts its tutorial strategy based on the performance and action of the individual student. The diagnostic model is like the corrective model in that its main function is to identify and determine if there are errors in the student’s knowledge base. The fifth type is classifieds as a predictive model and its primary function is to assist in understanding the response or interaction of the student with the system. The last of the six models is the evaluative model and as the names suggests this model is focused on assessing the overall progress of the student within the ITS (van der Bent et al., 2019). Since each ITS system is inherently unique there may be subsets of each of these models and quite often individual ITS programs will employ combinations of each of these different types into one system to make a better fit to their task and information subset (Dermeval et al., 2018b). It is interesting that while these six models were first described almost thirty years ago, and the functionality and specifics of the way in which the models preform their tasks has changed to some degree, the overall definition of each of these models is accurate and can be seen in the current interactions and design of most of the ITS’s currently being used (Mousavinasab et al., 2018). The following section of this chapter will discuss various approaches to ITS module design found in current literature and how each of these incorporate various aspects of the six models that Nwana outlined.

The Overlay Approach

The overlay approach was first designed by Stansfield, Carr and Gldostien in 1977 (Carr & Goldstein, 1977; Virvou & Manos, 2019). This has become a very common approach and can be seen in current ITS's such as ActiveMath, Cardiac Tutor and SHERLOCK that range from empowering lifelong learning of math to diagnosing electrical problems in F-15 jets (Alkhatlan & Kalita, 2018; Almasri et al., 2019; Virvou & Manos, 2019; Zawacki-Richter et al., 2019). In the overlay approach the student module is considered a subset of the domain set or expert module and the two are compared (Virvou & Manos, 2019). The differences between the two are assumed to be a deficit, gap or bug in the student's perception of the material and interventions are applied by the tutoring module to try and correct or erase the discrepancies (Dermeval et al., 2018a). In the simplest sense the overlay approach uses a Boolean value for each distinct educational element, 0 to 1, where 0 is false and 1 is true. Several of these instances are measured in concert to develop a picture of the level of student knowledge on that subject or specific subset of subject material. Generally, the student is ranked in some sense as poor, average or good and different interventions were applied to each of these levels (Szulc, 2019).

A 2016 study by Shiue and Chen found that students using automated grammatical error detection program that applied the overlay approach achieved accuracies of 0.8423, precision of 0.8998, recall of 0.7705, and F1 of 0.8301 with random forest in the 15000s dataset. This is almost one standard deviation better than those students that did not use the ITS in their preparation and study for the same courses. They also reported that by utilizing this suitable model and combination of features, they could construct a word usage error system that favors precision, up to 0.9536 (Shiue & Chen, 2016). These are similar to the results found by Cakir (2019) when he investigated the effect of web-based ITSs on students' achievement in a computer introduction course(Cakir, 2019). The study showed positive improvement in both learning strategies and motivation based on pre and post test scores (Malik et al., 2019). Based on these results it was the recommendation of the investigators in both studies to encourage the use of the ITS and make it available for all students as part of their normal curriculum.

At the time of this study there were several current ITS programs that used the overlay model such as LS-Plamn, Pdinamet and ICICLE, these ITS help students to learn new e-learning systems, advanced physics and proficiency in computer-based languages (Bradac & Walek, 2017; Yang & Zhang, 2019). Specific studies testing the efficacy of these particular systems is scarce to nonexistent but development continues in this area (Yang & Zhang, 2019). The inherent flaw in this subset of ITS design is that it is not a complete system. The overlay approach needs to be paired with other approaches as it cannot take into account the incorrect knowledge on the part of the student, their cognitive needs, learning styles, or preferred learning methods (Bernard et al., 2017). To offset these deficiencies the overlay approach is often paired with the stereotype approach, machine learning, design elements based on perturbation theory and fuzzy logic to provide insight into the learner and their specific needs (Crockett et al., 2017).

The Stereotypes Approach

In the stereotype approach, the program groups common responses for learners into categories. It then measures responses and interactions from the student over time and based on those interactions it projects common mistakes and patterns on past cases and formulates recommendations for remediation on what has worked well for that group in the past (Malik et al., 2019). Designers and advocates of this design method feel that this is one of the strengths of this approach in that the program can select and sequence material based on best case scenarios from previous users (Dermeval et al., 2018a). Proponents of this approach also say that this decreases the cognitive load for the learner as there is a very limited path of information to look into at any given time, whereas in other systems the student is allowed to choose more of their own content they may be working on material that is too easy or too difficult for them (Almasri et al., 2019).

The stereotype approach is commonly used in adaptive tutoring systems and are often paired with other student modeling approaches (Szulc, 2019). In programs like Web Passive Voice Tutor (Web-PVT), machine learning and stereotypes are used to provide tailored instruction and feedback to individual non-native speaking learners on how to master the passive voice of the English language (Bradac & Walek, 2017). The model begins by using a unique combination of predetermined stereotypes as well as a distance weighted k-nearest algorithm to determine which subject set is closest to the students current acumen level and then starts remediation at that point (McClain, 2016).

Perturbation Approach

In the simplest terms the perturbation model is an extension of the overlay model discussed earlier. The main difference between the two lies in the fact that the perturbation model also includes a possible misconceptions library, which allows the program to identify wrong ideas or incorrect information held by the student which helps the leaner purge those from their knowledge base (Alkhatlan & Kalita, 2018). To do this the program will present the learner with common misconceptions on the topic being examined and if the student identifies one of these as true or correct the ITS will generate a bug library for the student (Kumar & Ahuja, 2020). The ITS then uses this information to form a predictive model of the student and possible errors that this student might encounter in the future allowing the tutoring module to provide better material for review and correction (Yang & Zhang, 2019). This approach is able to provide a more detailed picture of the actual knowledge state of the user than the basic overlay model previously described. However, this type of ITS is more time consuming and costly to design and build as the amount of background information within the subject matter dataset has to be much more detailed and in depth. (Malik et al., 2019).

Constraint Based Approach

As with the expert module the constraint-based approach (CBA) uses predefined constraints for the student knowledge module. The process of determining the learner's knowledge base is managed by a set of relevance conditions and satisfaction conditions. Based on the matches and errors within these conditions the ITS can assign certain attributes to the learner as they relate to the knowledge base (Alkhatlan & Kalita, 2018).

According to Mitrovic and Ohlsson (2016) this CBA can allow for the elimination of the primary expert module as well as the bug library allowing for shorter creation and development times which allow for computational simplicity and lower costs for implementation.

Cognitive Theories Approach

Student modeling based on a cognitive theory approach strives to interpret human behavior during the learning process, by applying cognitive learning theories to the evaluation of the student, the ITS attempts to understand the learners process of thinking and understanding (Dermeval et al., 2018a). As described, the two cognitive theories that best apply to the dynamic study modules being considered in this study are the MADM theory and the HPR theory. The MADM theory is based on the principle of making preference decisions such as prioritization, choice selection and assessment of specific criteria, over other available options, that are generally characterized by multiple, usually conflicting, attributes (Jankowski, 2016).

The MADM theory and its’ foundational tenant to combine many different learner attributes into a coherent picture of the individual form the basis for describing the decision-making process and overall format and procedure of evaluation used in the design and implementation of the dynamic study modules. The MADM theory is currently being used in some of the newest areas of ITS design, and that is with programs that incorporate emotion recognition techniques into the knowledge database for the student module (Luna-Urquizo, 2019). One such system that has not been widely tested, but is being incorporated into some of the most cutting edge ITS designs like the one developed by Alepis and Kabassi (2020) incorporate bimodal emotion recognition though mobile device microphones and keyboard interaction to help determine the emotional state of the learner (Kabassi & Alepis, 2020; Sotiropoulos et al., 2019; Virvou et al., 2020).

Bayesian Network Approach

Another approach that is used in ITS design is Bayesian networks, these networks allow the program to determine the current educational state of the learner. This is particularly applicable for this chapter, as the ITS being studied uses both cognitive design previously described as well as Bayesian networks to determine the constructs of the student Module with in the dynamic study modules that were examined in this study (Williamson, 2017). Bayesian networks can be described as a set of attribute nodes that can be interlinked for use in probability calculations and computations (Kondo & Hatanaka, 2019). The purpose of this network is to determine conditional dependence of specific attributes to help make inferences and determinations of the learner's educational state (Virvou & Manos, 2019). Once determined this information may be compared with the expert knowledge model and then recommendations may be made by the tutoring module on how to specifically tailor hints, recommendations for study and remediation on a student by student basis (Kondo & Hatanaka, 2019).

Bayseian networks have been proven useful in modeling problems that involve a certain degree of ambiguity and uncertainty (Aziz et al., 2020; Gan et al., 2019; Kondo & Hatanaka, 2019; Kumar & Ahuja, 2020; Nafea et al., 2019). This is true of the overall student module as in well-developed ITSs as there are fine degrees of nuance between the educational state of different students, therefore a method of accurately identifying the strengths and weakness of each individual is very useful (Plass & Pawar, 2020). Andes is an ITS that uses a Bayesian network structure to help students master Newtonian Physics (Zawacki-Richter et al., 2019). Researchers found that by using the Andes ITS that included meta-hints students experienced an increased frequency of getting a strep right on the first attempt by d=0.682 and an increased problem completion rate of d=0.727 (VanLehn, 2016).

Fuzzy Student Modeling Approach

Determining a student's current state of knowledge is not a straightforward task, as it is constant flux, and can be effected by factors that cannot be directly observed or measured, especially in an ITS where there is an inherent lack of direct real life interaction between teachers and students (Alkhatlan & Kalita, 2018). One approach that is used to overcome this deficit is using fuzzy logic, first introduced in 1965 by mathematician, computer scientist and artificial intelligence researcher Lofti Zahden, as a methodology using subjective words, for computing and reasoning, instead of numbers (Zadeh, 1965). The fuzzy logic approach allows the ITS to deal with imprecise and incomplete data as well as human subjectivity by using values and words, or series of words, such as "good", "excellent", "I don't know" or "I am not sure" rather than Boolean values of yes/no or True/false (Troussas et al., 2019).

The ITS being examined in the study employs fuzzy logic in its initial assessment of student knowledge in each dynamic study module. The student is presented with a series of questions and activities that must be answered and completed. As the student choses each answer they may also indicate their level of confidence in that answer with three levels of assurance ranging from “I don’t know” to “I am sure” with an intermediate of “I think this is correct”. This allows the ITS to diagnose the level of knowledge for the specific concept being questioned and make predications or inference on other related content (Williamson, 2017). A 2019 study by Troussas et al found that the inclusion of a fuzzy logic component in a computer assisted learning ITS increased learner satisfaction overall performance while also improving the ability of the system to make reliable decisions for intervention (Troussas et al., 2019). The use of this type of computational analysis is gaining popularity it ITS design as it allows the system to deal with computational complexity while also mimicking some of the human based interactions a learner might encounter in a traditional tutoring session (Alkhatlan & Kalita, 2018; Kumar et al., 2017; Mousavinasab et al., 2018; Troussas et al., 2019).

Tutoring Module

The tutor model or pedagogical model, as it is sometimes called, is the most critical component of the ITS and how it works with the student to modify misconceptions, incomplete knowledge or solidify correct understanding of core concepts (Luna-Urquizo, 2019). There are several tasks or functions that the tutor model must perform to work well in the remediation of students and also mimic the behavior of a real human tutor. In most ITSs the pedagogical component can do three things, it can present a specific content fact, a full lesson of material or test the student on acquired knowledge. To function well the ITS must blend these three components in a seamless natural manner that encourages engagement and facilitates accurate knowledge acquisition (Alkhatlan &

Kalita, 2018). Throughout each session the tutoring model must tailor the material presented based on the specific profile that is stored in the student model. This were different for every learner and the pedagogical model must match its tutorial plan based on the unique features of the learner that it is engaging (Aziz et al., 2020).

The tutoring module communicates with the other two components of the system, the expert module and the student module and acts a bridge between all three to allow the ITS system to function as autonomous AI (van der Bent et al., 2019). The tutoring module for the dynamic study modules being evaluated in this study first presents the learner with a series of content specific questions for the knowledge set being considered. While answering the questions the student is asked to identify their level of confidence in the answer that they are selecting. The student may also ask for a hint or help during the assessment sessions. Based on the correctness of the learners responses, the number of hints requested, as well as the confidence level of the student, the ITS then evaluates the students' knowledge as compared with the expert knowledge module for this particular set of content as well as the overall knowledge set for the content as a whole (Kumar & Ahuja, 2020). The tutoring module from the dynamic study modules then makes recommendations for reading, presents short videos for review as well as making suggestions for further study. Once those items are reviewed the learner is asked to complete another series of assessments to test for further knowledge acquisition and to assess the remaining gaps in student knowledge. The dynamic study module sessions alternate between assessment and review periods at random intervals and generally last for 20 to 30 minutes based on the overall knowledge level of the learner.

This particular ITS delays correct and incorrect answer feedback to the student during initial assessment to allow for a period of cognitive dissonance, as previous research suggests that delayed feedback heightens the learners anticipation of the correct information increasing their level of attention and potentiating a memory of the correct information more quickly once it is presented (Gan et al., 2019). This is considered a second-generation architecture, first generation ITSs gave the feedback immediately after each question.

In cognitive and constraint based tutors, of which the dynamic study module used for this study is one, learner feedback is given in several ways (Kumar & Ahuja, 2020), flag feedback, buggy messages or chain of hints are common formulations. The dynamic study modules use all three of these methods to communicate correct information to the student and modify misconceptions or wrong information. Flag feedback is presented with color schemes that denote correct and incorrect information, for instance correct answers are highlighted in green while wrong answers are color coded in red. Buggy messages are pre-coded communications delivered to the student when they are identified by the tutoring model of harboring an area of common misconception. The chain of hints method is used when the student has self-identified or been determined to be unsure or lack confidence in a particular content area (Kumar & Ahuja, 2020). The chain of hints is monitored and sent by the tutoring module and can be more or less specific based on the individual needs of the learner (Malik et al., 2019).

Summary and Conclusion

This chapter has defined the terms used within the study as well as the parameters of the research that were used to evaluate the change in assessment scores relative to the student's use of the ITS over the course or a full 16 week semester. The cognitive theory and more specifically the multiple attribute decision making theory and the human plausible reasoning theory were used to guide and frame the research. These theories provided a background and understanding for the overall design of the dynamic study modules and how that relates to the overall field of ITS research and design from its' inception in the 1970's to today.

This chapter also detailed how the ITS being evaluated in this study combines several design elements from the overall palette of common ITS structures. The dynamic study modules use an expert model approach with an overall cognitive design, as well as a fuzzy modeling approach while also maintaining a bug model for each student for each module completed. By comparing the results of the control and experimental groups assessments, the study answered the research question and provided further data on the efficacy of ITSs and their ability to help online and remote leaners process and retain information.

The next chapter in this dissertation discusses the research design and rationale of this study. It also provides specifics on the sampling procedure and population as well as the bases and methods for archival information retrieval. Chapter 3 ends with an in-depth discussion of the control and experimental variables and threats to internal and external validity.

Chapter 3: Research Method

At the time this study was completed nearly one third of current higher education students at public institutions took at least one online course (Redmond et al., 2018). Though there is evidence to support the online model of education, the national average for student to teacher ratios in higher education are 16 to one (Seaman et al., 2018), and the need for on-demand individualized attention and remediation within the online environment could be instrumental in better outcomes in learning, retention, and proficiency (Nakata et al., 2017; Saultz & Fusarelli, 2017; Sottilare et al., 2017). A systematic and formulaic ITS can provide personalized remediation for each student, increasing foundational knowledge and overall scores as well as individual self-efficacy. This could lead to increased completion rates in the courses being studied, allowing for faster completion of the nursing curriculum and ultimately helping to address the overall nursing shortage particularly prevalent in rural and underserved areas (Thill, 2019).

The nature of this study was a nonexperimental quantitative study using a MANCOVA test. There were 14 dependent variables that related to the individual's test scores: (a) 12 individual chapter test scores, (b) the midterm test scores, and (c) the final test score for the selected groups. For this study there were four groups of online anatomy and physiology students selected from classes taken between the fall of 2018 through the spring 2020. There was one control group and three experimental groups composed of students who elected to use the ITS to varying degrees. The ITS evaluated in this study was composed of 48 individual dynamic study modules. Students who completed between 0 and 10 modules were considered to have *no significant use* and will serve as the control group. The three experimental groups were composed of students who completed between 11 and 20 modules and were placed in a *nominal use* group, students who completed 21 to 30 modules were placed in a *moderate use* group, and students who completed 31 to 48 modules were placed in a *saturated use* group. The covariate of prior GPA was applied to allow for a truer comparison between the experimental and control groups when evaluating differences in academic achievement on the selected assessments. Evaluation of the data answered the research question of whether use of an ITS could alter student scores on individual tests, or midterm and final test scores, for the Bio 2121 advanced anatomy and physiology course. This information contributed to the overarching purpose, which was to better understand the efficacy of ITSs for use in improving student performance in an undergraduate online anatomy and physiology course.

This chapter details the research design and rationale as well as the specific research question for this study and will also include the specific variables used to elucidate differences between individual experimental groups. The chapter also contains sections that provide a detailed description of the methodology used the population that was sampled as well as the sampling methods that were employed. Also included in this chapter is a description of the methods used to obtain the archival data as well as its statistical analysis. The chapter will conclude with a description of the process employed to control threats to internal and external validity as well as an overall summary.

Research Design and Rationale

In this research study, a nonexperimental design was utilized. This design was chosen due to the fact that the learners self-selected into the four research groups by their use of the dynamic study modules and strict randomization of learners does not exist (Biesta & van Braak, 2020). The independent variable in this study was the students' use of the dynamic study modules over the course of a sixteen-week semester. There was one independent variable for this study, with four different levels, and all relate to the proficiency of the learner with the assigned material. The dependent variables for this study were the test scores for the 12 individual chapter tests, the students' midterm test scores, and the students' final exam test scores. The midterm was a cumulative exam over the material from the first half of the semester and the final assessed the accumulation of knowledge from the midterm to the end of the course. Total scores for each assessment were obtained from an archived database for each individual section and compiled to form a total pool of data from all sections considered for this study. Individual chapter test scores ranged from 0–25 points, and midterm and final test scores ranged from 0–150 points.

A nonexperimental design was used to compare the proficiency and overall difference in achievement of each group of students relative to their completion of the overall number of dynamic study modules (Biesta & van Braak, 2020). The nonexperimental design is a useful design structure when testing hypotheses for similar natural subjects where strict randomization is not possible (Horsley et al., 2020). By controlling for the prior grade point average, the study also addressed one of the most obvious confounding variables. Because the groups for this study were similar, but not specifically the same, and not randomly assigned, the study used the non-equivalent design structure. The non-equivalent design study is sometimes considered to be a weaker design as compared to true scientific studies, but research has shown that studies focusing on comparison of the dependent variable can be credible (Schäfer & Schwarz, 2019). In this study, all four research groups were compared using their dependent research data, specifically the test scores for individual chapter tests and cumulative assessments. The no significant use group allows for a control comparison of dependent variable data between all groups measuring the overall effects of ITS use between the four subject groups.

Methodology

In this study an ITS, called Pearson Dynamic Study Modules, was evaluated in its ability to help students accumulate foundational knowledge on college level anatomy and physiology concepts on a chapter-by-chapter, midterm evaluation, and final evaluation basis. The control group for this study were students that had no significant use of the dynamic study modules program (i.e., used fewer than 10% of the offered modules and only students who completed the course were included in the sample). Because this was a nonrandomized group, as were the other categorical groups in this study, the nonexperimental design was the best approach for comparison and analyzing the data. Assessments that were used for evaluation in this study used a randomized pool of questions from the publisher's database and were standardized across all sections and individual sample groups.

In preparation for the assessments, students were provided with four to five dynamic study modules for each chapter with a .5 bonus point incentive for successful completion of each module. The bonus points increased the overall point total for each individual student at the end of the course but had no bearing on the individual chapter by chapter test scores or on the cumulative assessment scores. See Appendix B and C for a sample of the dynamic study module questions as well as a sample of the chapter test questions. The student's GPA prior to the course was used as a covariant within the study to help control for individual student variation and acumen. Together, the data analyzed to answer RQ1: How does the level of ITS utilization in a first semester online anatomy and physiology course differentiate academic achievement, as measured by assessment scores over the course of a 16-week semester, when controlling for GPA?

The study considered correlation on more than fifty percent of the assessments to validate the alternative hypothesis and less than fifty percent correlation on the fourteen assessments to validate the null hypothesis of the study. The student's individual college GPA, prior to taking the course under review, was used as a covariate within the study. The specific data and results are explained and elucidated in Chapters 4 and 5.

For this study, I compared the scores on the twelve tests, as well as midterm and final exam assessments from twelve sections of a first semester anatomy and physiology course. The twelve sections selected were taught by two separate instructors between the fall of 2018 and the summer of 2020 and the scores from these tests were compared using the nonexperimental design for the four test groups. The original data were collected, not as part of a research study, but rather as part of the requirements for initial course completion and assignment of a final grade for the course. Due to the nature of the study, it was not feasible or ethical to enroll students in sections where the dynamic study modules were not offered. Also, because the students self-selected their level of interaction and use of the dynamic study models the nonexperimental design was deemed the best fit for comparison of the data. A G*Power assessment of a F-test MANCOVA was used to evaluate the potential number of students required for a valid study of this type. The initial G-Power analysis showed that a student sample of at least 128 participants would be needed for an effect size d of .25, an alpha error prob. of .05, and a power of .80.

Sample Population

The population for this study were students enrolled in pre-health majors at a small Midwestern community college that had chosen to take the first semester of an advanced anatomy and physiology course online. Students who elect to take this course are generally pre-med, physical therapy assistant students or, pre-nursing students. The pre-nursing students make up the largest percentage of students taking the course with approximately 86 percent of the enrolled student population in this course from semester to semester.

The students that take this course range in age from 17 to 67 years of age with the largest percentage of the population being between 20 and 26 years of age. Students taking this first semester anatomy and physiology course must have taken one of the prescribed prerequisite courses, a general biology or general chemistry course within the last five years and have completed that course with a letter grade of C or better prior to starting the class. No prior online course experience was required for students taking an online course at this institution.

The course that was examined for this study is offered in a traditional, hybrid, and fully online format, but only those students who completed the first semester course in the online format between fall of 2018 through the spring 2020 were considered for this study. The students self-selected into the online course sections based on their individual preferences. Prior GPAs were used as a covariant for this study, however the course prerequisites themselves have no parameter or prerequisite for student's prior GPA. The sample population were sections of students from two different instructors who taught the course during the specified period. This sample yielded a total of 257 students.

Possible Types and Sources of Data

Archived data were the primary source of data for this study, comparing results from the first semester of multiple sections of a fully online anatomy and physiology course at a small midwestern community college. The college has three campus sites with a little over 6,000 full time students each semester. The students can choose from classes in three different modes of instruction; fully traditional, hybrid, and fully online. In the spring of 2020, the online offerings accounted for approximately 26% of the credit hours at this institution. The course that was used for the study is identified by the college as Bio 2121 and is the first class in a two-course sequence of advanced anatomy and physiology.

The student population for the course is approximately 86% pre-nursing or nursing students enrolled in an associate level nursing program, another 12% of the students are enrolled in the school's physical therapy assistants' program; approximately 2% of the students are a mix of pre-med students and students taking the course as an elective. During the 18 months of this study approximately 60% of students enrolled in the course took it in the traditional format with 38% elected to take it fully online and the other 2% completed the course in the hybrid format.

The groups that were compared for this study were three experimental groups and a control group. The experimental groups consisted of students from multiple sections who completed the course between the Fall of 2019 through the end of the summer semester of 2020. Their overall use of the courses dynamic study modules was logged within the publisher data management site as part of their preparation for the content within the selected course. The control group consisted of students from these same sections who had no significant use of the ITS, in that they utilized the ITS for less than 10% of the selected material.

For all sections, the materials used and assigned to the students were the same as well as the objectives and assessments with the only variable being the students' use of the ITS as a study aid, with its' use strongly encouraged by all instructors. The use of the dynamic study modules was also incentivized by the inclusion of a small bonus point allocation for each completed module, and while this did effect the overall final grade it did not affect the individual assessment scores that were used in this study. Because this study includes multiple sections over 18 months, two instructors were identified, and their sections were selected for the purpose of this study for both the control and experimental groups. Each section, regardless of instructor included the same content and was assessed on the same objectives using the same assessments.

The sample for this study will consisted of 12 sections of online anatomy and physiology, yielding a sample size of 257 students. The similarity of the online sections was very close, as all online students' courses are created using the same master shell and are the same regardless of instructor. The only influence of the different instructors would be the answers given to individual student emails if they contacted the instructor with questions on content or clarification of instructions. The data, which in this study were test scores, from the three test groups, were compared to the scores of the control group. The data were analyzed to see if any significant difference existed in the individual chapter test scores, or within the midterm and final assessments. The students' scores were also analyzed using a covariant of student's prior GPA to help eliminate confounding factors that might alter or skew the observed results.

Threats to Validity

One of the biggest threats to external validity of this study was the fact that the subjects were not chosen or assigned to randomized groups for the purpose of this research. Rather the research groups, and the students within each group, were self-selected based on the amount of use of the ITS that was evaluated in this study. Two strategies to mitigate this threat were the inclusion of the covariate of prior GPA, as well as differentiating between failing students who did not fully complete all the assigned units within the semester long course and those who did, but still failed the course. Students who did not complete all the assignments will likely have participated in very little ITS, thereby skewing the control group data. Removing those students from the study, therefore, helped to mitigate that threat to validity from the study

By contrast the internal validity of this study was quite strong as there is no significant difference between the four research groups, aside from the amount of time the individuals spent with the ITS being studied. Therefore, any noted deference in the research groups was attributed to the independent variable, which was~~,~~ the number of dynamic study modules completed. Because these groups were not randomly assigned there was no specific way to know if the overall demographics of the groups were similar as there was no control for age, gender, socioeconomic status, etcetera. Further study of these differences could be an area of future research to elucidate any difference between these groups. As Fisher et al. (2018) aptly noted, a researcher can only control for those variables that are known to exist, and only then if the construct of the current study allows (Fisher et al., 2018).

The construct of the study was designed to eliminate as many cofounding variables as possible, adding strength to both construct and statistical validity. Another factor adding to the statistical validity of this study was the relatively large sample size. A G*Power analysis determined that at least 128 individuals would be needed for a valid study and the inclusion of all viable sections for the 18-month period should provide almost twice that number of individuals. As Yu et al. have noted in their recent study on evaluating different sources of student data, larger sample sizes give more reliable results with greater precision and power (Yu et al., 2020).

Archived data was used for this study alleviating much of the concern for ethical treatment of subjects. Each individual student account within the individual section was transferred to a randomly assigned numerical identifier to allow for anonymity throughout the data review process. IRB approval for this study was obtained from Walden University as the host institution has agreed to allow Walden to act as the IRB of record for this study. No one outside the scope of the study had access to the data or individual student information at any time during the duration of the study and once analysis was completed the data were securely stored for future analysis if any is warranted or required.

Ethical Procedures

There were no ethical issues with the data proposed for use in this study for even though I work at the same institution where these classes are taught, I have no direct contact with the students or instructors within these sections once the semester begins. I do work with the adjunct faculty that taught these courses, but there was no interaction or direction given by myself to these individuals that would in any way impact the data or results of this study.

Summary

The purpose of this nonexperimental quantitative study was to determine if there was a significant difference in assessment scores for students who had used an ITS while taking a first semester online anatomy and physiology course. The study also determined if there was a causal relationship between the amount of use of the ITS and the grades for cumulative assessments such as midterm and finals for this course. The study was designed to address a gap in literature which existed surrounding the effectiveness of current ITS and their ability to alter basic knowledge acquisition and long-term knowledge retention in a fully online undergraduate college level anatomy and physiology course. Archived data were collected from 12 sections over the course of 18 months from two different instructors teaching an online anatomy and physiology course. A covariant of prior GPA was used in this study to increase the validity of the findings. The use of a covariant along with the relatively large sample size allowed for an acceptable level of confidence in the findings presented. This chapter has addressed the specifics of the student population that were studied, the collection of data and mechanism for analysis, as well as threats to internal and external validity of the study.

A more detailed description of the data and its analysis are provided in Chapter 4 along with the specifics of the demographics, numbers of constituents in each research group as well as the overall findings of the study and the answer to the proposed research question. Chapter 4 also includes the statistical analysis of the test results along with figures and tables detailing the data obtained from the four research groups. The chapter concludes with a discussion of the answer to the research question and its validity.

Chapter 4: Results

The purpose of this quantitative study was to answer whether the use of an ITS, Person's Dynamic Study Modules, alters knowledge acquisition in a fully online undergraduate college level anatomy and physiology course while controlling for the students' prior GPA. To test the hypothesis of this study a MANCOVA test was selected to evaluate the data presented within the study. The MANCOVA test allows for analysis where there is more than one dependent variable and where the control of concomitant continuous independent variables—covariates—is required (Xu & Goodacre, 2018). There are four main assumptions that must be addressed within a MANCOVA study, those are the assumption of homogeneity of covariances, then second and third would be the assumption that there are no significant univariate or multivariate outliers in the independent variable in terms of each dependent variable; and lastly the assumption of normality. These assumptions allowed me to test the significance of effect that the independent variable, of ITS use, had on the students' assessment scores, of individual chapters as well as midterm and final assessments, while controlling for the students' prior GPA. The study considered correlation on more than 50% of the assessments to validate the alternative hypothesis and less than 50% correlation on the 14 assessments to validate the null hypothesis of the study. This chapter presents the data collected for this study, the manner in which it was obtained, as well as the statistical analysis of this data and the results as they relate to the research question and hypothesis.

Data Collection

In this study, I analyzed a compiled data set of archival student information from students completing an online anatomy and physiology course between the Fall of 2018 and the Spring of 2020 with and mean age of 29.31. The overall statistical distribution of this student subset was representative of the overall college demographics in respect to characteristics such as age, male to female ratio, and ethnicity. Bio 2121 is a first semester course, and the participants' data that were used were only from those students who had a prior college GPA, fully completed the course, and received a final letter grade upon completion of the course. The fully online sections for two identified instructors from the fall of 2018 through the spring of 2020 were used.

A G*Power analysis for this study showed that a student sample of at least 128 participants would be needed for an effect size d of .25, an alpha error prob. of .05, and a power of .80. The initial student group from the 12 sections used in this studies data set yielded 257 initial individual student records. After students who dropped the course before completion were eliminated, the pool was left with approximately 156 students. When only students with a prior college GPA were considered the number of possible subjects dropped to 99, as many of the students taking this particular course were first or second semester freshman with no recorded college GPA prior to attempting this course. Because the number of participants was well below the significance threshold estimated by G*Power analysis, any conclusions based on this studies MANCOVA data analysis would need to be validated with further research using a larger sample size (Barrett & Lockhart, 2019).

The study was confined to archived data from 12 chapter tests, one midterm, and one final exam resulting in 14 dependent variables. These scores were assigned to the research groups based on archived data of each student's self-selected participation and use of the ITS. The data were archived at the course web site, which could be accessed through a weblink within the online course shell as well as the individual chapter assessment information that was stored in the college's black board course management system for these individual classes.

To understand the relationships between the assigned variables, the Statistical Package for the Social Sciences (SPSS) software program was used to create a MANCOVA study with resulting data tables that explain the relationship of the variables in question. Select tables and figures have been included in this chapter to facilitate the presentation of findings, while the full data exploration is provided in Appendix A. The results of each relevant test within the MANCOVA study were explained then analyzed with the conclusion to accept the null hypothesis proposed for this study: The level of ITS use in a first semester online anatomy and physiology course does not alter academic achievement when controlling for GPA.

Results

The SPSS software program was utilized to run a MANCOVA analysis of 14 criterion test variables reflecting student performance and one independent variable with four different levels of ITS utilization with each student's prior GPA as a covariate. The 14 dependent variables were 12 chapter tests, one midterm, and one final exam from an online anatomy and physiology course taken between the fall of 2018 and the spring of

2020. In the course under review there were 48 individual ITS modules that the students could elect to complete as they progressed through the homework portion of the course and based on their level of participation, they were placed in one of four groups. Students who completed 0–10 of the 48 modules were placed in the no significant use group, students who completed 11–20 modules were placed in the nominal use group, students completing 21–30 modules were placed in the moderate use group, and students who completed 31–48 modules were placed in the saturated use group. The assignment of these groups was based on an equal division of the 48 possible modules.

Table 1 shows the between subjects factors with roughly equal numbers of subjects in the first three categorical groups. Table 2 presents the descriptive statistics with relatively uniform standard deviations between the groups. As shown in Table 1, the highest use group (saturated), had more than double the number of students compared to the other groups. This skewed distribution is likely due to several factors. First, participation and use of the dynamic study modules is incentivized within the course as completion of each module will net the student .5 bonus points. This is a small point incentive because there are over 1,300 points in the overall course; thus, saturated use of the ITS will only increase the students overall final point total by 1–2%. However, even small point incentives greatly increases online student participation in extra credit activities (Felker & Chen, 2019). Second, the research group for this study included only students who had fully completed the course and received a final grade. In this way the study favored the more motivated, prepared, and diligent students within the overall population (Hopkins et al., 2020). Lastly, student comments within the course anecdotally noted that they felt the dynamic study modules were one of the most effective ways to prepare for the online tests. Even though this perception does not seem to be empirically proven within the data of this study, the perception of students does drive use of this teaching tool within the course. This perception is validated by a decade long review of learning strategies in higher education, published in the journal of Education and Information Technologies, that shows students only use educational tools that they find effective (Anthonysamy et al., 2020).

Table 1

Between Subjects Factors

Module Categories	Dependent Variable Groups	*N*
1	No Use	19
2	Nominal	14
3	Moderate	13
4	Saturated	53

Table 2

Descriptive Statistics

Chapter Assessments	Module Categories	Mean	*SD*	*N*
Chapter 3 Test	No Use	17.45	3.118	19
[Total Pts: 25]	Nominal	19.18	4.158	14
	Moderate	16.00	3.035	13
	Saturated	18.71	2.797	53
	Total	18.18	3.222	99
Chapter 3-b Test	No Use	16.58	6.466	19
[Total Pts: 23.5]	Nominal	17.61	4.015	14
	Moderate	14.77	4.781	13
	Saturated	16.51	3.542	53
	Total	16.45	4.455	99
Chapter 4 Test	No Use	21.21	3.225	19
[Total Pts: 25]	Nominal	21.04	2.678	14
	Moderate	19.58	1.579	13
	Saturated	22.22	1.938	53
	Total	21.51	2.444	99
Chapter 5 Test	No Use	20.92	2.323	19
[Total Pts: 25]	Nominal	21.43	1.708	14
	Moderate	21.12	1.673	13
	Saturated	21.25	2.127	53
	Total	21.19	2.036	99
Chapter 6 Test	No Use	20.55	2.409	19
[Total Pts: 25]	Nominal	21.36	1.550	14
	Moderate	20.42	1.644	13
	Saturated	21.70	2.006	53
	Total	21.26	2.036	99
Chapter 9 Test	No Use	19.16	3.300	19
[Total Pts: 25]	Nominal	20.07	3.018	14
	Moderate	19.31	2.898	13
	Saturated	20.07	3.182	53
	Total	19.79	3.126	99
Chapter 11 Test	No Use	19.18	3.101	19
[Total Pts: 25]	Nominal	20.21	2.992	14
	Moderate	18.62	2.073	13
	Saturated	20.45	2.646	53
	Total	19.93	2.773	99
Chapter 12 Test	No Use	19.61	4.786	19
[Total Pts: 25]	Nominal	21.71	2.614	14
	Moderate	20.58	4.061	13
	Saturated	21.90	2.198	53
	Total	21.26	3.246	99
Chapter 13 Test	No Use	20.05	3.763	19
[Total Pts: 25]	Nominal	22.89	1.274	14
	Moderate	21.54	2.259	13
	Saturated	22.14	2.187	53
	Total	21.77	2.610	99
Chapter 14 Test	No Use	19.29	2.557	19
[Total Pts: 25]	Nominal	20.64	2.070	14
	Moderate	19.69	2.087	13
	Saturated	21.15	2.267	53
	Total	20.53	2.373	99

(table continues)

Chapter Assessments	Module Categories	Mean	SD	N
Chapter 15 Test	No Use	19.79	2.434	19
[Total Pts: 25]	Nominal	20.93	2.209	14
	Moderate	19.23	2.342	13
	Saturated	21.01	2.309	53
	Total	20.53	2.309	99
Chapter 16 Test	No Use	17.89	2.861	19
[Total Pts: 25]	Nominal	17.32	5.434	14
	Moderate	18.69	1..640	13
	Saturated	19.61	2.274	53
	Total	18.84	3.053	99
Bio 2121 Lec Midterm	No Use	100.53	21.795	19
[Total Pts: 150]	Nominal	104.93	20.593	14
	Moderate	97.85	21.610	13
	Saturated	111.06	19.571	53
	Total	106.43	20.883	99
Bio 2121 Lec Final	No Use	98.21	14.142	19
[Total Pts: 150]	Nominal	103.86	19.837	14
	Moderate	100.46	21.403	13
	Saturated	111.19	20.646	53
	Total	106.25	20.189	99

Visual inspection of the difference between means in each of the comparisons from Table 2 indicates that there could be a difference in the overall scores for the saturated group as compared to the other two groups for a few of the assessments, but there is no way to tell using this particular table and comparison if the differences are statistically significant (see Borenstein, 2022). Values for the midterm and final tests show a 10% difference between the scores of the saturated group and the no use group. Also, rough comparisons do not seem to follow a direct linear pattern as there is a notable difference between the scores of the no use group and the saturated use group, but in many of the comparisons, such as chapter 3, 3-b, 5, 6, 9, 11, 12 and 15 the nominal use group had almost equal to, if not better scores than the saturated use group.

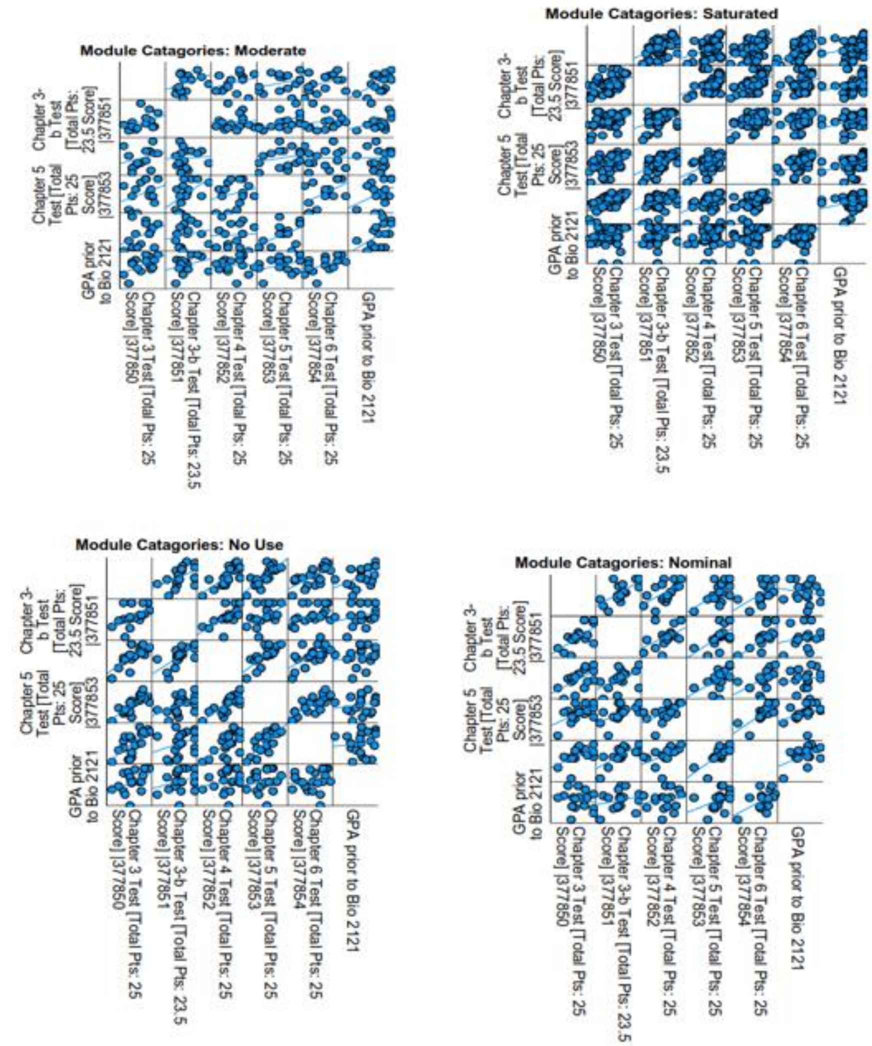
To ascertain if the difference noted in the previous charts are significant within the MANCOVA test the data must be evaluated for linearity. In a one-way MANCOVA such as the one used in this study there are two linearity assumptions that must be met (Y.

Hu & Plonsky, 2021). The first assumption is that there is linearity between each pair of dependent variables within each group of independent variables and the second is that there is also linearity between each dependent variable and the covariate within each group of independent variables (Gwelo, 2019). If the independent variables within the study are not linearly related, the power of the one-way MANCOVA to detect statistically significant difference between the groups will be reduced (Perugini et al., 2018). For this study it was important to assess for linearity to determine the legitimacy of difference, if found, between the independent variable groups of ITS use and the assessment scores while adjusting for the covariate of prior GPA.

In this study there were 14 assessment scores for each student, these scores served as the dependent variables which were compared with the four categorical groups of independent variable and both were compared for linearity with the covariate of prior GPA. To form these graphs, the data set for this study was split within the SPSS software file and individual scatterplots were created for each of these relationships and each scatterplot was evaluated for linearity. Examples of these results are included here for the relationships between test scores and the student's prior GPA as Figure 3. This figure is a representation of best fit lines for chapter test 3, 3b, 4, 5 and 6 as they relate to one another and to the student's prior GPA for all four groups of the independent variable. Though there are only 5 of the 14 assessments noted in Figure 3, linearity data sheets have been included for all the relationships between dependent and independent variables (see Appendix B). By looking at the best fit line in each of the comparison boxes it can be noted in all four categorical groups that there is evident linearity between the dependent variable groups as they relate to the independent variables of assessment scores. It is also noted that student's prior GPA shows linearity and therefore a useful covariate for this study. This evaluation can be done by visual inspection of the scatterplots and since linearity is present, the MANCOVA test is a good choice for evaluation of the selected data with no need to transform any of the variables (Z. Li & Chen, 2019; Shanthi, 2019).

Figure 3

Scatterplot Matrixes with Categorical Variables and Covariate of Prior GPA



Because both assumptions of linearity for this study were met the next step for a study of this type is to address the assumption of homogeneity of regressions slopes (Flatt & Jacobs, 2019). An important assumption of the one-way MANCOVA is that the slope, or coefficient, between the covariate and each of the dependent and independent variables is the same (Moscalu et al., 2018; Shanthi, 2019). For this study a homogeneity of regression slope was run to evaluate the relationship between the student's covariate of prior GPA, and each of the dependent variables within the groupings of independent variables and the resulting data is presented in Table 3. By consulting the Wilks' Lambda row, there was homogeneity of regression slopes as assessed by the interaction term between student's prior GPA and the categorical independent variable of ITS utilization as (F = 1.115, p = .302). In the case of homogeneity of regression the p-value of greater than .05 means that there is not a statistically significant interaction between the covariate and the dependent and independent variable groupings and this study meets the assumption of homogeneity of regression slopes (Moscalu et al., 2018).

Table 3

Homogeneity of Regression Slopes – Multivariate Tests

Effect	Statistical Tests	Value	F	Hypothesis df	Error df	Sig.
Module Rates GPA prior to Bio 2121	Pillai's Trace	.488	1.110	42.000	240.000	.308
	Wilk's Lambda	.580	1.115	42.000	232.151	.302
	Hotelling's Trace	.613	1.119	42.000	230.000	.297
	Roy's Largest Root	.351	2.007	14.000	80.000	.027

Having met both assumptions of linearity and the assumption of homogeneity of regression slopes, I proceeded with the MOCOVA analysis and the next matter to consider is to insure that there are no significant univariate or multivariate outliers in the groups of independent variables as they are compared with each dependent variable (Mishra et al., 2019; Shanthi, 2019). The one-way MANCOVA is sensitive to multivariate outliers, and it is therefore important to calculate a measure called the Mahalanobis distance that can be used to determine whether there are significant outliers within the studies data set (Moscalu et al., 2018). To accomplish this the data set was once again split, this time, by the independent variable identifier and a new ID column was created to allow for a liner regression of the data to be performed. This data analysis has been included as part of Appendix A. The linear regression general analysis showed that there were no univariate outliers in the data, as assessed by standardized residuals greater than ± 3 standard deviations. This measurement helped to validate the results and insure that Type I basis within the results is limited (Borenstein, 2022; Dashdondov & Kim, 2021; Perugini et al., 2018). At the same time this output was reviewed for multivariate outliers, and it was determined that there were no significant multivariate outliers in the current data set as assessed by Mahalanobis distance ($p > .001$). The Mahalanobis distance is the commonly accepted measurement value for multivariate validity within a MANCOVA test (Dashdondov & Kim, 2021; X. Li et al., 2019).

Having determined that there were no significant outliers the study proceeded to the next test of validity for a MANCOVA study. Since the one-way MANCOVA assumes that the variances and covariances of the dependent variables in question are equal across all groups of the independent variables in is imperative to test for equality of variance (Perugini et al., 2018). Within the MANCOVA study the best evaluation of equality of variance is the Box's M Test and since this test is sensitive to data that is not normally distributed the level for statistical significance for this test is commonly set at $p < .001$ (Flatt & Jacobs, 2019; Mishra et al., 2019; Perugini et al., 2018). Using this parameter, there was homogeneity of variances and covariances, as assessed by Box's M test, $p = .202$, meaning the null hypothesis can be accepted and that all means are equivalent for the four categorical groups in question as they relate to the independent variables and look further into the results to determine if there are significant difference between the specific groups while controlling for the student's prior GPA.

Table 4

Box's Test of Equality of Covariance Matrices

Box's M	182.747
F	1.115
df1	105.000
df2	2957.527
Sig.	.202

Once it was confirmed that there was equality of variance within the current data base the overall results of the MANCOVA test could be evaluated to see if there was a significant influence on assessment scores based on students' use of the dynamic study modules. Table 5 shows the results of the multivariate tests, and more specifically the Pillai's Trace test, as it would be the best suited for a study of this type (Ateş et al., 2019). This test demonstrates that there was not a statistically significant difference, $p < .054$, between the groups on the combined dependent variables after controlling for GPA.

However, the value is very close to the traditional .05 cutoff for significance and some further reflection on the data was warranted to see if there were any of the specific chapter tests or midterm/final tests that might have met the statistical significance threshold.

Table 5

Multivariate Tests

Effect	Statistical Tests	Value	F	Hypothesis df	Error df	Sig.
Module Rates GPA prior to Bio 2121	Pillai's Trace	.580	1.422	42.000	249.000	.054
	Wilk's Lambda	.523	1.402	42.000	241.050	.062
	Hotelling's Trace	.728	1.381	42.000	239.000	.071
	Roy's Largest Root	.314	1.864	14.000	83.000	.043

Table 6

Pairwise Comparisons for Chapter 16 Comparing Assessment scores and ITS use while controlling for Student's prior GPA

Dependent Variable	Module Categories(I)	Module Categories (J)	Mean Difference (I-J)	Std. Error
Chapter 16 Test [Total Pts: 25]	No Use	Nominal	1.000	-1.517
		Moderate	1.000	-2.964
		Saturated	.573	-3.509
	Nominal	No Use	1.000	-4.005
		Moderate	1.000	-4.356
		Saturated	.022	-4.937
	Moderate	No Use	1.000	-2.666
		Nominal	1.000	-1.571
		Saturated	1.000	-3.624
	Saturated	No Use	.573	-.809
		Nominal	.022	.250
		Moderate	1.000	-1.221

By evaluating the pairwise comparisons, in Table 6, as well as the estimated means that were generated for each group based on the influence of the students' prior

GPA, all comparisons were essentially equal with no significant effect of ITS use. The only significant measurable effect was in the Chapter 16 test which was the final chapter assessment in this course's semester curriculum. Because there was no other significant difference related to the 14 dependent variables, the Chapter 16 result should be judged with caution and considered an outlier within the study. These comparisons are discussed further in Chapter 5 along with additional comments and reflections.

Summary

The analysis of data indicated that there was no significant correlation between the amount of ITS use and the students' resulting grades on individual tests or cumulative midterm or final assessments while controlling for the student's prior GPA. The sample size of this group is small, with only 99 total student records, and is smaller than the recommended number from G*power analysis which called for 129 subjects for this trial. Therefore, any conclusions of this study would be suspect and need further analysis with a larger data set to confirm with confidence. There were two primary limiting factors in obtaining a larger overall group size. One was the fact that all students were required to have a previous college GPA to satisfy the corequisite requirement of this study and the other was that all subjects must have fully completed the course to be included in the sample. The courses used in this study had a high attrition rate over the course of the semester with only a 62% completion rate for the period of this study.

Because the test grades in this course are on a 0–25 scale, there is not much variance between the individual chapter tests themselves, so future studies might alter the dependent variable to be a composite of test scores for three or more tests to perhaps give a wider range of variance within the dependent variables. Additional studies might also look at individual tests and the specific use of the ITS within that chapter to see if there is any effect on ITS use on scores within the individual chapters.

This study in and of itself shows little to no correlation on test scores as it relates to ITS utilization so the null hypothesis would be supported in that there is no significant difference in assessment scores for those using or not using this ITS. The possible implications for social change are limited, as there was no relationship between the independent and dependent variables of this study, but future investigation might look for other effects of this relationship within other variables from these subject groups or simply consider that time spent on the ITS modules is not effective is overall grade change for the cumulative tests and student study time might be better spent in other areas. These possibilities are discussed further in Chapter 5.

Chapter 5: Discussion, Conclusions, and Recommendations

The topic of this study was the investigation of the efficacy of an ITS for increasing student performance in a college level online anatomy and physiology course. The specific ITS explored in this study was the Pearson Dynamic Study Modules program for Anatomy and Physiology. Acceptance rates of this technology have been low since its inception more than forty years ago and little has been explored about the efficacy of the technology for curriculums outside of math and computer science applications (Almasri et al., 2019; Kulik & Fletcher, 2016; Wang et al., 2020). With instructors citing a lack of apparent advantage, compatibility, and perceived trust as contributing determinants in their willingness to adopt and implement AI strategies and specifically ITS in their curriculum (S. Wang et al., 2020), it was deemed a logical next step to investigate whether there was an educational advantage to implementing this technology within the academic program at the partnering college (Cavanagh et al., 2019; Lim et al., 2019; Shim & Lee, 2020).

The current study addressed the gap in research by looking at the efficacy of one specific ITS program called dynamic study modules used in an undergraduate online anatomy and physiology course. This study provided some insight into the change in assessment scores relative to the students' use of the dynamic study modules over the course or a full semester an aspect of ITS evaluation that had been absent in scholarly research up to this point (see Almasri et al., 2019; Cavanagh et al., 2019; Lim et al., 2019). In the 14 assessments that were analyzed for this study, only one showed any significant difference in student grades for the assessment, in correlation with the amount of time spent with the ITS, while controlling for the students' prior GPA. Furthermore, since 13 of the 14 assignments showed no significant relationship, it was determined that the Chapter 16 assessment, that did show correlation, would be treated as an outlier for this study and the overall determination of the study would be that no significant effect was noted for the use of this ITS on the assessment scores of students within this online anatomy and physiology course.

Interpretation of Findings

As stated in Chapter 2, the majority of studies that relate to educational technology show that there is no significant difference for courses that incorporate the technology over those taught traditionally (Huda et al., 2019). This lack of efficacy is due in part to the fact that technology additions do not replace the learning process but rather facilitate the delivery of educational instruction to the learner (Burbules et al., 2020; Müller & Mildenberger, 2021). In that sense this quantitative study confirmed the broad conclusions about the inclusion of technology in education that there is no significant difference between outcomes for learners that utilize technology when compared to those that do not utilize technology. With the exception of one of the chapter tests, there were no statistically significant differences in chapter test performance, or cumulative test (i.e., midterm and final exam) performance based on technology utilization between four categorical groups while controlling for prior GPA. The one significant difference found between the saturated and moderate groups for the Chapter 16 test should be interpreted with caution and should be considered and outlier in the overall data, due to the insignificant results for the other 13 criterion variable tests. These findings support previous publications suggesting that ITS has little efficacy in education of college level students (Csapó & Molnár, 2019; Slavin, 2019).

According to this MANCOVA study of 99 individual students within an online anatomy and physiology course there was a *p* value greater than .05 for all comparisons of student use from, no use, to saturated use, when controlling for prior GPA of the dynamic study modules for this ITS. The results from this MANCOVA study affirm the null hypothesis that the level of ITS use in a first semester online anatomy and physiology course does not alter academic achievement when controlling for the individual's GPA. Previous studies have given mixed results on the efficacy of ITS in both math and computer-based curricula (Kulik & Fletcher, 2016; McCarthy et al., 2018; Sottilare et al., 2018). The results of this study align with findings from other studies, like that of Kulik and Fletcher (2016a), that showed no significant difference for the use of ITS technology. Like this study, however, Kulik and Flether's study also had a limited number of student participants. In retrospect, most of the studies that showed a positive relationship between ITS utilization and student performance focused on smaller chunks of content to be learned and assimilated (McCarthy et al., 2018). Future studies with this particular dataset could consider chapter by chapter assessments and the study modules that are associated with that particular chapter to discern if there is any relationship in these smaller chapter by chapter cases.

Limitations of the Study

One of the primary limitations of the study was the number of students that could be compiled within the parameters that were established. A G*Power assessment of a F-test MANCOVA was used to evaluate the potential number of students required for a valid study. The initial G*Power analysis showed that a student sample of at least 128 participants would be needed for an effect size d of .25, an alpha error prob. of .05, and a power of .80. The initial student group from the 12 sections identified between fall of 2018 and the spring of 2020 yielded 257 initial records with selection criteria for participation notwithstanding. After students who dropped the course before completion were eliminated, the pool was left with approximately 156 students. This attrition is normal for this course at this particular college, as it has a high level of complexity, and anatomy and physiology is considered a gateway course to the health care curriculums (Forgey et al., 2020). This attrition was also consistent with attrition rates for this type of course across most colleges and universities with the national average for attrition in a first semester anatomy and physiology being approximately 38% (Eudy & Brooks, 2022; Goradia & Bugarcic, 2019). When only students with a prior college GPA were considered the actual number of possible subjects dropped to 99, as many of the students taking this particular course were first or second semester freshman with no recorded college GPA prior to attempting this course. Because the number of participants was well below the significance threshold estimated by G*Power analysis, any conclusions based on my MANCOVA data analysis would need to be validated with further research using a more appropriate sample sizes (Barrett & Lockhart, 2019).

Another limitation when considering this study is that it looked at the semester long use of the ITS over the course of 16 weeks and how this impacted individual chapter assessment scores even though the chapter assessments occurred over the span of the semester. For example, the analysis of the Chapter 3 assessment compared the scores of the four categorical groups of test subjects, based on their overall use of the 48 individual dynamic study modules, even though at the time the students took the Chapter 3 assessment they could not have completed more than four of the dynamic study modules at that time of the test. In retrospect there might be more useful evaluations that could be completed with individual assessments, for individual chapters, and the amount of student ITS use within that specific chapter. Upon reflection in the design of the study this seems to be a structural conflict as I was essentially looking back in time for correlation of ITS use before it has occurred.

As stated, the small sample size limits the validity of this study and therefore the generalizability and trustworthiness for reported results and suggested application (Xu & Goodacre, 2018). Future studies could extend the timeline for sampling, but as explained in Chapter 2, the timeline for this study was established to limit the influence of increased online course utilization due to the COVID pandemic. This unique situation would need to be a consideration when planning the analysis if additional courses are included in a sample from after the spring of 2020.

Recommendations

Recommendations for further study would be to use a similar study format and analysis technique with the inclusion of parameters to evaluate the ITS use on a chapter-by-chapter basis and also increase the sample size to increase the validity of measured results. Increasing the sample size would need to be done with the understanding that data from additional online sections, gathered during the COVID pandemic time period, might show aberrations. These aberrations could be due in part to the fact that students taking the online course during this time had no other modality options and selected the online course even though that modality might not be their preferred method of instruction and might not be the best fit for their individual learning styles. Additionally, because the test grades in this course are on a 0–25 scale, there is not much variance between the individual chapter tests themselves. Therefore, future studies might alter the dependent variable to be a composite of test scores for three or more tests to give a wider range of variance within the dependent variables.

Additional studies could also be done with the current data set to look for short term correlations between dynamic study module use within each chapter and corelate chapter assessments while still controlling for students' prior GPA. This study would be in line with research already in the field that has shown correlation between ITS use on small subsets of data form within specific course curricula (Akyuz, 2020; Almasri et al., 2019; Cavanagh et al., 2019).

Another area of interest with merit would be to include students who did not complete the entire course within the current study to determine if there is a correlation between ITS use and successful completion of the course. It was noted that 53 out of the total 99 students who completed the course had saturated use of the ITS in this particular study, and more than 80% had moderate to saturated use. As noted in Chapter 2, there are few current studies that include data for an entire semester or discuss how ITS use effects course completion rate (Alkhatlan & Kalita, 2018; Almasri et al., 2019; Hartley, 1977). It would be valuable to see if there is any correlation between overall completion and the use of the ITS program in question.

One other area that could be of use would be an additional study to elucidate the connection between prior GPA and scores on the individual assessments as well as overall completion of the course. Although the current study failed to show a direction correlation between ITS use and assessments scores it was noted that there was a correlation between prior GPA and students' scores on most of the assessments in question. This correlation would be in line with a recent study in the *Journal of Teaching and Nursing* that showed one of the strongest indicators of student success in fundamentals courses within associate degree nursing track was a student's prior GPA (Eudy & Brooks, 2022).

Implications and Conclusion

The possible implications for positive social change are complicated by the lack of significant quantitative findings in this study, combined with similar findings from other studies, for the efficacy of ITS utilization and student performance. One recommendation would be to direct student study time to other areas within the course and supplementary materials that might be more effective for grade improvement. However, it was also noted that more that 80% of those students who successfully completed the course did use the ITS to some degree, so even though there was not a correlation between time spent on task with the dynamic study modules and assessment scores in this study, it does not mean that students did not find the dynamic study modules helpful in their study efforts. Qualitatively, research is needed to determine what perceived effects the dynamic study modules are providing to the students who choose to use them. More quantitative research could also help expose any relationships that might exist between dynamic study module use and successful completion of the online anatomy and physiology course.

Though this study failed to find a correlation between the Pearson Dynamic Study Modules and student assessment scores, there was a correlation noted between overall student success and students' prior GPA. This information could be shared with counselors and other educators that work with pre-nursing and pre-health students to encourage them that overall academic strength is a good indicator of future success within health care programs. Counseling students with lower GPAs to do more foundational academic work before attempting higher level courses could save them time and money over the course of their academic careers as well as help them be more successful in their nursing majors.

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Appendix A: SPSS Data for MANCOVA Study of ITS Effects on Assessment Scores with Covariate of Prior GPA

```
GLM Chapter3TestTotalPts25Score377850 Chapter3bTestTotalPts23.5Score377851
    Chapter4TestTotalPts25Score377852 Chapter5TestTotalPts25Score377853
    Chapter6TestTotalPts25Score377854 Chapter9TestTotalPts25Score377855
    Chapter11TestTotalPts25Score377798 Chapter12TestTotalPts25Score377856
    Chapter13TestTotalPts25Score377799 Chapter14TestTotalPts25Score377800
    Chapter15TestTotalPts25Score377857 Chapter16TestTotalPts25Score377858
    Bio2121LectureMidtermTotalPts150Score377864 Bio2121LectureFinalTotalPts150Score377865
 BY ModRates
    WITH GPApriortoBio2121
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /PRINT=DESCRIPTIVE ETASQ HOMOGENEITY
  /CRITERIA=ALPHA(.05)
  /DESIGN=GPApriortoBio2121 ModRates.
```

General Linear Model

Between-Subjects Factors

		Value Label	N
Module Catagories	1.00	No Use	19
	2.00	Nominal	14
	3.00	Moderate	13
	4.00	Saturated	53

Descriptive Statistics

	Module Categories	Mean	Std. Deviation	N
Chapter 3 Test [Total Pts: 25 Score] |377850	No Use	17.45	3.118	19
	Nominal	19.18	4.158	14
	Moderate	16.00	3.035	13
	Saturated	18.71	2.797	53
	Total	18.18	3.222	99
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	No Use	16.58	6.466	19
	Nominal	17.61	4.015	14
	Moderate	14.77	4.781	13
	Saturated	16.51	3.542	53
	Total	16.45	4.455	99
Chapter 4 Test [Total Pts: 25 Score] |377852	No Use	21.21	3.225	19
	Nominal	21.04	2.678	14
	Moderate	19.58	1.579	13
	Saturated	22.22	1.938	53
	Total	21.51	2.444	99
Chapter 5 Test [Total Pts: 25 Score] |377853	No Use	20.92	2.323	19
	Nominal	21.43	1.708	14
	Moderate	21.12	1.673	13
	Saturated	21.25	2.127	53
	Total	21.19	2.036	99
Chapter 6 Test [Total Pts: 25 Score] |377854	No Use	20.55	2.409	19
	Nominal	21.36	1.550	14
	Moderate	20.42	1.644	13
	Saturated	21.70	2.006	53
	Total	21.26	2.036	99
Chapter 9 Test [Total Pts: 25 Score] |377855	No Use	19.16	3.300	19
	Nominal	20.07	3.018	14
	Moderate	19.31	2.898	13
	Saturated	20.07	3.182	53
	Total	19.79	3.126	99
Chapter 11 Test [Total Pts: 25 Score] |377798	No Use	19.18	3.101	19
	Nominal	20.21	2.992	14
	Moderate	18.62	2.073	13
	Saturated	20.45	2.646	53
	Total	19.93	2.773	99

Descriptive Statistics

	Module Catagories	Mean	Std. Deviation	N
Chapter 12 Test [Total Pts: 25 Score] |377856	No Use	19.61	4.786	19
	Nominal	21.71	2.614	14
	Moderate	20.58	4.061	13
	Saturated	21.90	2.198	53
	Total	21.26	3.246	99
Chapter 13 Test [Total Pts: 25 Score] |377799	No Use	20.05	3.763	19
	Nominal	22.89	1.274	14
	Moderate	21.54	2.259	13
	Saturated	22.14	2.187	53
	Total	21.77	2.610	99
Chapter 14 Test [Total Pts: 25 Score] |377800	No Use	19.29	2.557	19
	Nominal	20.64	2.070	14
	Moderate	19.69	2.087	13
	Saturated	21.15	2.267	53
	Total	20.53	2.373	99
Chapter 15 Test [Total Pts: 25 Score] |377857	No Use	19.79	2.434	19
	Nominal	20.93	2.209	14
	Moderate	19.23	2.342	13
	Saturated	21.01	2.309	53
	Total	20.53	2.390	99
Chapter 16 Test [Total Pts: 25 Score] |377858	No Use	17.89	2.861	19
	Nominal	17.32	5.434	14
	Moderate	18.69	1.640	13
	Saturated	19.61	2.274	53
	Total	18.84	3.053	99
Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	No Use	100.53	21.795	19
	Nominal	104.93	20.593	14
	Moderate	97.85	21.610	13
	Saturated	111.06	19.751	53
	Total	106.43	20.883	99
Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	No Use	98.21	15.142	19
	Nominal	103.86	19.837	14
	Moderate	100.46	21.403	13
	Saturated	111.19	20.646	53
	Total	106.25	20.169	99

Box's Test of Equality of Covariance Matrices[a]

Box's M	194.836
F	1.284
df1	105
df2	3819.134
Sig.	.037

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + GPApriortoBio2121 + ModRates

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.932	79.850[b]	14.000	81.000	.000
	Wilks' Lambda	.068	79.850[b]	14.000	81.000	.000
	Hotelling's Trace	13.801	79.850[b]	14.000	81.000	.000
	Roy's Largest Root	13.801	79.850[b]	14.000	81.000	.000
GPAapriortoBio2121	Pillai's Trace	.205	1.493[b]	14.000	81.000	.133
	Wilks' Lambda	.795	1.493[b]	14.000	81.000	.133
	Hotelling's Trace	.258	1.493[b]	14.000	81.000	.133
	Roy's Largest Root	.258	1.493[b]	14.000	81.000	.133
ModRates	Pillai's Trace	.580	1.422	42.000	249.000	.054
	Wilks' Lambda	.523	1.402	42.000	241.050	.062
	Hotelling's Trace	.728	1.381	42.000	239.000	.071
	Roy's Largest Root	.314	1.864[c]	14.000	83.000	.043

Multivariate Tests[a]

Effect		Partial Eta Squared
Intercept	Pillai's Trace	.932
	Wilks' Lambda	.932
	Hotelling's Trace	.932
	Roy's Largest Root	.932
GPAapriortoBio2121	Pillai's Trace	.205
	Wilks' Lambda	.205
	Hotelling's Trace	.205
	Roy's Largest Root	.205
ModRates	Pillai's Trace	.193
	Wilks' Lambda	.194
	Hotelling's Trace	.195
	Roy's Largest Root	.239

a. Design: Intercept + GPAapriortoBio2121 + ModRates

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Levene's Test of Equality of Error Variances[a]

	F	df1	df2	Sig.
Chapter 3 Test [Total Pts: 25 Score] |377850	3.082	3	95	.031
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	3.546	3	95	.017
Chapter 4 Test [Total Pts: 25 Score] |377852	2.827	3	95	.043
Chapter 5 Test [Total Pts: 25 Score] |377853	1.051	3	95	.374
Chapter 6 Test [Total Pts: 25 Score] |377854	2.177	3	95	.096
Chapter 9 Test [Total Pts: 25 Score] |377855	.039	3	95	.990
Chapter 11 Test [Total Pts: 25 Score] |377798	.522	3	95	.668
Chapter 12 Test [Total Pts: 25 Score] |377856	6.061	3	95	.001
Chapter 13 Test [Total Pts: 25 Score] |377799	3.721	3	95	.014
Chapter 14 Test [Total Pts: 25 Score] |377800	.203	3	95	.894
Chapter 15 Test [Total Pts: 25 Score] |377857	.092	3	95	.965
Chapter 16 Test [Total Pts: 25 Score] |377858	2.144	3	95	.100
Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.117	3	95	.950
Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	1.012	3	95	.391

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + GPApriortoBio2121 + ModRates

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
Corrected Model	Chapter 3 Test [Total Pts: 25 Score] |377850	151.040[a]	4	37.760	4.096
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	152.738[b]	4	38.184	2.003
	Chapter 4 Test [Total Pts: 25 Score] |377852	111.820[c]	4	27.955	5.548
	Chapter 5 Test [Total Pts: 25 Score] |377853	44.508[d]	4	11.127	2.891
	Chapter 6 Test [Total Pts: 25 Score] |377854	57.313[e]	4	14.328	3.861
	Chapter 9 Test [Total Pts: 25 Score] |377855	74.338[f]	4	18.585	1.978
	Chapter 11 Test [Total Pts: 25 Score] |377798	75.933[g]	4	18.983	2.632
	Chapter 12 Test [Total Pts: 25 Score] |377856	94.384[h]	4	23.596	2.384
	Chapter 13 Test [Total Pts: 25 Score] |377799	98.780[i]	4	24.695	4.081
	Chapter 14 Test [Total Pts: 25 Score] |377800	74.667[j]	4	18.667	3.677
	Chapter 15 Test [Total Pts: 25 Score] |377857	85.456[k]	4	21.364	4.233
	Chapter 16 Test [Total Pts: 25 Score] |377858	133.451[l]	4	33.363	4.021
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	5109.005[m]	4	1277.251	3.191
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	6533.876[n]	4	1633.469	4.596
Intercept	Chapter 3 Test [Total Pts: 25 Score] |377850	1707.862	1	1707.862	185.248
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	1209.073	1	1209.073	63.422
	Chapter 4 Test [Total Pts: 25 Score] |377852	2627.678	1	2627.678	521.464
	Chapter 5 Test [Total Pts: 25 Score] |377853	2592.292	1	2592.292	673.425
	Chapter 6 Test [Total Pts: 25 Score] |377854	2658.167	1	2658.167	716.243
	Chapter 9 Test [Total Pts: 25 Score] |377855	2088.018	1	2088.018	222.239

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
Corrected Model	Chapter 3 Test [Total Pts: 25 Score] |377850	.004	.148
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.100	.079
	Chapter 4 Test [Total Pts: 25 Score] |377852	.000	.191
	Chapter 5 Test [Total Pts: 25 Score] |377853	.026	.110
	Chapter 6 Test [Total Pts: 25 Score] |377854	.006	.141
	Chapter 9 Test [Total Pts: 25 Score] |377855	.104	.078
	Chapter 11 Test [Total Pts: 25 Score] |377798	.039	.101
	Chapter 12 Test [Total Pts: 25 Score] |377856	.059	.091
	Chapter 13 Test [Total Pts: 25 Score] |377799	.004	.148
	Chapter 14 Test [Total Pts: 25 Score] |377800	.008	.135
	Chapter 15 Test [Total Pts: 25 Score] |377857	.003	.153
	Chapter 16 Test [Total Pts: 25 Score] |377858	.005	.146
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.017	.120
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.002	.164
Intercept	Chapter 3 Test [Total Pts: 25 Score] |377850	.000	.663
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.000	.403
	Chapter 4 Test [Total Pts: 25 Score] |377852	.000	.847
	Chapter 5 Test [Total Pts: 25 Score] |377853	.000	.878
	Chapter 6 Test [Total Pts: 25 Score] |377854	.000	.884
	Chapter 9 Test [Total Pts: 25 Score] |377855	.000	.703

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Chapter 11 Test [Total Pts: 25 Score] |377798	2295.263	1	2295.263	318.274
	Chapter 12 Test [Total Pts: 25 Score] |377856	2827.345	1	2827.345	283.247
	Chapter 13 Test [Total Pts: 25 Score] |377799	2963.729	1	2963.729	489.721
	Chapter 14 Test [Total Pts: 25 Score] |377800	2566.600	1	2566.600	505.531
	Chapter 15 Test [Total Pts: 25 Score] |377857	2366.028	1	2366.028	468.764
	Chapter 16 Test [Total Pts: 25 Score] |377858	1821.304	1	1821.304	219.501
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	54490.842	1	54490.842	136.121
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	49559.370	1	49559.370	139.442
GPAapriortoBio2121	Chapter 3 Test [Total Pts: 25 Score] |377850	50.351	1	50.351	5.461
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	96.764	1	96.764	5.076
	Chapter 4 Test [Total Pts: 25 Score] |377852	31.898	1	31.898	6.330
	Chapter 5 Test [Total Pts: 25 Score] |377853	42.103	1	42.103	10.938
	Chapter 6 Test [Total Pts: 25 Score] |377854	28.396	1	28.396	7.651
	Chapter 9 Test [Total Pts: 25 Score] |377855	58.576	1	58.576	6.235
	Chapter 11 Test [Total Pts: 25 Score] |377798	27.281	1	27.281	3.783
	Chapter 12 Test [Total Pts: 25 Score] |377856	11.951	1	11.951	1.197
	Chapter 13 Test [Total Pts: 25 Score] |377799	17.080	1	17.080	2.822
	Chapter 14 Test [Total Pts: 25 Score] |377800	15.692	1	15.692	3.091
	Chapter 15 Test [Total Pts: 25 Score] |377857	38.686	1	38.686	7.665
	Chapter 16 Test [Total Pts: 25 Score] |377858	52.219	1	52.219	6.293

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Chapter 11 Test [Total Pts: 25 Score] |377798	.000	.772
	Chapter 12 Test [Total Pts: 25 Score] |377856	.000	.751
	Chapter 13 Test [Total Pts: 25 Score] |377799	.000	.839
	Chapter 14 Test [Total Pts: 25 Score] |377800	.000	.843
	Chapter 15 Test [Total Pts: 25 Score] |377857	.000	.833
	Chapter 16 Test [Total Pts: 25 Score] |377858	.000	.700
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.000	.592
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.000	.597
GPAapriortoBio2121	Chapter 3 Test [Total Pts: 25 Score] |377850	.022	.055
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.027	.051
	Chapter 4 Test [Total Pts: 25 Score] |377852	.014	.063
	Chapter 5 Test [Total Pts: 25 Score] |377853	.001	.104
	Chapter 6 Test [Total Pts: 25 Score] |377854	.007	.075
	Chapter 9 Test [Total Pts: 25 Score] |377855	.014	.062
	Chapter 11 Test [Total Pts: 25 Score] |377798	.055	.039
	Chapter 12 Test [Total Pts: 25 Score] |377856	.277	.013
	Chapter 13 Test [Total Pts: 25 Score] |377799	.096	.029
	Chapter 14 Test [Total Pts: 25 Score] |377800	.082	.032
	Chapter 15 Test [Total Pts: 25 Score] |377857	.007	.075
	Chapter 16 Test [Total Pts: 25 Score] |377858	.014	.063

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] [377864	2322.869	1	2322.869	5.803
	Bio 2121 Lecture Final [Total Pts: 150 Score] [377865	3497.406	1	3497.406	9.840
ModRates	Chapter 3 Test [Total Pts: 25 Score] [377850	80.357	3	26.786	2.905
	Chapter 3-b Test [Total Pts: 23.5 Score] [377851	44.427	3	14.809	.777
	Chapter 4 Test [Total Pts: 25 Score] [377852	64.532	3	21.511	4.269
	Chapter 5 Test [Total Pts: 25 Score] [377853	1.661	3	.554	.144
	Chapter 6 Test [Total Pts: 25 Score] [377854	20.646	3	6.882	1.854
	Chapter 9 Test [Total Pts: 25 Score] [377855	8.884	3	2.961	.315
	Chapter 11 Test [Total Pts: 25 Score] [377798	37.413	3	12.471	1.729
	Chapter 12 Test [Total Pts: 25 Score] [377856	74.086	3	24.695	2.474
	Chapter 13 Test [Total Pts: 25 Score] [377799	75.324	3	25.108	4.149
	Chapter 14 Test [Total Pts: 25 Score] [377800	50.146	3	16.715	3.292
	Chapter 15 Test [Total Pts: 25 Score] [377857	34.232	3	11.411	2.261
	Chapter 16 Test [Total Pts: 25 Score] [377858	70.757	3	23.586	2.843
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] [377864	2033.107	3	677.702	1.693
	Bio 2121 Lecture Final [Total Pts: 150 Score] [377865	2194.008	3	731.336	2.058
Error	Chapter 3 Test [Total Pts: 25 Score] [377850	866.617	94	9.219	
	Chapter 3-b Test [Total Pts: 23.5 Score] [377851	1792.010	94	19.064	
	Chapter 4 Test [Total Pts: 25 Score] [377852	473.670	94	5.039	

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Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.018	.058
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.002	.095
ModRates	Chapter 3 Test [Total Pts: 25 Score] |377850	.039	.085
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.510	.024
	Chapter 4 Test [Total Pts: 25 Score] |377852	.007	.120
	Chapter 5 Test [Total Pts: 25 Score] |377853	.933	.005
	Chapter 6 Test [Total Pts: 25 Score] |377854	.143	.056
	Chapter 9 Test [Total Pts: 25 Score] |377855	.814	.010
	Chapter 11 Test [Total Pts: 25 Score] |377798	.166	.052
	Chapter 12 Test [Total Pts: 25 Score] |377856	.066	.073
	Chapter 13 Test [Total Pts: 25 Score] |377799	.008	.117
	Chapter 14 Test [Total Pts: 25 Score] |377800	.024	.095
	Chapter 15 Test [Total Pts: 25 Score] |377857	.086	.067
	Chapter 16 Test [Total Pts: 25 Score] |377858	.042	.083
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.174	.051
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.111	.062
Error	Chapter 3 Test [Total Pts: 25 Score] |377850		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851		
	Chapter 4 Test [Total Pts: 25 Score] |377852		

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Chapter 5 Test [Total Pts: 25 Score] |377853	361.845	94	3.849	
	Chapter 6 Test [Total Pts: 25 Score] |377854	348.859	94	3.711	
	Chapter 9 Test [Total Pts: 25 Score] |377855	883.167	94	9.395	
	Chapter 11 Test [Total Pts: 25 Score] |377798	677.890	94	7.212	
	Chapter 12 Test [Total Pts: 25 Score] |377856	938.298	94	9.982	
	Chapter 13 Test [Total Pts: 25 Score] |377799	568.876	94	6.052	
	Chapter 14 Test [Total Pts: 25 Score] |377800	477.242	94	5.077	
	Chapter 15 Test [Total Pts: 25 Score] |377857	474.453	94	5.047	
	Chapter 16 Test [Total Pts: 25 Score] |377858	779.964	94	8.297	
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	37629.318	94	400.312	
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	33408.810	94	355.413	
Total	Chapter 3 Test [Total Pts: 25 Score] |377850	33726.750	99		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	28732.750	99		
	Chapter 4 Test [Total Pts: 25 Score] |377852	46391.250	99		
	Chapter 5 Test [Total Pts: 25 Score] |377853	44867.000	99		
	Chapter 6 Test [Total Pts: 25 Score] |377854	45164.000	99		
	Chapter 9 Test [Total Pts: 25 Score] |377855	39741.750	99		
	Chapter 11 Test [Total Pts: 25 Score] |377798	40094.250	99		
	Chapter 12 Test [Total Pts: 25 Score] |377856	45769.250	99		
	Chapter 13 Test [Total Pts: 25 Score] |377799	47577.000	99		

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Chapter 5 Test [Total Pts: 25 Score] |377853		
	Chapter 6 Test [Total Pts: 25 Score] |377854		
	Chapter 9 Test [Total Pts: 25 Score] |377855		
	Chapter 11 Test [Total Pts: 25 Score] |377798		
	Chapter 12 Test [Total Pts: 25 Score] |377856		
	Chapter 13 Test [Total Pts: 25 Score] |377799		
	Chapter 14 Test [Total Pts: 25 Score] |377800		
	Chapter 15 Test [Total Pts: 25 Score] |377857		
	Chapter 16 Test [Total Pts: 25 Score] |377858		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865		
Total	Chapter 3 Test [Total Pts: 25 Score] |377850		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851		
	Chapter 4 Test [Total Pts: 25 Score] |377852		
	Chapter 5 Test [Total Pts: 25 Score] |377853		
	Chapter 6 Test [Total Pts: 25 Score] |377854		
	Chapter 9 Test [Total Pts: 25 Score] |377855		
	Chapter 11 Test [Total Pts: 25 Score] |377798		
	Chapter 12 Test [Total Pts: 25 Score] |377856		
	Chapter 13 Test [Total Pts: 25 Score] |377799		

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Chapter 14 Test [Total Pts: 25 Score] |377800	42279.750	99		
	Chapter 15 Test [Total Pts: 25 Score] |377857	42287.750	99		
	Chapter 16 Test [Total Pts: 25 Score] |377858	38047.000	99		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	1164237.000	99		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	1157613.000	99		
Corrected Total	Chapter 3 Test [Total Pts: 25 Score] |377850	1017.657	98		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	1944.747	98		
	Chapter 4 Test [Total Pts: 25 Score] |377852	585.490	98		
	Chapter 5 Test [Total Pts: 25 Score] |377853	406.354	98		
	Chapter 6 Test [Total Pts: 25 Score] |377854	406.172	98		
	Chapter 9 Test [Total Pts: 25 Score] |377855	957.505	98		
	Chapter 11 Test [Total Pts: 25 Score] |377798	753.823	98		
	Chapter 12 Test [Total Pts: 25 Score] |377856	1032.682	98		
	Chapter 13 Test [Total Pts: 25 Score] |377799	687.657	98		
	Chapter 14 Test [Total Pts: 25 Score] |377800	551.909	98		
	Chapter 15 Test [Total Pts: 25 Score] |377857	559.909	98		
	Chapter 16 Test [Total Pts: 25 Score] |377858	913.414	98		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	42738.323	98		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	39942.687	98		

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Chapter 14 Test [Total Pts: 25 Score] |377800		
	Chapter 15 Test [Total Pts: 25 Score] |377857		
	Chapter 16 Test [Total Pts: 25 Score] |377858		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865		
Corrected Total	Chapter 3 Test [Total Pts: 25 Score] |377850		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851		
	Chapter 4 Test [Total Pts: 25 Score] |377852		
	Chapter 5 Test [Total Pts: 25 Score] |377853		
	Chapter 6 Test [Total Pts: 25 Score] |377854		
	Chapter 9 Test [Total Pts: 25 Score] |377855		
	Chapter 11 Test [Total Pts: 25 Score] |377798		
	Chapter 12 Test [Total Pts: 25 Score] |377856		
	Chapter 13 Test [Total Pts: 25 Score] |377799		
	Chapter 14 Test [Total Pts: 25 Score] |377800		
	Chapter 15 Test [Total Pts: 25 Score] |377857		
	Chapter 16 Test [Total Pts: 25 Score] |377858		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865		

a. R Squared = .148 (Adjusted R Squared = .112)

b. R Squared = .079 (Adjusted R Squared = .039)

c. R Squared = .191 (Adjusted R Squared = .157)

d. R Squared = .110 (Adjusted R Squared = .072)

e. R Squared = .141 (Adjusted R Squared = .105)

f. R Squared = .078 (Adjusted R Squared = .038)

g. R Squared = .101 (Adjusted R Squared = .062)

h. R Squared = .091 (Adjusted R Squared = .053)

i. R Squared = .148 (Adjusted R Squared = .112)

j. R Squared = .135 (Adjusted R Squared = .098)

k. R Squared = .153 (Adjusted R Squared = .117)

l. R Squared = .146 (Adjusted R Squared = .110)

m. R Squared = .120 (Adjusted R Squared = .082)

n. R Squared = .164 (Adjusted R Squared = .128)

```
GLM Chapter3TestTotalPts25Score377850 Chapter3bTestTotalPts23.5Score377851
    Chapter4TestTotalPts25Score377852 Chapter5TestTotalPts25Score377853
    Chapter6TestTotalPts25Score377854 Chapter9TestTotalPts25Score377855
    Chapter11TestTotalPts25Score377798 Chapter12TestTotalPts25Score377856
    Chapter13TestTotalPts25Score377799 Chapter14TestTotalPts25Score377800
    Chapter15TestTotalPts25Score377857 Chapter16TestTotalPts25Score377858
    Bio2121LectureMidtermTotalPts150Score377864 Bio2121LectureFinalTotalPts150Score377865
 BY ModRates
    WITH GPApriortoBio2121
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /EMMEANS=TABLES(ModRates) WITH(GPApriortoBio2121=MEAN) COMPARE ADJ(BONFERRONI)
  /PRINT=DESCRIPTIVE ETASQ HOMOGENEITY
  /CRITERIA=ALPHA(.05)
  /DESIGN=GPApriortoBio2121 ModRates.
```

General Linear Model

Between-Subjects Factors

		Value Label	N
Module Categories	1.00	No Use	19
	2.00	Nominal	14
	3.00	Moderate	13
	4.00	Saturated	53

Descriptive Statistics

	Module Categories	Mean	Std. Deviation	N
Chapter 3 Test [Total Pts: 25 Score] |377850	No Use	17.45	3.118	19
	Nominal	19.18	4.158	14
	Moderate	16.00	3.035	13
	Saturated	18.71	2.797	53
	Total	18.18	3.222	99
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	No Use	16.58	6.486	19
	Nominal	17.61	4.015	14
	Moderate	14.77	4.781	13
	Saturated	16.51	3.542	53
	Total	16.45	4.455	99
Chapter 4 Test [Total Pts: 25 Score] |377852	No Use	21.21	3.225	19
	Nominal	21.04	2.678	14
	Moderate	19.58	1.579	13
	Saturated	22.22	1.938	53
	Total	21.51	2.444	99
Chapter 5 Test [Total Pts: 25 Score] |377853	No Use	20.92	2.323	19
	Nominal	21.43	1.708	14
	Moderate	21.12	1.673	13
	Saturated	21.25	2.127	53
	Total	21.19	2.036	99
Chapter 6 Test [Total Pts: 25 Score] |377854	No Use	20.55	2.409	19
	Nominal	21.36	1.550	14
	Moderate	20.42	1.644	13
	Saturated	21.70	2.006	53
	Total	21.26	2.036	99
Chapter 9 Test [Total Pts: 25 Score] |377855	No Use	19.16	3.300	19
	Nominal	20.07	3.018	14
	Moderate	19.31	2.898	13
	Saturated	20.07	3.182	53
	Total	19.79	3.126	99
Chapter 11 Test [Total Pts: 25 Score] |377798	No Use	19.18	3.101	19
	Nominal	20.21	2.992	14
	Moderate	18.62	2.073	13
	Saturated	20.45	2.646	53
	Total	19.93	2.773	99

Descriptive Statistics

	Module Categories	Mean	Std. Deviation	N
Chapter 12 Test [Total Pts: 25 Score] |377856	No Use	19.61	4.786	19
	Nominal	21.71	2.614	14
	Moderate	20.58	4.061	13
	Saturated	21.90	2.198	53
	Total	21.26	3.246	99
Chapter 13 Test [Total Pts: 25 Score] |377799	No Use	20.05	3.763	19
	Nominal	22.89	1.274	14
	Moderate	21.54	2.259	13
	Saturated	22.14	2.187	53
	Total	21.77	2.610	99
Chapter 14 Test [Total Pts: 25 Score] |377800	No Use	19.29	2.587	19
	Nominal	20.64	2.070	14
	Moderate	19.69	2.087	13
	Saturated	21.15	2.287	53
	Total	20.53	2.373	99
Chapter 15 Test [Total Pts: 25 Score] |377857	No Use	19.79	2.434	19
	Nominal	20.93	2.209	14
	Moderate	19.23	2.342	13
	Saturated	21.01	2.309	53
	Total	20.53	2.390	99
Chapter 16 Test [Total Pts: 25 Score] |377858	No Use	17.89	2.881	19
	Nominal	17.32	5.434	14
	Moderate	18.69	1.640	13
	Saturated	19.61	2.274	53
	Total	18.84	3.053	99
Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	No Use	100.53	21.795	19
	Nominal	104.93	20.593	14
	Moderate	97.85	21.610	13
	Saturated	111.06	19.751	53
	Total	106.43	20.883	99
Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	No Use	98.21	15.142	19
	Nominal	103.86	19.837	14
	Moderate	100.46	21.403	13
	Saturated	111.19	20.646	53
	Total	106.25	20.189	99

Box's Test of Equality of Covariance Matrices[a]

Box's M	194.836
F	1.264
df1	105
df2	3819.134
Sig.	.037

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + GPApriortoBio2121 + ModRates

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.932	79.850[b]	14.000	81.000	.000
	Wilks' Lambda	.068	79.850[b]	14.000	81.000	.000
	Hotelling's Trace	13.801	79.850[b]	14.000	81.000	.000
	Roy's Largest Root	13.801	79.850[b]	14.000	81.000	.000
GPApriortoBio2121	Pillai's Trace	.205	1.493[b]	14.000	81.000	.133
	Wilks' Lambda	.795	1.493[b]	14.000	81.000	.133
	Hotelling's Trace	.258	1.493[b]	14.000	81.000	.133
	Roy's Largest Root	.258	1.493[b]	14.000	81.000	.133
ModRates	Pillai's Trace	.580	1.422	42.000	249.000	.054
	Wilks' Lambda	.523	1.402	42.000	241.050	.062
	Hotelling's Trace	.728	1.381	42.000	239.000	.071
	Roy's Largest Root	.314	1.864[c]	14.000	83.000	.043

Multivariate Tests[a]

Effect		Partial Eta Squared
Intercept	Pillai's Trace	.932
	Wilks' Lambda	.932
	Hotelling's Trace	.932
	Roy's Largest Root	.932
GPApriortoBio2121	Pillai's Trace	.205
	Wilks' Lambda	.205
	Hotelling's Trace	.205
	Roy's Largest Root	.205
ModRates	Pillai's Trace	.193
	Wilks' Lambda	.194
	Hotelling's Trace	.195
	Roy's Largest Root	.239

a. Design: Intercept + GPApriortoBio2121 + ModRates

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Levene's Test of Equality of Error Variances[a]

	F	df1	df2	Sig.
Chapter 3 Test [Total Pts: 25 Score] |377850	3.082	3	95	.031
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	3.546	3	95	.017
Chapter 4 Test [Total Pts: 25 Score] |377852	2.827	3	95	.043
Chapter 5 Test [Total Pts: 25 Score] |377853	1.051	3	95	.374
Chapter 6 Test [Total Pts: 25 Score] |377854	2.177	3	95	.096
Chapter 9 Test [Total Pts: 25 Score] |377855	.039	3	95	.990
Chapter 11 Test [Total Pts: 25 Score] |377798	.522	3	95	.668
Chapter 12 Test [Total Pts: 25 Score] |377856	6.061	3	95	.001
Chapter 13 Test [Total Pts: 25 Score] |377799	3.721	3	95	.014
Chapter 14 Test [Total Pts: 25 Score] |377800	.203	3	95	.894
Chapter 15 Test [Total Pts: 25 Score] |377857	.092	3	95	.965
Chapter 16 Test [Total Pts: 25 Score] |377858	2.144	3	95	.100
Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.117	3	95	.950
Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	1.012	3	95	.391

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + GPAapriortoBio2121 + ModRates

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
Corrected Model	Chapter 3 Test [Total Pts: 25 Score] |377850	151.040[a]	4	37.760	4.096
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	152.738[b]	4	38.184	2.003
	Chapter 4 Test [Total Pts: 25 Score] |377852	111.820[c]	4	27.955	5.548
	Chapter 5 Test [Total Pts: 25 Score] |377853	44.508[d]	4	11.127	2.891
	Chapter 6 Test [Total Pts: 25 Score] |377854	57.313[e]	4	14.328	3.861
	Chapter 9 Test [Total Pts: 25 Score] |377855	74.338[f]	4	18.585	1.978
	Chapter 11 Test [Total Pts: 25 Score] |377798	75.933[g]	4	18.983	2.632
	Chapter 12 Test [Total Pts: 25 Score] |377856	94.384[h]	4	23.596	2.384
	Chapter 13 Test [Total Pts: 25 Score] |377799	98.780[i]	4	24.695	4.081
	Chapter 14 Test [Total Pts: 25 Score] |377800	74.667[j]	4	18.667	3.677
	Chapter 15 Test [Total Pts: 25 Score] |377857	85.456[k]	4	21.364	4.233
	Chapter 16 Test [Total Pts: 25 Score] |377858	133.451[l]	4	33.363	4.021
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	5109.005[m]	4	1277.251	3.191
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	6533.876[n]	4	1633.469	4.596
Intercept	Chapter 3 Test [Total Pts: 25 Score] |377850	1707.862	1	1707.862	185.248
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	1209.073	1	1209.073	63.422
	Chapter 4 Test [Total Pts: 25 Score] |377852	2627.678	1	2627.678	521.464
	Chapter 5 Test [Total Pts: 25 Score] |377853	2592.292	1	2592.292	673.425
	Chapter 6 Test [Total Pts: 25 Score] |377854	2658.167	1	2658.167	716.243
	Chapter 9 Test [Total Pts: 25 Score] |377855	2088.018	1	2088.018	222.239

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
Corrected Model	Chapter 3 Test [Total Pts: 25 Score] |377850	.004	.148
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.100	.079
	Chapter 4 Test [Total Pts: 25 Score] |377852	.000	.191
	Chapter 5 Test [Total Pts: 25 Score] |377853	.026	.110
	Chapter 6 Test [Total Pts: 25 Score] |377854	.006	.141
	Chapter 9 Test [Total Pts: 25 Score] |377855	.104	.078
	Chapter 11 Test [Total Pts: 25 Score] |377798	.039	.101
	Chapter 12 Test [Total Pts: 25 Score] |377856	.059	.091
	Chapter 13 Test [Total Pts: 25 Score] |377799	.004	.148
	Chapter 14 Test [Total Pts: 25 Score] |377800	.008	.135
	Chapter 15 Test [Total Pts: 25 Score] |377857	.003	.153
	Chapter 16 Test [Total Pts: 25 Score] |377858	.005	.146
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.017	.120
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.002	.164
Intercept	Chapter 3 Test [Total Pts: 25 Score] |377850	.000	.863
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.000	.403
	Chapter 4 Test [Total Pts: 25 Score] |377852	.000	.847
	Chapter 5 Test [Total Pts: 25 Score] |377853	.000	.878
	Chapter 6 Test [Total Pts: 25 Score] |377854	.000	.884
	Chapter 9 Test [Total Pts: 25 Score] |377855	.000	.703

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Chapter 11 Test [Total Pts: 25 Score] |377798	2295.263	1	2295.263	318.274
	Chapter 12 Test [Total Pts: 25 Score] |377856	2827.345	1	2827.345	283.247
	Chapter 13 Test [Total Pts: 25 Score] |377799	2963.729	1	2963.729	489.721
	Chapter 14 Test [Total Pts: 25 Score] |377800	2566.600	1	2566.600	505.531
	Chapter 15 Test [Total Pts: 25 Score] |377857	2366.028	1	2366.028	468.764
	Chapter 16 Test [Total Pts: 25 Score] |377858	1821.304	1	1821.304	219.501
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	54490.842	1	54490.842	136.121
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	49559.370	1	49559.370	139.442
GPAприortoBio2121	Chapter 3 Test [Total Pts: 25 Score] |377850	50.351	1	50.351	5.461
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	96.764	1	96.764	5.076
	Chapter 4 Test [Total Pts: 25 Score] |377852	31.898	1	31.898	6.330
	Chapter 5 Test [Total Pts: 25 Score] |377853	42.103	1	42.103	10.938
	Chapter 6 Test [Total Pts: 25 Score] |377854	28.396	1	28.396	7.651
	Chapter 9 Test [Total Pts: 25 Score] |377855	58.576	1	58.576	6.235
	Chapter 11 Test [Total Pts: 25 Score] |377798	27.281	1	27.281	3.783
	Chapter 12 Test [Total Pts: 25 Score] |377856	11.951	1	11.951	1.197
	Chapter 13 Test [Total Pts: 25 Score] |377799	17.080	1	17.080	2.822
	Chapter 14 Test [Total Pts: 25 Score] |377800	15.692	1	15.692	3.091
	Chapter 15 Test [Total Pts: 25 Score] |377857	38.686	1	38.686	7.665
	Chapter 16 Test [Total Pts: 25 Score] |377858	52.219	1	52.219	6.293

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Chapter 11 Test [Total Pts: 25 Score] |377798	.000	.772
	Chapter 12 Test [Total Pts: 25 Score] |377856	.000	.751
	Chapter 13 Test [Total Pts: 25 Score] |377799	.000	.839
	Chapter 14 Test [Total Pts: 25 Score] |377800	.000	.843
	Chapter 15 Test [Total Pts: 25 Score] |377857	.000	.833
	Chapter 16 Test [Total Pts: 25 Score] |377858	.000	.700
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.000	.592
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.000	.597
GPAapriortoBio2121	Chapter 3 Test [Total Pts: 25 Score] |377850	.022	.055
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.027	.051
	Chapter 4 Test [Total Pts: 25 Score] |377852	.014	.063
	Chapter 5 Test [Total Pts: 25 Score] |377853	.001	.104
	Chapter 6 Test [Total Pts: 25 Score] |377854	.007	.075
	Chapter 9 Test [Total Pts: 25 Score] |377855	.014	.062
	Chapter 11 Test [Total Pts: 25 Score] |377798	.055	.039
	Chapter 12 Test [Total Pts: 25 Score] |377856	.277	.013
	Chapter 13 Test [Total Pts: 25 Score] |377799	.098	.029
	Chapter 14 Test [Total Pts: 25 Score] |377800	.082	.032
	Chapter 15 Test [Total Pts: 25 Score] |377857	.007	.075
	Chapter 16 Test [Total Pts: 25 Score] |377858	.014	.063

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	2322.869	1	2322.869	5.803
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	3497.406	1	3497.406	9.840
ModRates	Chapter 3 Test [Total Pts: 25 Score] |377850	80.357	3	26.786	2.905
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	44.427	3	14.809	.777
	Chapter 4 Test [Total Pts: 25 Score] |377852	64.532	3	21.511	4.269
	Chapter 5 Test [Total Pts: 25 Score] |377853	1.661	3	.554	.144
	Chapter 6 Test [Total Pts: 25 Score] |377854	20.646	3	6.882	1.854
	Chapter 9 Test [Total Pts: 25 Score] |377855	8.884	3	2.961	.315
	Chapter 11 Test [Total Pts: 25 Score] |377798	37.413	3	12.471	1.729
	Chapter 12 Test [Total Pts: 25 Score] |377856	74.086	3	24.695	2.474
	Chapter 13 Test [Total Pts: 25 Score] |377799	75.324	3	25.108	4.149
	Chapter 14 Test [Total Pts: 25 Score] |377800	50.146	3	16.715	3.292
	Chapter 15 Test [Total Pts: 25 Score] |377857	34.232	3	11.411	2.261
	Chapter 16 Test [Total Pts: 25 Score] |377858	70.757	3	23.586	2.843
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	2033.107	3	677.702	1.693
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	2194.008	3	731.336	2.058
Error	Chapter 3 Test [Total Pts: 25 Score] |377850	866.617	94	9.219	
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	1792.010	94	19.064	
	Chapter 4 Test [Total Pts: 25 Score] |377852	473.670	94	5.039	

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.018	.058
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.002	.095
ModRates	Chapter 3 Test [Total Pts: 25 Score] |377850	.039	.085
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	.510	.024
	Chapter 4 Test [Total Pts: 25 Score] |377852	.007	.120
	Chapter 5 Test [Total Pts: 25 Score] |377853	.933	.005
	Chapter 6 Test [Total Pts: 25 Score] |377854	.143	.056
	Chapter 9 Test [Total Pts: 25 Score] |377855	.814	.010
	Chapter 11 Test [Total Pts: 25 Score] |377798	.166	.052
	Chapter 12 Test [Total Pts: 25 Score] |377856	.066	.073
	Chapter 13 Test [Total Pts: 25 Score] |377799	.008	.117
	Chapter 14 Test [Total Pts: 25 Score] |377800	.024	.095
	Chapter 15 Test [Total Pts: 25 Score] |377857	.086	.067
	Chapter 16 Test [Total Pts: 25 Score] |377858	.042	.083
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	.174	.051
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	.111	.062
Error	Chapter 3 Test [Total Pts: 25 Score] |377850		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851		
	Chapter 4 Test [Total Pts: 25 Score] |377852		

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Chapter 5 Test [Total Pts: 25 Score] |377853	361.845	94	3.849	
	Chapter 6 Test [Total Pts: 25 Score] |377854	348.859	94	3.711	
	Chapter 9 Test [Total Pts: 25 Score] |377855	883.167	94	9.395	
	Chapter 11 Test [Total Pts: 25 Score] |377798	677.890	94	7.212	
	Chapter 12 Test [Total Pts: 25 Score] |377856	938.298	94	9.982	
	Chapter 13 Test [Total Pts: 25 Score] |377799	568.876	94	6.052	
	Chapter 14 Test [Total Pts: 25 Score] |377800	477.242	94	5.077	
	Chapter 15 Test [Total Pts: 25 Score] |377857	474.453	94	5.047	
	Chapter 16 Test [Total Pts: 25 Score] |377858	779.964	94	8.297	
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	37629.318	94	400.312	
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	33408.810	94	355.413	
Total	Chapter 3 Test [Total Pts: 25 Score] |377850	33726.750	99		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	28732.750	99		
	Chapter 4 Test [Total Pts: 25 Score] |377852	46391.250	99		
	Chapter 5 Test [Total Pts: 25 Score] |377853	44867.000	99		
	Chapter 6 Test [Total Pts: 25 Score] |377854	45164.000	99		
	Chapter 9 Test [Total Pts: 25 Score] |377855	39741.750	99		
	Chapter 11 Test [Total Pts: 25 Score] |377798	40094.250	99		
	Chapter 12 Test [Total Pts: 25 Score] |377856	45769.250	99		
	Chapter 13 Test [Total Pts: 25 Score] |377799	47577.000	99		

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Chapter 5 Test [Total Pts: 25 Score] |377853		
	Chapter 6 Test [Total Pts: 25 Score] |377854		
	Chapter 9 Test [Total Pts: 25 Score] |377855		
	Chapter 11 Test [Total Pts: 25 Score] |377798		
	Chapter 12 Test [Total Pts: 25 Score] |377856		
	Chapter 13 Test [Total Pts: 25 Score] |377799		
	Chapter 14 Test [Total Pts: 25 Score] |377800		
	Chapter 15 Test [Total Pts: 25 Score] |377857		
	Chapter 16 Test [Total Pts: 25 Score] |377858		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865		
Total	Chapter 3 Test [Total Pts: 25 Score] |377850		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851		
	Chapter 4 Test [Total Pts: 25 Score] |377852		
	Chapter 5 Test [Total Pts: 25 Score] |377853		
	Chapter 6 Test [Total Pts: 25 Score] |377854		
	Chapter 9 Test [Total Pts: 25 Score] |377855		
	Chapter 11 Test [Total Pts: 25 Score] |377798		
	Chapter 12 Test [Total Pts: 25 Score] |377856		
	Chapter 13 Test [Total Pts: 25 Score] |377799		

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F
	Chapter 14 Test [Total Pts: 25 Score] |377800	42279.750	99		
	Chapter 15 Test [Total Pts: 25 Score] |377857	42287.750	99		
	Chapter 16 Test [Total Pts: 25 Score] |377858	36047.000	99		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	1164237.000	99		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	1157613.000	99		
Corrected Total	Chapter 3 Test [Total Pts: 25 Score] |377850	1017.657	98		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851	1944.747	98		
	Chapter 4 Test [Total Pts: 25 Score] |377852	585.490	98		
	Chapter 5 Test [Total Pts: 25 Score] |377853	406.354	98		
	Chapter 6 Test [Total Pts: 25 Score] |377854	406.172	98		
	Chapter 9 Test [Total Pts: 25 Score] |377855	957.505	98		
	Chapter 11 Test [Total Pts: 25 Score] |377798	753.823	98		
	Chapter 12 Test [Total Pts: 25 Score] |377856	1032.682	98		
	Chapter 13 Test [Total Pts: 25 Score] |377799	667.657	98		
	Chapter 14 Test [Total Pts: 25 Score] |377800	551.909	98		
	Chapter 15 Test [Total Pts: 25 Score] |377857	559.909	98		
	Chapter 16 Test [Total Pts: 25 Score] |377858	913.414	98		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	42738.323	98		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	39942.687	98		

Tests of Between-Subjects Effects

Source	Dependent Variable	Sig.	Partial Eta Squared
	Chapter 14 Test [Total Pts: 25 Score] |377800		
	Chapter 15 Test [Total Pts: 25 Score] |377857		
	Chapter 16 Test [Total Pts: 25 Score] |377858		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865		
Corrected Total	Chapter 3 Test [Total Pts: 25 Score] |377850		
	Chapter 3-b Test [Total Pts: 23.5 Score] |377851		
	Chapter 4 Test [Total Pts: 25 Score] |377852		
	Chapter 5 Test [Total Pts: 25 Score] |377853		
	Chapter 6 Test [Total Pts: 25 Score] |377854		
	Chapter 9 Test [Total Pts: 25 Score] |377855		
	Chapter 11 Test [Total Pts: 25 Score] |377798		
	Chapter 12 Test [Total Pts: 25 Score] |377856		
	Chapter 13 Test [Total Pts: 25 Score] |377799		
	Chapter 14 Test [Total Pts: 25 Score] |377800		
	Chapter 15 Test [Total Pts: 25 Score] |377857		
	Chapter 16 Test [Total Pts: 25 Score] |377858		
	Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864		
	Bio 2121 Lecture Final [Total Pts: 150 Score] |377865		

a. R Squared = .148 (Adjusted R Squared = .112)
b. R Squared = .079 (Adjusted R Squared = .039)
c. R Squared = .191 (Adjusted R Squared = .157)
d. R Squared = .110 (Adjusted R Squared = .072)
e. R Squared = .141 (Adjusted R Squared = .105)
f. R Squared = .078 (Adjusted R Squared = .038)
g. R Squared = .101 (Adjusted R Squared = .062)
h. R Squared = .091 (Adjusted R Squared = .053)
i. R Squared = .148 (Adjusted R Squared = .112)
j. R Squared = .135 (Adjusted R Squared = .098)
k. R Squared = .153 (Adjusted R Squared = .117)
l. R Squared = .146 (Adjusted R Squared = .110)
m. R Squared = .120 (Adjusted R Squared = .082)
n. R Squared = .164 (Adjusted R Squared = .128)

Estimated Marginal Means

Module Catagories

Estimates

Dependent Variable	Module Catagories	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Chapter 3 Test [Total Pts: 25 Score] |377850	No Use	17.540[a]	.698	16.155	18.925
	Nominal	19.175[a]	.811	17.564	20.787
	Moderate	16.221[a]	.847	14.538	17.903
	Saturated	18.621[a]	.419	17.790	19.452
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	No Use	16.708[a]	1.003	14.716	18.700
	Nominal	17.603[a]	1.167	15.286	19.920
	Moderate	15.075[a]	1.219	12.656	17.495
	Saturated	16.389[a]	.602	15.194	17.585
Chapter 4 Test [Total Pts: 25 Score] |377852	No Use	21.284[a]	.516	20.260	22.309
	Nominal	21.033[a]	.600	19.842	22.224
	Moderate	19.753[a]	.626	18.509	20.996
	Saturated	22.148[a]	.310	21.533	22.763
Chapter 5 Test [Total Pts: 25 Score] |377853	No Use	21.006[a]	.451	20.111	21.901
	Nominal	21.426[a]	.524	20.385	22.467

Estimates

Dependent Variable	Module Categories	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
	Moderate	21.317[a]	.548	20.230	22.404
	Saturated	21.166[a]	.271	20.629	21.703
Chapter 6 Test [Total Pts: 25 Score] |377854	No Use	20.622[a]	.443	19.743	21.501
	Nominal	21.355[a]	.515	20.332	22.377
	Moderate	20.589[a]	.538	19.521	21.656
	Saturated	21.633[a]	.266	21.106	22.161
Chapter 9 Test [Total Pts: 25 Score] |377855	No Use	19.258[a]	.704	17.859	20.656
	Nominal	20.068[a]	.819	18.441	21.695
	Moderate	19.546[a]	.855	17.847	21.244
	Saturated	19.973[a]	.423	19.133	20.812
Chapter 11 Test [Total Pts: 25 Score] |377798	No Use	19.253[a]	.617	18.027	20.478
	Nominal	20.212[a]	.718	18.787	21.637
	Moderate	18.778[a]	.749	17.290	20.266
	Saturated	20.389[a]	.370	19.654	21.124
Chapter 12 Test [Total Pts: 25 Score] |377856	No Use	19.650[a]	.726	18.209	21.092
	Nominal	21.713[a]	.844	20.036	23.389
	Moderate	20.684[a]	.882	18.934	22.435
	Saturated	21.854[a]	.436	20.989	22.719
Chapter 13 Test [Total Pts: 25 Score] |377799	No Use	20.107[a]	.565	18.984	21.229
	Nominal	22.891[a]	.657	21.586	24.196
	Moderate	21.667[a]	.687	20.304	23.030
	Saturated	22.091[a]	.339	21.418	22.765
Chapter 14 Test [Total Pts: 25 Score] |377800	No Use	19.341[a]	.518	18.313	20.369
	Nominal	20.641[a]	.602	19.445	21.837
	Moderate	19.815[a]	.629	18.567	21.064
	Saturated	21.103[a]	.311	20.486	21.720
Chapter 15 Test [Total Pts: 25 Score] |377857	No Use	19.871[a]	.516	18.846	20.896
	Nominal	20.926[a]	.600	19.734	22.118
	Moderate	19.424[a]	.627	18.179	20.669
	Saturated	20.934[a]	.310	20.318	21.549

Estimates

Dependent Variable	Module Catagories	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Chapter 16 Test [Total Pts: 25 Score] [377858	No Use	17.989[a]	.662	16.675	19.303
	Nominal	17.318[a]	.770	15.790	18.847
	Moderate	18.917[a]	.804	17.321	20.513
	Saturated	19.525[a]	.397	18.736	20.314
Bio 2121 Lecture Midterm [Total Pts: 150 Score] [377864	No Use	101.157[a]	4.598	92.028	110.285
	Nominal	104.907[a]	5.347	94.290	115.524
	Moderate	99.345[a]	5.584	88.258	110.432
	Saturated	110.469[a]	2.759	104.991	115.947
Bio 2121 Lecture Final [Total Pts: 150 Score] [377865	No Use	98.984[a]	4.332	90.383	107.585
	Nominal	103.831[a]	5.039	93.827	113.835
	Moderate	102.300[a]	5.261	91.854	112.747
	Saturated	110.467[a]	2.600	105.305	115.629

a. Covariates appearing in the model are evaluated at the following values: GPA prior to Bio 2121 = 3.09.

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Mean Difference (I-J)	Std. Error
Chapter 3 Test [Total Pts: 25 Score] |377850	No Use	Nominal	-1.635	1.070
		Moderate	1.320	1.094
		Saturated	-1.081	.816
	Nominal	No Use	1.635	1.070
		Moderate	2.955	1.173
		Saturated	.554	.913
	Moderate	No Use	-1.320	1.094
		Nominal	-2.955	1.173
		Saturated	-2.400	.949
	Saturated	No Use	1.081	.816
		Nominal	-.554	.913
		Moderate	2.400	.949
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	No Use	Nominal	-.895	1.539
		Moderate	1.633	1.574
		Saturated	.318	1.173
	Nominal	No Use	.895	1.539
		Moderate	2.528	1.687
		Saturated	1.213	1.313
	Moderate	No Use	-1.633	1.574
		Nominal	-2.528	1.687
		Saturated	-1.314	1.365
	Saturated	No Use	-.318	1.173
		Nominal	-1.213	1.313
		Moderate	1.314	1.365
Chapter 4 Test [Total Pts: 25 Score] |377852	No Use	Nominal	.251	.791
		Moderate	1.532	.809
		Saturated	-.864	.603
	Nominal	No Use	-.251	.791
		Moderate	1.281	.868
		Saturated	-1.115	.675
	Moderate	No Use	-1.532	.809
		Nominal	-1.281	.868
		Saturated	-2.396*	.702

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Sig.[b]	95% Confidence [b]... Lower Bound
Chapter 3 Test [Total Pts: 25 Score] |377850	No Use	Nominal	.779	-4.520
		Moderate	1.000	-1.630
		Saturated	1.000	-3.279
	Nominal	No Use	.779	-1.249
		Moderate	.081	-.208
		Saturated	1.000	-1.907
	Moderate	No Use	1.000	-4.269
		Nominal	.081	-6.117
		Saturated	.078	-4.958
	Saturated	No Use	1.000	-1.117
		Nominal	1.000	-3.015
		Moderate	.078	-.157
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	No Use	Nominal	1.000	-5.043
		Moderate	1.000	-2.609
		Saturated	1.000	-2.843
	Nominal	No Use	1.000	-3.253
		Moderate	.825	-2.020
		Saturated	1.000	-2.326
	Moderate	No Use	1.000	-5.874
		Nominal	.825	-7.075
		Saturated	1.000	-4.992
	Saturated	No Use	1.000	-3.479
		Nominal	1.000	-4.752
		Moderate	1.000	-2.363
Chapter 4 Test [Total Pts: 25 Score] |377852	No Use	Nominal	1.000	-1.881
		Moderate	.368	-.649
		Saturated	.932	-2.489
	Nominal	No Use	1.000	-2.384
		Moderate	.859	-1.057
		Saturated	.612	-2.934
	Moderate	No Use	.368	-3.712
		Nominal	.859	-3.619
		Saturated	.006	-4.286

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	95% Confidence Interval for b. Upper Bound
Chapter 3 Test [Total Pts: 25 Score] |377850	No Use	Nominal	1.249
		Moderate	4.269
		Saturated	1.117
	Nominal	No Use	4.520
		Moderate	6.117
		Saturated	3.015
	Moderate	No Use	1.630
		Nominal	.208
		Saturated	.157
	Saturated	No Use	3.279
		Nominal	1.907
		Moderate	4.958
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	No Use	Nominal	3.253
		Moderate	5.874
		Saturated	3.479
	Nominal	No Use	5.043
		Moderate	7.075
		Saturated	4.752
	Moderate	No Use	2.609
		Nominal	2.020
		Saturated	2.363
	Saturated	No Use	2.843
		Nominal	2.326
		Moderate	4.992
Chapter 4 Test [Total Pts: 25 Score] |377852	No Use	Nominal	2.384
		Moderate	3.712
		Saturated	.761
	Nominal	No Use	1.881
		Moderate	3.619
		Saturated	.705
	Moderate	No Use	.649
		Nominal	1.057
		Saturated	-.505

Pairwise Comparisons

Dependent Variable	(I) Module Catagories	(J) Module Catagories	Mean Difference (I-J)	Std. Error
	Saturated	No Use	.864	.603
		Nominal	1.115	.675
		Moderate	2.396*	.702
Chapter 5 Test [Total Pts: 25 Score] |377853	No Use	Nominal	-.420	.692
		Moderate	-.311	.707
		Saturated	-.160	.527
	Nominal	No Use	.420	.692
		Moderate	.109	.758
		Saturated	.260	.590
	Moderate	No Use	.311	.707
		Nominal	-.109	.758
		Saturated	.151	.613
	Saturated	No Use	.160	.527
		Nominal	-.260	.590
		Moderate	-.151	.613
Chapter 6 Test [Total Pts: 25 Score] |377854	No Use	Nominal	-.732	.679
		Moderate	.034	.694
		Saturated	-1.011	.517
	Nominal	No Use	.732	.679
		Moderate	.766	.744
		Saturated	-.278	.579
	Moderate	No Use	-.034	.694
		Nominal	-.766	.744
		Saturated	-1.044	.602
	Saturated	No Use	1.011	.517
		Nominal	.278	.579
		Moderate	1.044	.602
Chapter 9 Test [Total Pts: 25 Score] |377855	No Use	Nominal	-.810	1.080
		Moderate	-.288	1.105
		Saturated	-.715	.823
	Nominal	No Use	.810	1.080
		Moderate	.522	1.185
		Saturated	.095	.922

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Sig.[b]	95% Confidence [b]...
				Lower Bound
	Saturated	No Use	.932	-.761
		Nominal	.612	-.705
		Moderate	.006	.505
Chapter 5 Test [Total Pts: 25 Score] |377853	No Use	Nominal	1.000	-2.284
		Moderate	1.000	-2.217
		Saturated	1.000	-1.581
	Nominal	No Use	1.000	-1.444
		Moderate	1.000	-1.935
		Saturated	1.000	-1.331
	Moderate	No Use	1.000	-1.595
		Nominal	1.000	-2.152
		Saturated	1.000	-1.502
	Saturated	No Use	1.000	-1.260
		Nominal	1.000	-1.850
		Moderate	1.000	-1.804
Chapter 6 Test [Total Pts: 25 Score] |377854	No Use	Nominal	1.000	-2.563
		Moderate	1.000	-1.838
		Saturated	.322	-2.405
	Nominal	No Use	1.000	-1.098
		Moderate	1.000	-1.241
		Saturated	1.000	-1.840
	Moderate	No Use	1.000	-1.905
		Nominal	1.000	-2.773
		Saturated	.516	-2.667
	Saturated	No Use	.322	-.384
		Nominal	1.000	-1.283
		Moderate	.516	-.578
Chapter 9 Test [Total Pts: 25 Score] |377855	No Use	Nominal	1.000	-3.722
		Moderate	1.000	-3.265
		Saturated	1.000	-2.934
	Nominal	No Use	1.000	-2.102
		Moderate	1.000	-2.670
		Saturated	1.000	-2.389

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	95% Confidence Interval for b. Upper Bound
	Saturated	No Use	2.489
		Nominal	2.934
		Moderate	4.286
Chapter 5 Test [Total Pts: 25 Score] |377853	No Use	Nominal	1.444
		Moderate	1.595
		Saturated	1.260
	Nominal	No Use	2.284
		Moderate	2.152
		Saturated	1.850
	Moderate	No Use	2.217
		Nominal	1.935
		Saturated	1.804
	Saturated	No Use	1.581
		Nominal	1.331
		Moderate	1.502
Chapter 6 Test [Total Pts: 25 Score] |377854	No Use	Nominal	1.098
		Moderate	1.905
		Saturated	.384
	Nominal	No Use	2.563
		Moderate	2.773
		Saturated	1.283
	Moderate	No Use	1.838
		Nominal	1.241
		Saturated	.578
	Saturated	No Use	2.405
		Nominal	1.840
		Moderate	2.667
Chapter 9 Test [Total Pts: 25 Score] |377855	No Use	Nominal	2.102
		Moderate	2.690
		Saturated	1.504
	Nominal	No Use	3.722
		Moderate	3.715
		Saturated	2.580

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Mean Difference (I-J)	Std. Error
	Moderate	No Use	.288	1.105
		Nominal	-.522	1.185
		Saturated	-.427	.958
	Saturated	No Use	.715	.823
		Nominal	-.095	.922
		Moderate	.427	.958
Chapter 11 Test [Total Pts: 25 Score] |377798	No Use	Nominal	-.959	.947
		Moderate	.475	.968
		Saturated	-1.137	.721
	Nominal	No Use	.959	.947
		Moderate	1.434	1.038
		Saturated	-.177	.808
	Moderate	No Use	-.475	.968
		Nominal	-1.434	1.038
		Saturated	-1.611	.839
	Saturated	No Use	1.137	.721
		Nominal	.177	.808
		Moderate	1.611	.839
Chapter 12 Test [Total Pts: 25 Score] |377856	No Use	Nominal	-2.062	1.114
		Moderate	-1.034	1.139
		Saturated	-2.204	.849
	Nominal	No Use	2.062	1.114
		Moderate	1.028	1.221
		Saturated	-.141	.950
	Moderate	No Use	1.034	1.139
		Nominal	-1.028	1.221
		Saturated	-1.170	.987
	Saturated	No Use	2.204	.849
		Nominal	.141	.950
		Moderate	1.170	.987
Chapter 13 Test [Total Pts: 25 Score] |377799	No Use	Nominal	-2.784*	.867
		Moderate	-1.560	.887
		Saturated	-1.984*	.661

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Sig.[b]	95% Confidence [b] Lower Bound
	Moderate	No Use	1.000	-2.690
		Nominal	1.000	-3.715
		Saturated	1.000	-3.009
	Saturated	No Use	1.000	-1.504
		Nominal	1.000	-2.580
		Moderate	1.000	-2.155
Chapter 11 Test [Total Pts: 25 Score] |377798	No Use	Nominal	1.000	-3.511
		Moderate	1.000	-2.134
		Saturated	.711	-3.081
	Nominal	No Use	1.000	-1.592
		Moderate	1.000	-1.363
		Saturated	1.000	-2.354
	Moderate	No Use	1.000	-3.083
		Nominal	1.000	-4.231
		Saturated	.347	-3.873
	Saturated	No Use	.711	-.807
		Nominal	1.000	-1.999
		Moderate	.347	-.651
Chapter 12 Test [Total Pts: 25 Score] |377856	No Use	Nominal	.403	-5.064
		Moderate	1.000	-4.103
		Saturated	.066	-4.491
	Nominal	No Use	.403	-.939
		Moderate	1.000	-2.262
		Saturated	1.000	-2.702
	Moderate	No Use	1.000	-2.035
		Nominal	1.000	-4.319
		Saturated	1.000	-3.831
	Saturated	No Use	.066	-.084
		Nominal	1.000	-2.419
		Moderate	1.000	-1.492
Chapter 13 Test [Total Pts: 25 Score] |377799	No Use	Nominal	.011	-5.121
		Moderate	.490	-3.950
		Saturated	.021	-3.765

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	95% Confidence Interval for b. Upper Bound
	Moderate	No Use	3.265
		Nominal	2.670
		Saturated	2.155
	Saturated	No Use	2.934
		Nominal	2.389
		Moderate	3.009
Chapter 11 Test [Total Pts: 25 Score] [377798	No Use	Nominal	1.592
		Moderate	3.083
		Saturated	.807
	Nominal	No Use	3.511
		Moderate	4.231
		Saturated	1.999
	Moderate	No Use	2.134
		Nominal	1.363
		Saturated	.651
	Saturated	No Use	3.081
		Nominal	2.354
		Moderate	3.873
Chapter 12 Test [Total Pts: 25 Score] [377856	No Use	Nominal	.939
		Moderate	2.035
		Saturated	.084
	Nominal	No Use	5.064
		Moderate	4.319
		Saturated	2.419
	Moderate	No Use	4.103
		Nominal	2.262
		Saturated	1.492
	Saturated	No Use	4.491
		Nominal	2.702
		Moderate	3.831
Chapter 13 Test [Total Pts: 25 Score] [377799	No Use	Nominal	-.447
		Moderate	.829
		Saturated	-.204

Pairwise Comparisons

Dependent Variable	(I) Module Catagories	(J) Module Catagories	Mean Difference (I-J)	Std. Error
	Nominal	No Use	2.784*	.887
		Moderate	1.224	.951
		Saturated	.800	.740
	Moderate	No Use	1.560	.887
		Nominal	-1.224	.951
		Saturated	-.424	.769
	Saturated	No Use	1.984*	.661
		Nominal	-.800	.740
		Moderate	.424	.769
Chapter 14 Test [Total Pts: 25 Score] |377800	No Use	Nominal	-1.300	.794
		Moderate	-.474	.812
		Saturated	-1.761*	.605
	Nominal	No Use	1.300	.794
		Moderate	.826	.871
		Saturated	-.462	.678
	Moderate	No Use	.474	.812
		Nominal	-.826	.871
		Saturated	-1.287	.704
	Saturated	No Use	1.761*	.605
		Nominal	.462	.678
		Moderate	1.287	.704
Chapter 15 Test [Total Pts: 25 Score] |377857	No Use	Nominal	-1.055	.792
		Moderate	.447	.810
		Saturated	-1.063	.603
	Nominal	No Use	1.055	.792
		Moderate	1.502	.868
		Saturated	-.008	.676
	Moderate	No Use	-.447	.810
		Nominal	-1.502	.868
		Saturated	-1.509	.702
	Saturated	No Use	1.063	.603
		Nominal	.008	.676
		Moderate	1.509	.702

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Sig.[b]	95% Confidence [b]...
				Lower Bound
	Nominal	No Use	.011	.447
		Moderate	1.000	-1.338
		Saturated	1.000	-1.194
	Moderate	No Use	.490	-.829
		Nominal	1.000	-3.786
		Saturated	1.000	-2.498
	Saturated	No Use	.021	.204
		Nominal	1.000	-2.794
		Moderate	1.000	-1.648
Chapter 14 Test [Total Pts: 25 Score] |377800	No Use	Nominal	.630	-3.440
		Moderate	1.000	-2.663
		Saturated	.027	-3.392
	Nominal	No Use	.630	-.841
		Moderate	1.000	-1.521
		Saturated	1.000	-2.288
	Moderate	No Use	1.000	-1.714
		Nominal	1.000	-3.173
		Saturated	.424	-3.185
	Saturated	No Use	.027	.130
		Nominal	1.000	-1.365
		Moderate	.424	-.611
Chapter 15 Test [Total Pts: 25 Score] |377857	No Use	Nominal	1.000	-3.189
		Moderate	1.000	-1.736
		Saturated	.489	-2.689
	Nominal	No Use	1.000	-1.079
		Moderate	.522	-.838
		Saturated	1.000	-1.829
	Moderate	No Use	1.000	-2.629
		Nominal	.522	-3.842
		Saturated	.205	-3.402
	Saturated	No Use	.489	-.564
		Nominal	1.000	-1.813
		Moderate	.205	-.383

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	95% Confidence Interval for b. Upper Bound
	Nominal	No Use	5.121
		Moderate	3.786
		Saturated	2.794
	Moderate	No Use	3.950
		Nominal	1.338
		Saturated	1.648
	Saturated	No Use	3.765
		Nominal	1.194
		Moderate	2.496
Chapter 14 Test [Total Pts: 25 Score] [377800	No Use	Nominal	.841
		Moderate	1.714
		Saturated	-.130
	Nominal	No Use	3.440
		Moderate	3.173
		Saturated	1.365
	Moderate	No Use	2.663
		Nominal	1.521
		Saturated	.611
	Saturated	No Use	3.392
		Nominal	2.288
		Moderate	3.185
Chapter 15 Test [Total Pts: 25 Score] [377857	No Use	Nominal	1.079
		Moderate	2.629
		Saturated	.564
	Nominal	No Use	3.189
		Moderate	3.842
		Saturated	1.813
	Moderate	No Use	1.736
		Nominal	.838
		Saturated	.383
	Saturated	No Use	2.689
		Nominal	1.829
		Moderate	3.402

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Mean Difference (I-J)	Std. Error
Chapter 16 Test [Total Pts: 25 Score] [377858	No Use	Nominal	.671	1.015
		Moderate	-.928	1.038
		Saturated	-1.536	.774
	Nominal	No Use	-.671	1.015
		Moderate	-1.599	1.113
		Saturated	-2.207	.866
	Moderate	No Use	.928	1.038
		Nominal	1.599	1.113
		Saturated	-.608	.900
	Saturated	No Use	1.536	.774
		Nominal	2.207	.866
		Moderate	.608	.900
Bio 2121 Lecture Midterm [Total Pts: 150 Score] [377864	No Use	Nominal	-3.750	7.052
		Moderate	1.812	7.211
		Saturated	-9.312	5.374
	Nominal	No Use	3.750	7.052
		Moderate	5.562	7.732
		Saturated	-5.562	6.017
	Moderate	No Use	-1.812	7.211
		Nominal	-5.562	7.732
		Saturated	-11.124	6.253
	Saturated	No Use	9.312	5.374
		Nominal	5.562	6.017
		Moderate	11.124	6.253
Bio 2121 Lecture Final [Total Pts: 150 Score] [377865	No Use	Nominal	-4.847	6.645
		Moderate	-3.316	6.794
		Saturated	-11.483	5.063
	Nominal	No Use	4.847	6.645
		Moderate	1.530	7.286
		Saturated	-6.637	5.669
	Moderate	No Use	3.316	6.794
		Nominal	-1.530	7.286
		Saturated	-8.167	5.892

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Sig.[b]	95% Confidence [b]... Lower Bound
Chapter 16 Test [Total Pts: 25 Score] [377858	No Use	Nominal	1.000	-2.066
		Moderate	1.000	-3.726
		Saturated	.300	-3.621
	Nominal	No Use	1.000	-3.408
		Moderate	.926	-4.599
		Saturated	.075	-4.542
	Moderate	No Use	1.000	-1.870
		Nominal	.926	-1.402
		Saturated	1.000	-3.034
	Saturated	No Use	.300	-.549
		Nominal	.075	-.128
		Moderate	1.000	-1.818
Bio 2121 Lecture Midterm [Total Pts: 150 Score] [377864	No Use	Nominal	1.000	-22.758
		Moderate	1.000	-17.622
		Saturated	.518	-23.796
	Nominal	No Use	1.000	-15.257
		Moderate	1.000	-15.278
		Saturated	1.000	-21.778
	Moderate	No Use	1.000	-21.246
		Nominal	1.000	-26.402
		Saturated	.471	-27.977
	Saturated	No Use	.518	-5.172
		Nominal	1.000	-10.655
		Moderate	.471	-5.729
Bio 2121 Lecture Final [Total Pts: 150 Score] [377865	No Use	Nominal	1.000	-22.757
		Moderate	1.000	-21.628
		Saturated	.154	-25.131
	Nominal	No Use	1.000	-13.063
		Moderate	1.000	-18.106
		Saturated	1.000	-21.917
	Moderate	No Use	1.000	-14.995
		Nominal	1.000	-21.167
		Saturated	1.000	-24.046

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	95% Confidence Interval for b. Upper Bound
Chapter 16 Test [Total Pts: 25 Score] [377858	No Use	Nominal	3.408
		Moderate	1.870
		Saturated	.549
	Nominal	No Use	2.066
		Moderate	1.402
		Saturated	.128
	Moderate	No Use	3.726
		Nominal	4.599
		Saturated	1.818
	Saturated	No Use	3.621
		Nominal	4.542
		Moderate	3.034
Bio 2121 Lecture Midterm [Total Pts: 150 Score] [377864	No Use	Nominal	15.257
		Moderate	21.246
		Saturated	5.172
	Nominal	No Use	22.758
		Moderate	26.402
		Saturated	10.855
	Moderate	No Use	17.622
		Nominal	15.278
		Saturated	5.729
	Saturated	No Use	23.796
		Nominal	21.778
		Moderate	27.977
Bio 2121 Lecture Final [Total Pts: 150 Score] [377865	No Use	Nominal	13.063
		Moderate	14.995
		Saturated	2.164
	Nominal	No Use	22.757
		Moderate	21.167
		Saturated	8.644
	Moderate	No Use	21.628
		Nominal	18.106
		Saturated	7.712

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Mean Difference (I-J)	Std. Error
	Saturated	No Use	11.483	5.063
		Nominal	6.637	5.669
		Moderate	8.167	5.892

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	Sig.[b]	95% Confidence...[a]
				Lower Bound
	Saturated	No Use	.154	-2.164
		Nominal	1.000	-8.644
		Moderate	1.000	-7.712

Pairwise Comparisons

Dependent Variable	(I) Module Categories	(J) Module Categories	95% Confidence Interval for [b]
			Upper Bound
	Saturated	No Use	25.131
		Nominal	21.917
		Moderate	24.046

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Pillai's trace	.580	1.422	42.000	249.000	.054	.193
Wilks' lambda	.523	1.402	42.000	241.050	.062	.194
Hotelling's trace	.728	1.381	42.000	239.000	.071	.195
Roy's largest root	.314	1.864[a]	14.000	83.000	.043	.239

Each F tests the multivariate effect of Module Categories. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. The statistic is an upper bound on F that yields a lower bound on the significance level.

Univariate Tests

Dependent Variable		Sum of Squares	df	Mean Square	F	Sig.
Chapter 3 Test [Total Pts: 25 Score] |377850	Contrast	80.357	3	26.786	2.905	.039
	Error	866.617	94	9.219		
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	Contrast	44.427	3	14.809	.777	.510
	Error	1792.010	94	19.064		
Chapter 4 Test [Total Pts: 25 Score] |377852	Contrast	64.532	3	21.511	4.269	.007
	Error	473.670	94	5.039		
Chapter 5 Test [Total Pts: 25 Score] |377853	Contrast	1.661	3	.554	.144	.933
	Error	361.845	94	3.849		
Chapter 6 Test [Total Pts: 25 Score] |377854	Contrast	20.646	3	6.882	1.854	.143
	Error	348.859	94	3.711		
Chapter 9 Test [Total Pts: 25 Score] |377855	Contrast	8.884	3	2.961	.315	.814
	Error	883.167	94	9.395		
Chapter 11 Test [Total Pts: 25 Score] |377798	Contrast	37.413	3	12.471	1.729	.166
	Error	677.890	94	7.212		
Chapter 12 Test [Total Pts: 25 Score] |377856	Contrast	74.086	3	24.695	2.474	.066
	Error	938.298	94	9.982		
Chapter 13 Test [Total Pts: 25 Score] |377799	Contrast	75.324	3	25.108	4.149	.008
	Error	568.876	94	6.052		
Chapter 14 Test [Total Pts: 25 Score] |377800	Contrast	50.146	3	16.715	3.292	.024
	Error	477.242	94	5.077		
Chapter 15 Test [Total Pts: 25 Score] |377857	Contrast	34.232	3	11.411	2.261	.086
	Error	474.453	94	5.047		
Chapter 16 Test [Total Pts: 25 Score] |377858	Contrast	70.757	3	23.586	2.843	.042
	Error	779.984	94	8.297		
Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	Contrast	2033.107	3	677.702	1.693	.174
	Error	37629.318	94	400.312		
Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	Contrast	2194.008	3	731.336	2.058	.111
	Error	33408.810	94	355.413		

Univariate Tests

Dependent Variable		Partial Eta Squared
Chapter 3 Test [Total Pts: 25 Score] |377850	Contrast	.085
	Error	
Chapter 3-b Test [Total Pts: 23.5 Score] |377851	Contrast	.024
	Error	
Chapter 4 Test [Total Pts: 25 Score] |377852	Contrast	.120
	Error	
Chapter 5 Test [Total Pts: 25 Score] |377853	Contrast	.005
	Error	
Chapter 6 Test [Total Pts: 25 Score] |377854	Contrast	.056
	Error	
Chapter 9 Test [Total Pts: 25 Score] |377855	Contrast	.010
	Error	
Chapter 11 Test [Total Pts: 25 Score] |377798	Contrast	.052
	Error	
Chapter 12 Test [Total Pts: 25 Score] |377856	Contrast	.073
	Error	
Chapter 13 Test [Total Pts: 25 Score] |377799	Contrast	.117
	Error	
Chapter 14 Test [Total Pts: 25 Score] |377800	Contrast	.095
	Error	
Chapter 15 Test [Total Pts: 25 Score] |377857	Contrast	.067
	Error	
Chapter 16 Test [Total Pts: 25 Score] |377858	Contrast	.083
	Error	
Bio 2121 Lecture Midterm [Total Pts: 150 Score] |377864	Contrast	.051
	Error	
Bio 2121 Lecture Final [Total Pts: 150 Score] |377865	Contrast	.062
	Error	

The F tests the effect of Module Categories. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Appendix B: Example Question from the First Dynamic Module Set in Chapter 6

Module 1: Section 6_01-6_03

Questions: Available: 30 Included: 30

Review

QUESTION

REVIEWING 2 OF 30

Match the description to the correct answer: Has a length greater than width.

ANSWER

100% CHOSE THE CORRECT ANSWER
Long bone

0%
Short bone

0%
Irregular bone

0%
Flat bone

0%
Sesamoid bone

0%
I DON'T KNOW YET

What You Need To Know

A **long bone** has a length greater than width.

Long bones, as their name suggests, are considerably longer than they are wide (see figure below). A long bone has a shaft plus two ends, which are often expanded. All limb bones except the patella (kneecap) and the wrist and ankle bones are long bones. Notice that these bones are named for their elongated shape, *not* their overall size. The three bones in each of your fingers are long bones, even though they are small.

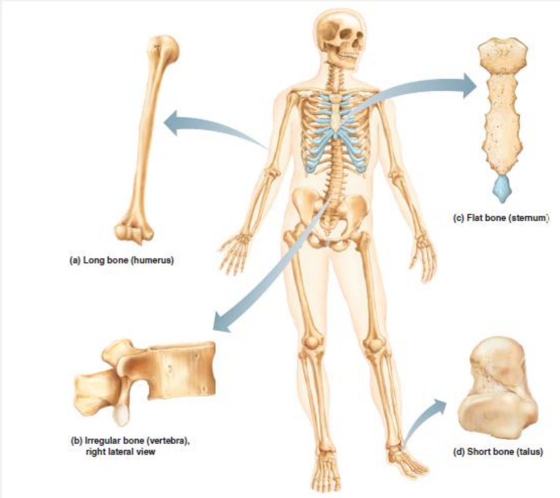

Figure 6.2 Classification of bones on the basis of shape.

Click to view larger image

Appendix C: Example Questions from Chapter 3B Test

Chapter 3B – 50

Question 1

1. Where does transcription of DNA take place?

- inside the cell nucleus
- inside the cell nucleus while the cell is undergoing mitosis
- within the cytoplasm of the cell
- within the interstitial fluid of the cell

0.5 points

Question 2

1. The fact that there are 64 possible codons and only about 20 amino acids is an example of:

- A. spliceosome activity.
- B. mitotic insufficiency.
- C. semi-conservative replication.
- D. genetic redundancy.
- E. base pairing.

0.5 points

1. Where is RNA assembled in this picture?

   - A. A
   - B. B
   - C. C
   - D. D
   - E. E

0.5 points

Question 50

1. During which stage of the cells life cycle does DNA replication occur?

   - Interphase
   - Metaphase
   - Telophase
   - Prophase