Interactive Learning Laboratories of Complex Models in Undergraduate Biomechanics

by

Dan Geneau
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Abstract

Undergraduate biomechanics is classically viewed as one of the most difficult courses included in kinesiology programs, often leading to poor student performance and attitudes. By adjusting the interactions students have with course material, it may be possible to positively impact student outcomes. Past work has shown that interactive learningepisodes can positively impact student attitudes toward difficult course content, as well asimprove student performance variables (Catena & Carbonneau, n.d.; Moreno & Mayer, 2007; Pandy, Petrosino, Austin, & Barr, 2004; Zhang, Zhou, Briggs, & Nunamaker, 2005). In the present study, I investigated the effectiveness of interactive, exploratory based learning episodes in undergraduate biomechanics laboratory sessions. Episodes consisted of a brief introduction of the laboratory topic, which was consistent across groups, followed immediately by a pre- laboratory assessment. Students then completed the laboratory, which either included exploration in interactive computer applications or still images of the applications displaying the necessary information for completion.

Intervention sessions utilized custom interactive computer applications where students were prompted to explore course concepts centered around reciprocal relationships between variables specific to each laboratory topic. Student performance was collected and assessed for Work Loop Muscle Mechanics and EMG signal processing laboratory topics at two independent instances. For both learning topics, intervention and control groups both, improved their scores between pre- and post-laboratory assessments indicating learning. In the post-laboratory testing, the intervention group significantly outperformed the control group on the most challenging assessment question ($P = 0.005$). Adversely, the intervention group achieved significantly lower scores for the simplest signal processing questionnaire item ($P < 0.001$). Although the present study contained mixed results, it supports the utilization of exploratory based learning episodes on typically challenging topics with abstract concepts. Further investigation is needed in order to explore the chronic learning effects of such instructional methods.

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Acknowledgments

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Dedication

This paper is dedicated to the teachers I had throughout my elementary and high school education specifically, Mr. Ian Emtage and Mr. Elson Morgan. Thank you for your support, guidance and leadership throughout the years, and for sparking my passion for education.

This paper is also dedicated to my family, my parents, Jennifer Barrett and Joseph Geneau, as well as my two sisters, Mary Claire and Grace. Without your support none of this would be possible. Thank you for always having my best interests at heart

Chapter 1: Introduction

Operational Definitions

Problem Based Learning (PBL):

A processed-oriented teaching strategy based on collaborative group inquiry centred around open-ended scenario problems. (Tempelaar et al., 2017)

Inquiry Based Learning:

Educational theory where students are enabled to learn about a topic through self-directed investigations. (Lazonder & Harmsen, 2016)

Constructivism:

Educational pedagogy which is centered around the formation of new student knowledge off of previous conceptual understanding (Bächtold, 2013; Cook, 2006; Kearney & Treagust, 2001)

Exploratory Based Learning:

Individual exploration of course content, using interactive materials designed to study the interrelationships of theoretical phenomenon.

Work Loop:

A model of voluntary muscular contraction which connects reductionist principles of force-time, force-velocity and, force-distance into one visual representation. This model is used in educational settings, to describe the larger picture of what is taking place during cyclical contractions which are characteristic of locomotion and other repetitive actions.

Assumptions and Limitations

In this study, it is assumed that participants performed to the best of their ability on all coursework including pre- and post-laboratory questionnaires, and midterm examinations. It is also assumed that all participants answered all survey questions accurately and honestly. Limitations of this study include the possibility of discrepancies between laboratory instructors and their presentation/implementation of teaching materials.

Interactive Teaching Techniques

Constructivist Teaching approach

The constructivist educational approach is increasing in popularity at all levels of education (Kearney & Treagust, 2001). Much as the name implies, constructivist teaching “constructs” new knowledge from previous student understanding (McCauley, Martins Gomes, & Davison, 2018). This teaching theory suggests that, by recruiting student prior knowledge and extending that understanding into new contexts or scenarios, students formulate new knowledge independent of instructor input. Ultimately, this educational theory postulates that knowledge formed independently by students will lead to better understanding as opposed to if that information was given to students. By fostering student development independent of explicit instruction, the responsibility of learning naturally shifts from the instructor to the student (Cook, 2006; Kearney & Treagust, 2001). Constructivist approaches often include peer interaction and group work, creating a dynamic dialog between learners in order to foster further understanding (Kearney & Treagust, 2001). However, constructivism does not require group work, simply the process of building new knowledge from previous understanding. This can take many forms, including but not limited to inquiry-based learning, problem based learning and exploratory learning.

Inquiry Based Learning

The inquiry-based learning model has recently been a central topic in many educational circles (Duran, Mcarthur, & Hook, 2004). Specifically, this teaching style is becoming very prominent in science education, in part as a response to a measurable decrease in learning and enrollment (Catena & Carbonneau, 2018). Applications of this teaching method has shown increases in student interest and student attitudes towards science materials (Connell, Donovan, & Chambers, 1996; Rissing & Cogan, 2009). Inquiry has also been widely cited as an effective method of increasing academic performance and increasing scientific literacy (Duran et al., 2004).

In its simplest form, inquiry-based learning enables students to autonomously explore a topic or concept through self-directed investigation (Lazonder & Harmsen, 2016). These practices are fundamentally encompassed by constructivist teaching methods, as students are developing their knowledgebase independent of explicit instruction, depending on prior knowledge to form new understanding. It has been shown that inquiry-based instruction can positively affect student outcomes, provided the appropriate scaffolds are present (Lazonder & Harmsen, 2016). The level of support and instruction provided for students can drastically alter the resultant outcomes of inquiry-based methods. Due to the open-ended nature of this teaching pedagogy, it is possible for students to become frustrated with the lack of explicit instruction, resulting in a negative learning experience (Nivalainen, Asikainen, & Hirvonen, 2013). Specifically, in course work encompassing physical and mathematical concepts, students may become frustrated and "stuck" due to the relative difficulty of the concepts being studied (Duran et al., 2004). By providing appropriate supports and scaffolds throughout instruction, students can be guided in their inquiry without simply providing solutions. Inversely, if too much guidance is given, students are no longer the driving force behind their cognitive processes, thus defeating the purpose of the instructional episode. The balance between student guided inquiry and explicit instruction is the principal factor influencing the effectiveness of this form of instruction (Duran et al., 2004). This optimal range of support is commonly referred to in the literature as the "proximal zone of development" for students (Eun, 2019). The proximal zone of development can be referred to as the range in which students are able to develop new knowledge based on previous understanding (Eun, 2019; Kapon, 2016). Another factor to consider with this instructional method is the age group(s) in which inquiry-based learning is most effective (Lazonder & Harmsen, 2016). These questions are largely in reference to primary students (ages 6 to 12) and their ability to problem solve independently. The results regarding older and adolescent populations, such as high school and undergraduate aged students, are more consistently positive when interacting in an inquiry based educational setting (Lazonder & Harmsen, 2016).

Problem Based Learning

Problem Based Learning (PBL) is a form of constructivist and inquiry based instruction which is widely used in many STEM (Science Technology Engineering and Mathematics) and medical education programs (Bate et al., 2014; Fan, Jiang, Shi, Wang, & Li, 2018; Mandeville & Stoner, 2015). In PBL, students have the opportunity to problem solve along-side their peers and work towards a unified goal. Unlike inquiry methods, PBL has a relatively convergent goal of solving the problem presented to the students. The general structure of PBL instruction is to pose a question for groups of students to critically analyse and solve, rather than provide a prescribed procedure to approach a task (Pandy et al., 2004). This provides students autonomy over their learning and analytical processes, allowing them to discover solutions in the best way they deem fit. In doing so, students become a more active agent in their education and knowledge acquisition (Bate et al., 2014; Mandeville & Stoner, 2015; Wouter R. van, Joolingen; Ton, 1998).

PBL promotes critical thinking in the educational environment, and shifts student thinking from outcome-oriented goals towards solution-oriented goals compared to classical laboratory instruction (Grooms, Sampson, & Golden, 2014). Typical questions used in PBL encompass general ideas which could be used to target a specific modality, concept, or theory (Pandy et al., 2004). For instance, in biomechanics an instructor may pose the question: “What separates a novice and expert jumper?”. Students could then collaborate in an attempt to find a viable solution. By placing students in a context where they shift into the mindset of a scientist rather than a student, they are placed in an environment where they can explore the problem independent of instruction (Pandy et al., 2004).

Certain applications of PBL have been shown to have positive a positive effect on student outcome measures including student attitude and performance (Bate et al., 2014; Fan et al., 2018; Nivalainen et al., 2013; Pandy et al., 2004; Prince, 2004). There are a number of different implementations of PBL, often being combined with other educational strategies to maximize learning. Student performance has been observed to be positively affected by the implementation of in-class “hands-on” learning activities relevant to course concepts and theory (Catena & Carbonneau, 2018). Furthermore, the combination of contextual and practical learning environments can result in increased student performance (Grooms et al., 2014). By combining authentic learning experiences as outlined above with PBL, it is possible that student outcomes be further improved.

While the potential positive effects of PBL on student outcomes is very encouraging, some students may not have the tools to autonomously move through obstacles in these types of learning environments (Wouter R. van, Joolingen; Ton, 1998). Recent work shows that students often struggle with generating hypotheses to test, developing experimental designs, and interpreting their data (Wouter R. van, Joolingen; Ton, 1998). Similar to inquiry-based methods, it is crucial to strike a balance between student autonomy and instruction in order to provide an authentic learning environment in which students have the opportunity to succeed. Furthermore, PBL is largely based on collaboration. While this is a valuable skill, it is possible that through collaboration, not all students are contributing equally and therefore missing valuable educational content.

Exploratory Based Learning

Exploratory Based Learning (EBL), similar to PBL is a subcategory of constructivist instructional pedagogy. Largely influenced by the Kolb model of experiential learning (Kolb, 1984), exploratory learning involves individual exploration into a contextual model in order to formulate new knowledge (Freitas & Neumann, 2009). In recent years, these models have become increasingly multimodal, using computer programs and digital representations of phenomenon to represent authentic experiences (Freitas & Neumann, 2009; Sun & Cheng, 2007).

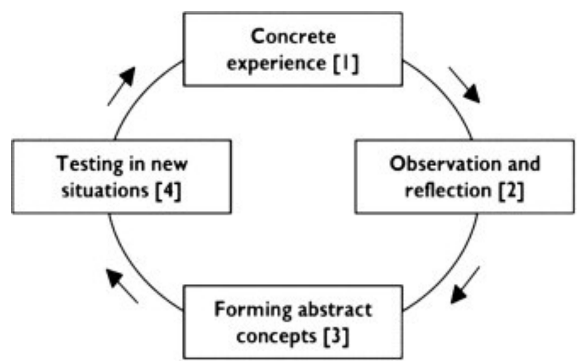


Figure 1.1 Kolb Model of experiential learning

One of the primary differences between EBL and other constructivist approaches, is the absence of a convergent question for students to solve. The focus of this application is to deepen student understanding of a subject topic or area as a whole, as opposed to a specific instance or example (Freitas & Neumann, 2009). By pairing of this learning theory with personal, interactive applications, students will be able to customize the interactions they have with complex course content. In doing so, students will be able to individualize learning episodes based on their needs. This may create an environment where students are able to interact with course materials at a level which may not be accessible in any other context. While exploratory learning episodes using customized computer programs is not novel, the effects on student performance in undergraduate biomechanics coursework has yet to be explored.

Multimodal Learning Environments

Multimodal Learning

Educational modalities classify the different sensory tools we use in order to interpret incoming information (Moreno & Mayer, 2007). Therefore "multimodal" learning is simply the presentation of material which recruits multiple modalities simultaneously. Multimodal learning tools can be divided into two categories; interactive and non-interactive, with the distinction that interactive tools require user action (Moreno & Mayer, 2007). It has been observed that interactive multimodal instructional tools recruit more student interest and engagement (Jan, Viceconti, & Clapworthy, 2004; Moreno & Mayer, 2007) which as a result may have implications on student performance.

Virtual Interactive Learning

Interactive virtual learning environments, such as digital laboratories, are becoming increasingly popular in educational settings of all levels (Condello et al., 2020; Freitas & Neumann, 2009; Kearney & Treagust, 2001; Moreno & Mayer, 2007). Learning tools such as these allow students to interact with relevant phenomenon which they may not readily have access to otherwise. For example, Wagner et al. (2006) used a virtual laboratory environment to model the Reynolds number experiment in undergraduate physics courses. While this phenomenon is widely understood, it can be difficult to obtain an accurate visual representation experimentally. Through the use of this tool, students were able to interact with course materials in a more meaningful and accurate way (Wagner et al., 2006). Previous research indicates that interactive learning environments, such as the example mentioned above, generate new avenues to accurately represent crucial course concepts, theory and phenomenon and as a result, may positively affect student performance outcomes (Rhodes, Rozell, & Shroyer, 2014). In the field of biomechanics, some of these positive effects have already been observed. Increases in student conceptual knowledge, novel transfer and application of theory, and factual knowledge have been observed when virtual modeling is integrated into undergraduate biomechanics classes (Pandy et al., 2004). This is crucial, as many of the concepts and phenomenon included in the biomechanics curriculum are not readily available for student observation or experimentation. For example, the topic of voluntary muscular contraction outcome measures requires integration of three reductionist properties; force-velocity, force-length, and force-time (activation and deactivation). This can be incredibly challenging to portray in an accurate, meaningful and contextual way without usingvirtual modeling tools.

While Interactive learning environments have been shown to be effective educational tools, the quality of the model is a significant factor to be considered. Student performance may actually be negatively impacted if tools are implemented incorrectly (Sun & Cheng, 2007). Further, the “richness” or quality of the tool directly effects student outcomes (Sun & Cheng, 2007). Tool richness refers to its capacity for immediate feedback, to transmit multiple cues, to have a personal focus, and for language variety (Sun & Cheng, 2007). Virtual tools have been observed to assist student learning, it is unlikely to be as effective as an independent teaching strategy (Schilling, 2009; Zhang et al., 2005). This indicates modeling independent of other educational supports may not adequately foster student learning, leaving the interactivity of the tool as a critical component. Furthermore, virtual tools and resources are most effective when paired with other learning tools, instruction, and contextual questions relating to content covered in the course material (Zhang et al., 2005).

Student Attitude

Student attitude is a very broad topic which can be drastically different across subject area and education level. (Evans, 2007). As such, the measurement of student attitude must be tailored to specific fields and environments. In the field of biomechanics, it was found that previous physics knowledge, positive student evaluations, previous GPA (grade point average), and perceived ability of course work all significantly influence student performance (Hsieh &Knudson, 2018). Biomechanics is traditionally viewed by undergraduate kinesiology students as one of the most difficult courses in their program, implying that student attitudes regarding their ability in biomechanics are largely negative (Wallace & Kernozek, 2017). It is reported that negative student attitude can lead to decreased effort both in and outside of class time (Wallace & Kernozek, 2017) thus, result in a decrease inacademic performance (Kaur & Zhao, 2017).

There are a number of factors which may affect student attitudes. These include, but are not limited to, teacher quality, perceived importance of material, and the learning environment (Kaur & Zhao, 2017), all of which may all play a role in poor student attitudes towards undergraduate biomechanics. Initial negative attitudes towards biomechanics may also be influenced by pre-requisite requirements (Wallace & Kernozek, 2017). Students may feel that their understanding of physical and mathematical concepts are inadequate for the successful completion of biomechanics course work, even if the course has been designed to accommodate students of all skill levels. The vast majority of biomechanics programs require Anatomy as a pre-requisite while only about one fifth require physics or mathematics coursework, despite the fact that both topics are frequently referenced within the course content (Catena & Carbonneau, 2018). In order to address this, program heads and instructors have recently pushed for basic mathematics, calculus and physics course work to be required pre-requisites for advanced biomechanics courses (Wallace & Kernozek, 2017). While this would assist in the development of foundational knowledge, this could lead to another issue. Students within Kinesiology programs have often reported negative interactions with their pre-requisite course work in these fields, which then carry over into biomechanics (Wallace & Kernozek, 2017). It would appear that pre-requisite work, although important to student performance, can work both positively and negatively towards student attitudes. Therefore, it is ever more important to create an environment within biomechanics courses which promotes a positive student experience. The teaching pedagogy in which biomechanics is taught may pose as a solution.

Teaching pedagogy has been shown to relate to student attitudes and performance. Student centred learning environments such as PBL have been shown to positively effect student attitudes towards coursework (Kaur & Zhao, 2017). On the other hand, more teacher centered classrooms, where the instructor dictates student discovery, have been reported to exhibit a noticeably negative relationship with student attitude outcomes when compared to student centered approaches (Kaur & Zhao, 2017). Students who have a more positive attitude toward their area of study have been shown to perform at a higher level, engage more frequently in course work, and sustain an interest in the field post course completion (Kaur & Zhao, 2017). By creating a student-centered environment where students are motivated to learn, it is possible that performance, along with attitudes, may improve.

Student Engagement

Student engagement is a requirement for learning on any level (Fuller et al., 2018). Engagement encompasses student behavioural, cognitive and emotional factors, however, there is no one clear definition (Fuller et al., 2018). In general terms, student engagement can be summarized as the level at which students are attentive, alert and actively participating in class work (Groccia, 2018). Instructional environments and structure can be tailored to further recruit student engagement. Students who participated in group work reported higher engagement than those in individual activities (Fuller et al., 2018). Furthermore, student centred approaches such as PBL report the highest levels of engagement compared to other common teaching pedagogies (Fuller et al., 2018; Prince, 2004). A significant increase in student engagement has also been observed when multimodal and multimedia learning content has been implemented (Elliot, Wilson, & Boyle, 2014; Schilling, 2009; Sun & Cheng, 2007).

Student engagement is crucial to student performance. A positive relationship between student engagement and academic achievement has been observed consistently throughout the literature (Fuller et al., 2018; Groccia, 2018; Prince, 2004; Schilling, 2009). It has also been found that students who are more engaged in course materials report higher attitude scores, while students who are less engaged report lower attitude scores (Evans, 2007; Pandy et al., 2004).

Fuller et al. developed a six item self-report tool to measure student engagement in active learning environments (2018). This tool was found to accurately represent student engagement in a variety of educational settings and frameworks including PBL environments (Fuller et al., 2018). One interesting result from this research is the rate of students who "faked" their engagement. Up to 25% of students reported pretending to be engaged in less active and interesting course material (Fuller et al., 2018). Some traditional methods of measuring engagement used in the process of tool validation reported high engagement where students self-reported significantly lower levels. This suggests that student engagement may increase in student centered environments and consequently, impact other student outcome measures.

EMG Analysis

Surface Electromyogram (EMG) is a common biomechanical measurement tool used to decern neuromuscular electoral stimulation and, as an extension, skeletal muscle activation measurements (Frigo, Ferrarin, Frasson, Pavan, & Thorsen, 2000). Virtually all EMG signal analysis conducted using computer-based algorithms used to help acquire, clean and process the raw EMG signal (De Luca, 2003). The techniques used in these algorithms can change drastically, based on the type of signal (sensor placement, frequency, dynamic vs static collection etc.) collected and the experimental goals. A number of factors such as filter selection, type and order vary greatly based on the specific experimental context. In order to properly implement an algorithm appropriate for your research design, a fundamental understanding of EMG algorithmic techniques is required.

While EMG is a common topic within undergraduate kinesiology programs, many phenomena are studied in isolation of one another, or simply automated by a computer program, removing all user input (Mathew, Nundy, Chandrashekaran, & Oommen, 2019). By implementing an interactive model into student laboratories, student outcome measures and comprehension of basic EMG signal processing theory may be affected.

Work Loop Analysis

During cyclical motion, such as running or cycling, muscle tendon units (MTU) undergo a stretch shortening cycle which adjusts dependent on activity demands in order to most efficiently produce work (Sawicki, Robertson, Azizi, & Roberts, 2015) . These contractions are largely influenced by a number of factors, such as neural activation, timing, load and context (Sawicki et al., 2015). Muscle work loops are a method of simulating these contractions in a comprehensive way, connecting all of the isolated properties which contribute to the production and execution of voluntary muscular contractions (Martin & Nichols, 2018). During work loop analysis, work is calculated using force generated by the muscle, and distance of shortening or lengthening. Positive work is defined as contractile force produced during muscle shortening, while negative work takes while contractile force is produced within the muscle during lengthening (Sawicki et al., 2015). The primary properties which determine the amount of work produced by a muscle are themuscle force-velocity, force-length, and force-time relationships (Josephson, 1999). These neuromechanical factors, also known as the reductionist properties of the muscle, can besimultaneously explored using simulated work loop analysis. While studying reductionist properties is valuable for fundamental understanding of foundational concepts, it is likely this approach underestimates the complexity of the system as a whole, leading to gaps in student understanding (Josephson 1999; Martin, 2007; Van Regenmortel, 2004)

Rationale

Biomechanics is one of the most notoriously difficult courses to complete for undergraduate kinesiology students (Wallace & Kernozek, 2017). There are a number of factors which go into student attitude, self-efficacy, and performance for undergraduate biomechanics students (Wallace & Kernozek, 2017). A number of recent studies have looked into the effectiveness of PBL or inquiry teaching methods in biomechanics and similar science subjects of study (Bate et al., 2014; Fan et al., 2018; Fuller et al., 2018; David Mandeville & Stoner, 2015; Pandy et al., 2004; Prince, 2004). The literature suggests that PBL and other student-centered teaching methods positively influence student outcomes (Bate et al., 2014; Fan et al., 2018; Fuller et al., 2018; David Mandeville & Stoner, 2015; Pandy et al., 2004; Prince, 2004). Multimedia learning implementation in science coursework has also been thoroughly studied. Well delivered multimedia integration typically has a positive effect on student engagement and attitudes (Elliot et al., 2014; Kearney & Treagust, 2001; Pandy et al., 2004; Rhodes et al., 2014; Schilling, 2009; Wagner, Altherr, Eckert, & Jodl, 2006). Many biomechanical phenomena are recorded and measured using multimedia tools such as video analysis and computer programs (Anicio de Magalhaes, Vannozzi, Gatta, Fantozzi, & Anicio Magalhaes, 2014; Beichner, 1996; De Froda, Thigpen, & Kriz, 2016) which naturally leads to the feasibility of integrating multimedia content into biomechanics lab and course work.

By creating rich, authentic and interactive learning tools which students use independently, a deeper understanding of the effectiveness of these tools may be achieved. The applications of educational models such as PBL and inquiry-based learning are widely understood. However, much of the work to date looks exclusively at group work and collaboration within these student-centred applications (Fan et al., 2018; David Mandeville & Stoner, 2015; Pandy et al., 2004; Rissing & Cogan, 2009; Tempelaar et al., 2017). While working collaboratively, it is difficult to decern if students are equally engaged in learning processes. Collaborative work also limits the amount if individual exposure students may have to learning tools such as the interactive models mentioned above. Furthermore, by having students work independently, it may be possible to isolate where learning takes place within student centered learning episodes.

Chapter 2: Manuscript

2.1 Introduction

Biomechanics is the study of physical mechanics in biological systems, largely focusing on human subjects, and a prominent field of study in undergraduate kinesiology (Garceau, Ebben, & Knudson, 2012; Lu & Chang, 2012). Although biomechanics is a fundamental course taught in almost every kinesiology program, it is frequently perceived as one of the most difficult courses in this area of study (Wallace & Kernozek, 2017). Biomechanics course work encompasses a number of fundamental physical and mathematical concepts which require higher order and abstract levels of thinking. Additionally, complex theoretical concepts of human biomechanics such as muscle mechanics, as well as signal processing techniques, require unique educational approaches to support learning for students in kinesiology that may have limited experience in math and physics. For example, Muscle mechanics is often taught using a reductionist approach where muscle characteristic relationships of force-velocity, force-length and force-time are taught separately. However, similar to other biological systems, muscle mechanical behaviour is a complex system whose emergent properties may not be explained or predicted well by studying individual parts (Josephson 1999). The reductionist approach as evident within muscle mechanics instruction underestimates complexity and may have a detrimental influence on many areas of biomechanical instruction, research and innovation (Van Regenmortel, 2004). In an effort to support learning experiences for students, many biomechanics courses include a laboratory component intended to providestudents the opportunity to interact with reductionist components and complex systems content within a dynamic environment (Catena & Carbonneau, n.d.; Garceau et al., 2012; Sadler, Puig, & Trutschel, 2011). Additionally, to support the potential to teach complex systems, interactive computer programs are often used to allow students to engage in the material using an exploratory constructivist approach (Freitas & Neumann, 2009; Stahre Wästberg et al., 2019). While these tools have shown promise in other areas, such as undergraduate physics, there is yet to be support for the value of interactive tools for learning concepts such as muscle mechanics and signal processing in biomechanics. Therefore, the purpose of this study was to assess the effectiveness of interactive modules on students test performance in an undergraduate biomechanics class for concepts of muscle mechanics and signal processing. We hypothesized that students who were taught using interactive learning modules would outperform control groups on post-laboratory assessments of complex systems content related to muscle mechanics and signal processing. This assessment of interactive learning modules will help to provide important insight into biomechanics instruction within a kinesiology curriculum.

2.2 Methods

2.2.1 Participants

Forty-seven undergraduate students (female = 30, male = 17) who were enrolled in Biomechanics during the spring of 2020 were asked to participate in this study. Policyand use of participants' data were approved by the University of Victoria institutional ethical review board (ethics number: 19-0386). Consent to participate in the study wereobtained either in person or electronically online.

2.2.2 Data Collection and Analysis

For both the muscle mechanics (MM) and signal processing (SP) interactive learning protocols, participants were assigned into a control or an intervention group. Both groups received an identical lecture-based introduction of the laboratory content. Participants in both the intervention and control groups were then required to complete a pre-laboratory assessment. During the laboratory session, the intervention group was required to answer questions using the interactive learning tool as support. The control group was given identical questions and cues but were not able to access the interactive learning tool. At the end of each laboratory, both the intervention and control group performed a post-laboratory assessment. All assessments took place within laboratory instructional time. The MM interactive learning module was completed before the SP interactive learning module and the intervention and control groups were swapped for each module such that the intervention group for the MM section was the control group for the SP section and vice-versa. This was in an effort to ensure equitable learning opportunities across groups. Students were not informed as to which group, they were placed in, or when they were participating in a control or intervention laboratory learning module.

The MM interactive tool was created in the R programming language, using the “Shiny” application framework, and displayed the physical and physiological principles present in a Work Loop, combining reductionist musculoskeletal properties into an interactive complex model (Josephson, 1999). The muscular reductionist properties included in the model are force-time, force-velocity, and force-length. A number of parameters altering the Work Loop outputs were included in the model, including muscle shortening length, shortening velocity, muscular onset/offset, force-velocity curvature, cycle frequency, maximum isometric force and activation/ deactivation times. Controls were provided in the model for users to change these parameters and observe their effects in real time. The SP interactive tool was constructed using the LabView programing language and combined a variety of signal processing properties into one larger complex system, in a similar fashion to the MM tool described above. These properties encompassed the fundamental principles for EMG signal processing analysis (De Luca, 2003)including; filter type (high-pass, band-pass, low-pass), signal rectification, normalization methods, filter cut-off values, gait cycle detection, phase averaging, Fast-Fourier Transform and power analysis.

During laboratory sessions, the intervention groups was provided access to an interactive learning tool in order to assist them in the completion of their assignment for either EMG signal processing or Work Loop lab modules. These tools modeled the various phenomena incorporated in the laboratory module and allowed students to interact with the variables to see the change in model outputs graphically (Figures 2, 3). Control groups were provided still images of the interactive tools along with a

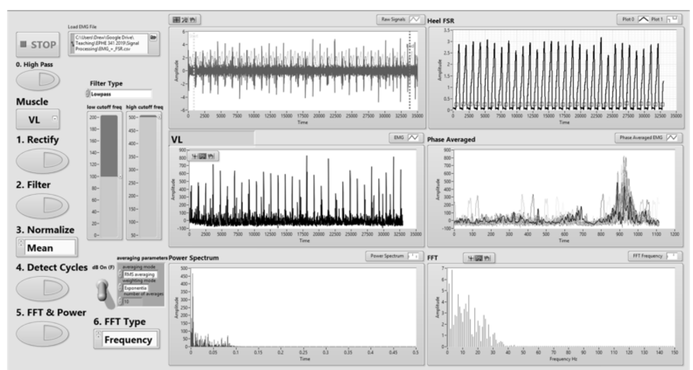


Figure 2.1 Virtual Interactive Muscle Mechanics EMG Signal Processing model

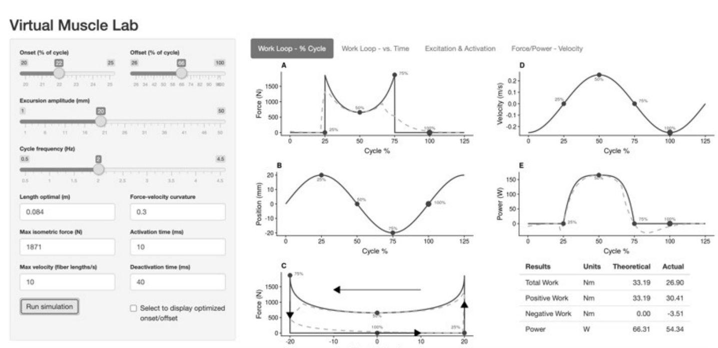


Figure 2.2 Virtual Interactive Muscle Mechanics Work Loop model

description of which variables were changed, removing the opportunity for students to independently explore the relationships between variables. This ensured that the necessary information to complete assignments was provided to both groups, while isolating the intervention (the interactivity of the program) as the only differentiating factor between groups.

Pre- and post- laboratory assessments consisted of four, block-randomized multiple-choice questions. One multiple choice option was entirely correct, another was only partially correct, while the remaining two were incorrect options. In partially correct responses, one to two reductionist properties were correctly identified, however the all-encompassing integrated outcomes of all reductionist components were missed. Responses were tiered in this fashion in an effort to accurately gauge the level of student understanding of course content based on their multiple-choice selection. Pre- and post-assessment items ranged in difficulty, based on the depth of understanding required to select the most correct response. Tier one questions were the most difficult, tier two the second most difficult and lastly, tier three the least difficult. The assessments were conducted immediately pre- and post-laboratory in order to best-represent student understanding as a result of the acute educational episode.

2.2.3 Statistical Analysis

When evaluating assessment items, submissions were ranked according to student responses. Each question was a four multiple choice question with two incorrect options, one partially correct option, and one most correct option. Students were awarded 0% for incorrect selections, 30% for partially correct submissions, and 100% on correct answers. For each of the separate MM and SP interventions, scores for each group and question and instance (pre- and post- laboratory) were compared using a 2 (group) by 4 (question) by 2 (instance) repeated measures multivariate analysis of variance (RM MANOVA). We hypothesized significant differences between groups following laboratory learning episodes so planned comparisons of student performance between groups for this assessment stage were performed. Planned comparisons were conducted for each post-laboratory question item as well as student averages for both Work Loop and EMG signal processing laboratories.

Prior to subjecting data to RM MANOVA analysis, Shapiro-Wilk, Skewness and Kurtosis, and Mauchly's test of sphericity analysis was used to assess data normality. In each measurement instance, Greenhouse-Geisser correction for sphericity were used for breaches of normality.

2.3 Results

2.3.1 Work Loop Analysis

The result of the RM ANOVA is presented in Table 2.1. For Work Loop assessment, there was no significant main effect for group found. There was a significant main effect for both question and time and a significant question by group interaction. Bonferroni Post hoc tests revealed that question 1 had a higher score than questions 2,3 and the average, Question 3 had a higher score than question 2 and Question 3 was not significantly different than the average. Bonferroni Post hoc tests revealed that post laboratory tests scores were significantly higher than pre laboratory test scores. Bonferroni Post hoc tests revealed that there were no significant differences between groups for each question. Planned comparisons showed significant differences between group performance in post-laboratory assessment questionnaire item number two (P= 0.005), with the intervention group achieving significantly higher scores than the control group.

Table 2.1 Repeated Measures Multivariate ANOVA

Cases	Sphericity Correction	Sum of Squares	df	Mean Square	F	p
Question	Greenhouse-Geisser	904.523	3	460.416	23.847	< .001**
Question ✻ Group	Greenhouse-Geisser	122.000	3	62.100	3.216	0.045*
Residuals	Greenhouse-Geisser	1782.703	141	19.307		
Instance	None	181.964	1	181.964	12.924	< .001**
Instance ✻ Group	None	8.132	1	8.132	0.578	0.451
Residuals	None	661.754	46	14.080		
Question ✻ Instance	Greenhouse-Geisser	9.944	3	4.504	0.609	0.562
Question ✻ Instance✻ Group	Greenhouse-Geisser	17.197	3	7.789	1.053	0.358
Group	None	21.296	1	21.296	0.690	0.410
Residuals	Greenhouse-Geisser	767.878	141	7.400		

Note. Sphericity corrections not available for factors with 2 levels.

Note. Type III Sum of Squares

Table 2.2 Contrasts of: Group ✻ Question ✻ Instance for MM Laboratory

Comparison	Estimate	SE	df	t	p
1	0.800	1.020	46	0.784	0.434
2	2.743	1.020	46	2.689	0.008*
3	-1.056	1.020	46	-1.035	0.302
4	0.158	1.020	46	0.155	0.877

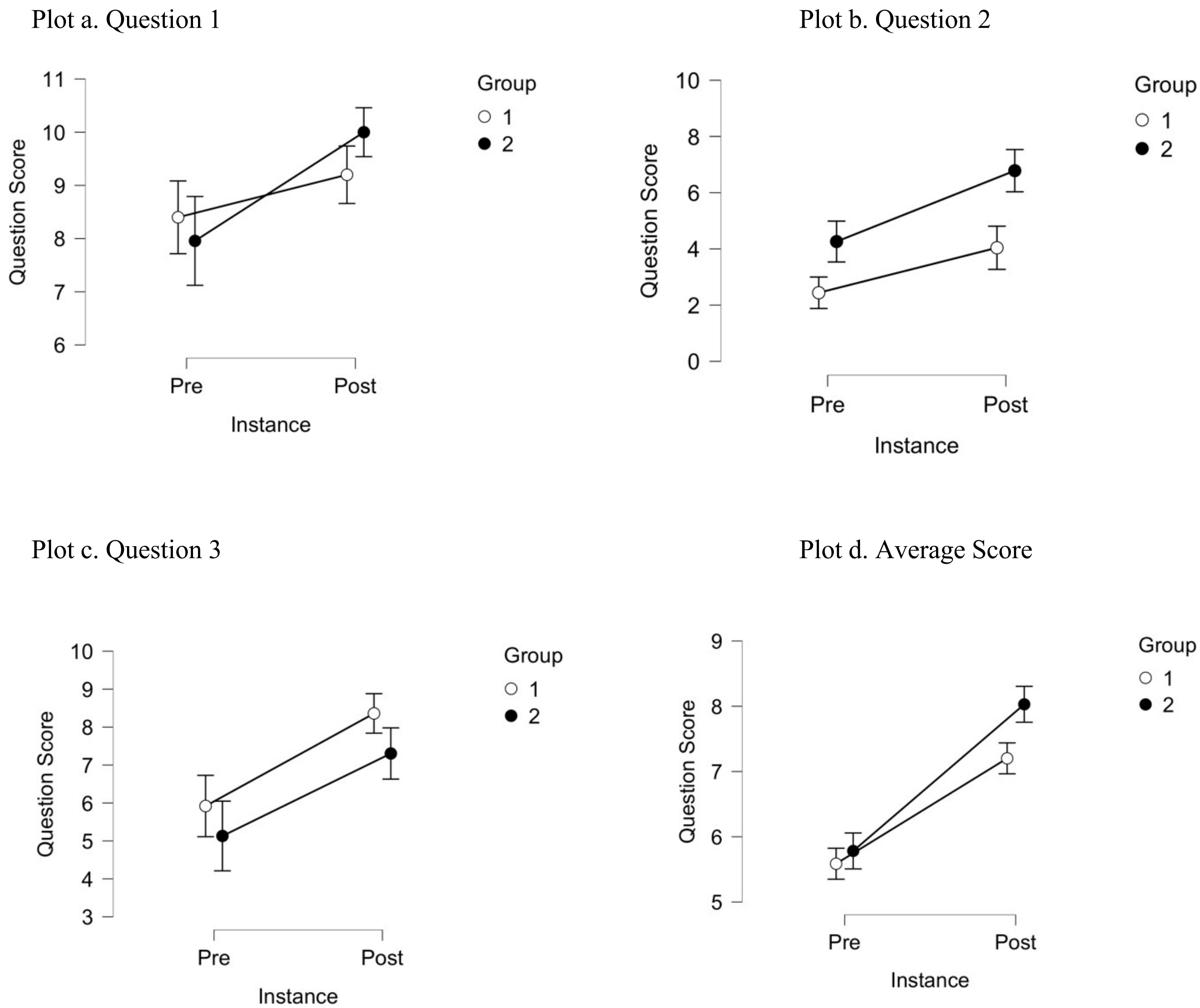


Figure 2.3 Between Group Comparisons of pre- and post- laboratory Work Loop questionnaire performance

2.3.2 EMG Analysis

The results of the RM ANOVA for EMG SP questionnaire items can be seen in table 2.3. For these assessments, similar to Work Loop MM, no significant main effect for groups was found. However, there was a significant main effect across questions with no significant interactions. Bonferroni Post hoc analysis for question revealed that question 2 was the lowest scoring, question 1 scored higher than question 2,4 and the average, question 3 was the highest scoring, and the average scored higher than question 4.

Bonferroni Post hoc tests for time revealed that post laboratory test scores were significantly higher than pre laboratory test scores. Planned comparisons displayed significant differences between group performance in post-laboratory assessment questionnaire item number one (P= <0.001), with the control group achieving significantly higher scores than the intervention group.

Table 2.3 EMG SP Repeated Measures Multivariate ANOVA

Cases	Sphericity Correction	Sum of Squares	df	Mean Square	F	p
Question	Greenhouse-Geisser	2544.112	4	987.936	87.531	< .001**
Question ✻ Group	Greenhouse-Geisser	67.539	4	26.227	2.324	0.088
Residuals	Greenhouse-Geisser	1337.007	184	11.287		
Instance	None	41.946	1	41.946	9.707	0.003*
Instance ✻ Group	None	4.875	1	4.875	1.128	0.294
Residuals	None	198.766	46	4.321		
Question ✻ Instance	Greenhouse-Geisser	16.208	4	6.551	0.898	0.429
Question ✻ Instance ✻ Group	Greenhouse-Geisser	30.926	4	12.500	1.713	0.177
Group	None	12.535	1	12.535	1.536	0.222
Residuals	None	830.328	184	4.513		
	Greenhouse-Geisser	830.328	184	7.296		

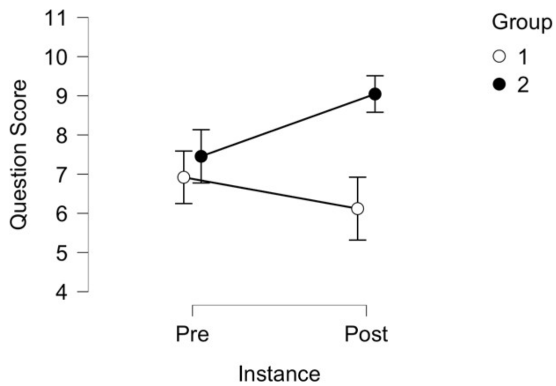
Note. Sphericity corrections not available for factors with 2 levels.

Note. Type III Sum of Squares

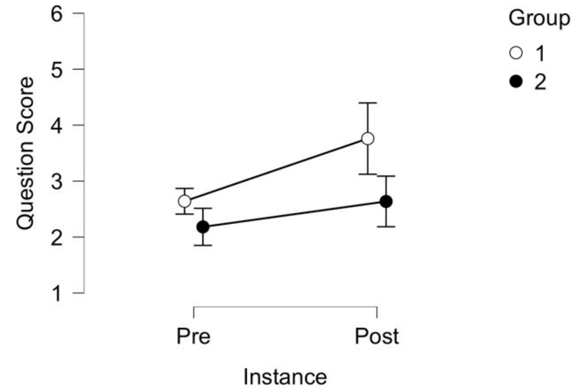
Table 2.4 Contrasts of: Group ✻ Question ✻ Instance

Comparison	Estimate	SE	df	t	p
1	2.663	0.705	46	3.775	< .001**
2	-1.108	0.705	46	-1.571	0.117
3	0.685	0.705	46	0.971	0.332
4	-0.139	0.705	46	-0.197	0.844
5	0.525	0.705	46	0.745	0.457

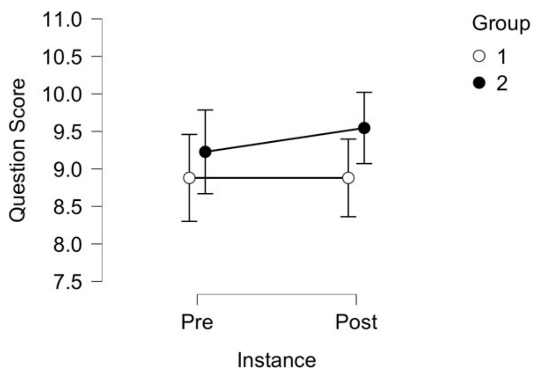
Plot a. Question 1



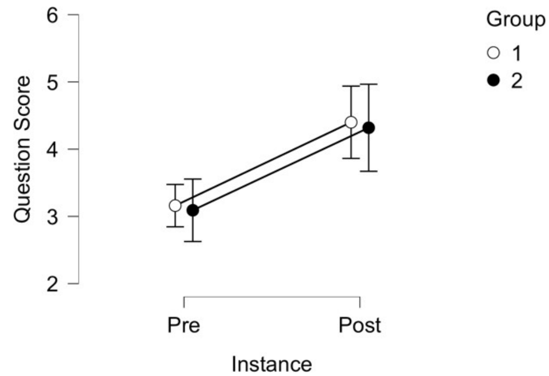
Plot b. Question 2



Plot c. Question 3



Plot c. Question 4



Plot d. Average Score

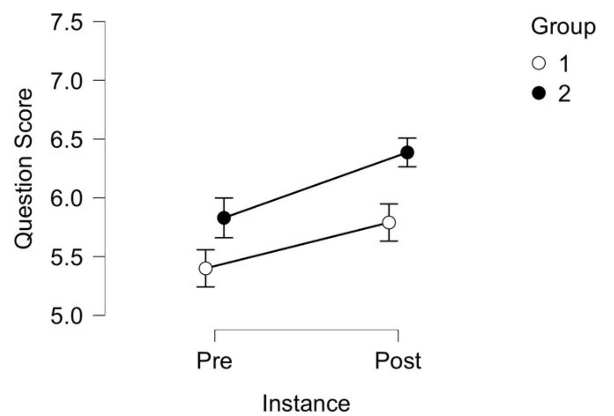


Figure 2.4 Between Group comparisons of pre- and post- laboratory EMG Signal Processing questionnaire performance

3.1 Discussion & Implications

The present study highlights important findings and considerations for the implementation of interactive learning laboratory modules in undergraduate Biomechanics. Within the MM lab sessions, it was found that both groups, with similar baseline performances, experienced a significant increase in performance between pre- and post-assessments, suggesting that all students experienced positive learning effects regardless of the mode of instruction. Further, when comparing post- laboratory scores for MM, the interactive learning group scored significantly higher than the control group on the most difficult question, suggesting that the interactive educational tool supported greater comprehension of complex systems. These findings support recent work, demonstrating that interactive teaching methods increase student performance for the previously lowest scored items, where complete comprehension is most challenging (Finn, FitzPatrick, & Yan, 2017). For the SP intervention, similar to what was seen in the MM module, both groups experienced a significant increase in performance between lab assessments. However, contrary to the MM module, when assessing between group post-laboratory performance, a significant difference was observed in the simplest question item where the intervention group scored lower than the control group (see Figure 2.2a). Taken together, these results suggest that interactive tools help with comprehension of complex systems with difficult assessments but may conflict with learning or maintenance of comprehension on simple concepts. This raises the question, are the benefits of interactive learning modules dependent on topic complexity and subject of study within undergraduate biomechanics? Greater exploration needs to be done to determine the nature of this interaction with a focus on controlling question and concept difficulty.

Across both laboratory topics, a significant interaction between student performance and time was observed. All students displayed improvement in their performance on post-laboratory assessments, indicating student learning. The pre-and post- laboratory assessments contained the same questions; the scoring of these items was structured to highlight the level of student understanding. In MM modules, student learning was not negatively impacted by the interactive learning intervention. In the MM laboratory, there was a significant question by assessment instance interaction where each question had a higher post score for each group. In the SP laboratory, a main effect for assessment instance was observed but with no interaction, making it difficult to assess individual student learning for each question. Further, the planned comparison for SP post-laboratory assessments revealed that the control group performed better than the intervention group for Question 1. Previous research has shown that regardless of the methods of instruction student learning is inevitable, assuming student engagement, with even basic lecture-based presentations (Fuller et al., 2018; Roselli & Brophy, 2006). This result in our present research is important to highlight as it may have implications regarding how instructional pedagogy effectiveness, specifically interactive learning episodes, may be related to content. There is evidence of differences between concepts as well as the questions evaluated that may provide more insight into the use on interactive tools.

Our next major findings suggest that interactive tools may help with comprehension of complex systems with difficult assessments, as seen within the MM module, but may conflict with learning or maintenance of comprehension on simple concepts and test items as observed in the SP module (Finn et al., 2017; Hsieh & Knudson, 2018). (Finn et al., 2017; Hsieh & Knudson, 2018). Recent research conducted by Finn et al (20l7) found that students who participated in interactive modules achieved higher scores on questions that previous students found the most challenging (Finn et al., 2017). This is consistent to our present finding where the interactive intervention group scored higher than the control group in the most difficult question in the MM module. Contrary to this finding, during the SP module, the intervention group performance was lower than the control group on the simplest question. This is may be consistent with studies of inquiry-based learning where overly dynamic and unguided inquiry can result in no improvement or decrease in student outcomes without appropriate supports in place (Lazonder & Harmsen, 2016) . This could be related to the nature of the content within the modules. In the MM module the concept of Work-loops is central to learning using the interactive module and dynamically combines reductionist properties in series and in parallel. Within the SP Module, complex concepts are connected only in series to properly process signals. However, the results of our study could be related to the depth of content knowledge assessed in our experiment and framing within laboratory modules for each topic.

The modules of instruction in the present study included concepts from different domains of biomechanics. These different concepts may indeed require unique approaches to education and may require specific interactive learning tools to optimize learning outcomes. It is possible that the teaching pedagogy and learning tools implemented may need to be tailored to specific content in order to optimize student learning outcomes. Many of the principles covered in the signal processing laboratory sessions are basic fundamental principles, focusing on outcomes rather than the theory behind the methods. The depth of understanding expected is outlined in the pre-post questionnaire for EMG signal processing (Appendix item I). The types of questions asked in this topic were geared towards recall of basic concepts, rather than in-depth understanding of biomechanical theory. On the other hand, Work Loop analysis combines the reductionist properties involved in voluntary muscular contractions, connecting force-velocity, force-time and force-length relationships. This type of analysis can be applied to any form of cyclical contraction and it was linked to strength training principles within the laboratory lecture. In order to successfully respond to the most difficult question items, students not only required understanding of Work Loops, but also in-depth comprehension of all reductionist properties and their reciprocal relationships. The findings in the current study support concepts presented in previous work, that the most effective means of instructing complex systems, such as work loops, is likely through interactive models and not explicit instruction of reductionist properties (Van Regenmortel, 2004). Furthermore, EMG SP analysis is covered in other courses within the faculty and it is likely students had previous or concurrent exposure to similar content, while Work Loop analysis would have been an entirely novel topic for students.

The results of this study suggest that interactive learning episodes may assist learning of more complex or abstract applications of theory, while potentially hindering learning of simpler topics. The long-term term learning effects of interactive modules have not previously been demonstrated and are an area still needing to be explored.

For both EMG signal processing and Work Loop laboratory topics, significant performance differences were observed between control and intervention groups for one post-laboratory questionnaire item. During Work Loop sessions, it was found that the intervention group scored higher compared to the control group on questionnaire item 2, the most difficult question provided in the questionnaire. Across both groups, this was the question with the lowest score in the pre-laboratory baseline testing (see figure 2.1). Recent work has found that interventions similar to those used in the present study significantly increased quiz scores when compared to the historical average (Finn et al., 2017). Specifically, it was observed that students performed higher on the quiz with the lowest achievement in the years prior (Finn et al., 2017). Further, there is evidence that the lowest performing students benefit the most from interactive learning episodes (Hsieh & Knudson, 2018). The present study supports these findings, with a strong suggestion that these learning tools and instructional pedagogy assists with understanding complex systems (such as Work Loop MM analysis) most readily seen in acute learning environments. The long-term effects of interactive exploratory based learning episodes as framed in this study are yet to be explored. The effects of exploratory based learning tools and learning environments on long term learning requires further investigation.

3.1.2 Limitations

The present study had several limitations which influenced the strength of the results. Firstly, pre- and post-laboratory assessments did not contribute to course grade which may have influenced student effort when answering question items. Consistency of instruction across lab sections is another limiting factor. Two different laboratory instructors taught the four lab sections, and although materials were consistent, it is possible that instructor descriptions for each topic differed slightly. Furthermore, the ability of assessment questions to accurately evaluate student knowledge limits the efficacy of student performance metrics as reported by pre, post-laboratory as well as midterm measurement instances. For SP assessments, it is important to note that aspects of EMG signal processing are taught in other upper-level courses at our university, so it is possible that some students were exposed to additional opportunities to engage with this content. This is of particular note as students may have had interactive lab modules in those courses that could have limited potential improvement in their pre-post laboratory assessments.

4.1 Conclusion

The present study partially supports the hypothesis that exploratory based learning episodes may positively influence student outcomes. A significant improvement in post-laboratory student scores for work-loop laboratory sessions was found for both control and intervention groups, indicating that learning took place for all students enrolled. The intervention group had a significantly higher post-laboratory score for questionnaire item 2, indicating a higher performance for those in the intervention cohort. Additionally, this item had the lowest baseline score for both groups, demonstrating that exploratory learning may have the largest effect on more difficult course questions or materials. However, for EMG signal processing analysis the control group scored significantly higher than the intervention group on one post-laboratory assessment item, and improvement between pre- and post-was only found in one questionnaire item. These results strongly suggest the merits of exploratory based learning methods and tools to support learning of complex systems. In the future, instructors should employ interactive learning modules in their courses, particularly for complex topics, as there was little to no negative effect and the possibility to significantly increase acute student performance outcomes was observed. Further research is needed to assess the long-term efficacy of exploratory learning applications.

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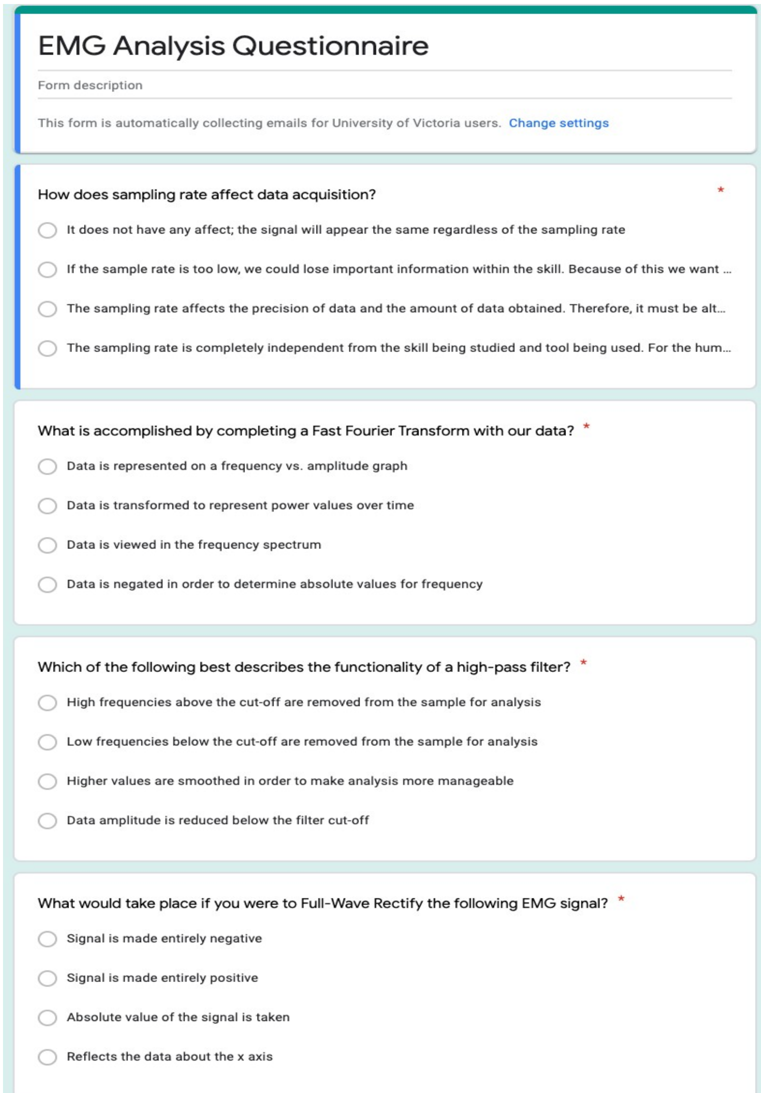
Appendix

Appendix I

EMG Signal Processing Questionnaire



EMG Analysis Questionnaire

Form description

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How does sampling rate affect data acquisition? *

- It does not have any affect; the signal will appear the same regardless of the sampling rate
- If the sample rate is too low, we could lose important information within the skill. Because of this we want ...
- The sampling rate affects the precision of data and the amount of data obtained. Therefore, it must be alt...
- The sampling rate is completely independent from the skill being studied and tool being used. For the hum...

What is accomplished by completing a Fast Fourier Transform with our data? *

- Data is represented on a frequency vs. amplitude graph
- Data is transformed to represent power values over time
- Data is viewed in the frequency spectrum
- Data is negated in order to determine absolute values for frequency

Which of the following best describes the functionality of a high-pass filter? *

- High frequencies above the cut-off are removed from the sample for analysis
- Low frequencies below the cut-off are removed from the sample for analysis
- Higher values are smoothed in order to make analysis more manageable
- Data amplitude is reduced below the filter cut-off

What would take place if you were to Full-Wave Rectify the following EMG signal? *

- Signal is made entirely negative
- Signal is made entirely positive
- Absolute value of the signal is taken
- Reflects the data about the x axis

Appendix II

Work Loop Analysis Questionnaire

Work Loops Lab Questionnaire

B01

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How is peak power altered when undergoing a "Heavy" strength training protocol. *

- Overall power production is increased vs other training methods
- The optimal zone for power production is shifted to a lower cadence
- Overall power production is decreased
- The optimal zone for power production is shifted to a higher cadence

In reference to excursion length, when does peak positive velocity take place. *

- At rest length during the cycle
- At maximum excursion
- At minimum excursion
- At rest length during shortening

If we were to double the cycle frequency from 2- 4 Hz which of the following would experience the largest change (assuming onset and offset are adjusted for optimization)? *

- Isometric force production
- Power production
- Positive and negative work values
- Activation and deactivation time

Which of the following best describes the effects of fatigue on cycle performance *

- Power production decreases
- Force increases while deactivation time decreases
- Activation time decreases along with peak power production
- Deactivation time increases and force production decreases