ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022 ASEE

Paper ID #36592

Mastery Learning in Undergraduate Engineering Courses: A Systematic Review

Carlos Luis Perez

Dina Verdin

Dina Verdín, PhD is an Assistant Professor of Engineering Education Systems and Design in the Ira A. Fulton Schools of Engineering at Arizona State University. She graduated from San José State University with a BS in Industrial Systems Engineering and from Purdue University with an MS in Industrial Engineering and PhD in Engineering Education. Her research broadly focuses on broadening participation in engineering by focusing on the issues of access and persistence. She uses asset-based approaches to understand minoritized students' lived experiences (i.e., including first-generation college students and Latinx). Specifically, she seeks to understand how first-generation college students and Latinx students author their identities as engineers and negotiate their multiple identities in the current culture of engineering.

Mastery Learning in Undergraduate Engineering Courses: A Systematic Literature Review

Abstract

This theory paper focuses on understanding how mastery learning has been implemented in undergraduate engineering courses through a systematic literature review. Academic environments that encourage learning, mastery, and continuous improvement rather than inherent ability can promote performance and persistence. Scholarship has argued that students could achieve mastery of the course material when the time available to master concepts and the quality of instruction was made appropriate to each learner. Increasing time to demonstrate mastery involves a course structure that allows for repeated attempts on learning assessments (i.e., homework, quizzes, projects, exams). Students are not penalized for failed attempts but are rewarded for achieving eventual mastery. The mastery learning approach recognizes that mastery is not always achieved on first attempts and learning from mistakes and persisting is fundamental to how we learn. This singular concept has potentially the greatest impact on students' mindset in terms of their belief they can be successful in learning the course material. A significant amount of attention has been given to mastery learning courses in secondary education and mastery learning has shown an exceptionally positive effect on student achievement. However, implementing mastery learning in an undergraduate course can be a cumbersome process as it requires instructors to significantly restructure their assignments and exams, evaluation process, and grading practices. In light of these challenges, it is unclear the extent to which mastery learning has been implemented in undergraduate engineering courses or if similar positive effects can be found.

Therefore, we conducted a systematic literature review to elucidate, how in the U.S., (1) has mastery learning been implemented in undergraduate engineering courses from 1990 to 2021 and (2) the student outcomes that have been reported for these implementations. Using the systematic process outlined by Borrego et al. (2014), we surveyed seven databases and a total of 584 articles consisting of engineering and non-engineering courses were identified. We focused our review on studies that were centered on applying the mastery learning pedagogical method in undergraduate engineering courses. All peer-reviewed and practitioner articles and conference proceedings that were within our scope were included in the synthetization phase of the review.

Twelve studies focused on applying mastery learning to undergraduate engineering courses. The mastery learning method was mainly applied on midterm exams, few studies used the method on homework assignments, and no study applied the method to the final exam. Students reported an increase in learning as a result of applying mastery learning. Several studies reported that students' grades in a traditional final exam were not affected by mastery learning. Students' self-reported evaluation of the course suggests that students prefer the mastery learning approach over traditional methods. Although a clear consensus on the effect of the mastery learning approach could not be achieved as each article applied different survey instruments to capture students' perspectives. Responses to open-ended questions have mixed results. Two studies report more positive student comments on opened-ended questions, while one study reports receiving more negative comments regarding the implementation of the mastery learning method.

Introduction

This theory paper focuses on understanding how mastery learning has been implemented in undergraduate engineering courses through a systematic literature review. Academic environments that promote learning, mastery, and continuous improvement rather than inherent ability subsequently lead to increased student performance and persistence (Feldman, 2019; Malcom & Feder, 2016). Scholarship has argued that students could achieve mastery of the course material when the time available to master concepts and the quality of instruction was made appropriate to each learner (Bloom, 1971). Increasing time to demonstrate mastery involves a course structure that allows for repeated attempts on learning assessments (i.e., homework, quizzes, projects, exams). Students are not penalized for failed attempts but are rewarded for achieving eventual mastery. The mastery learning (ML) approach recognizes that mastery is not always achieved on first attempts and learning from mistakes and persisting is fundamental to how we learn. This singular concept has potentially the greatest impact on students' mindset in terms of their belief they can be successful in learning the course material.

A significant amount of attention has been given to mastery learning courses in secondary education and mastery learning has shown an exceptionally positive effect on student achievement (Kulik et al., 1990). Several meta-analyses of mastery learning applied in elementary and secondary education have found a strong positive effects in raising students' final grades (Guskey & Gates, 1985; Kulik et al., 1990; Kulik et al., 1979). In the engineering undergraduate setting, mastery learning has been shown to produce a variety of positive results including improvements in content mastery (Averill et al., 2018; Hjelmstad & Baisley, 2020; Ranalli & Moore, 2015). Averill et al. (2018) described a comparison of mastery learning sections of a mechanics of materials course to traditional sections of the same course. They concluded that mastery learning sections scored three letter grades higher in a partial credit final exam when compared with traditional sections. Ranalli and Moore (2015) implemented mastery learning in engineering dynamics and thermodynamics courses. Students thought that mastery learning was fairer than the traditional partial credit system because disputes over points taken off for specific errors had less importance. Homework grades were found to be higher in mastery learning sections compared to the traditional course sections and students' response to mastery learning was largely positive (Ranalli & Moore, 2015). Hjelmstad and Baisley (2020) conducted a study that used mastery learning in a sophomore level mechanics course. In this mechanics course mastery learning allowed students to focus on learning outcomes rather than on the grade they need to pass the class and students generally embraced the values of mastery learning. Overall, these findings present preliminary evidence of the effects that the mastery learning approach has on undergraduate engineering students. This preliminary evidence shows that there are a number of studies that deal with mastery learning applied to engineering undergraduate courses.

However, implementing mastery learning in an undergraduate course can be a cumbersome process as it requires instructors to significantly restructure their assignments, exams, evaluation processes, and grading practices (Green, 2000; Harsy, 2020; Kelley, 1999). In light of these challenges, it is unclear the extent to which mastery learning has been implemented in undergraduate engineering courses. There is a need to understand the type of ML implementations that have been reported and the student outcomes from ML implementations that have been described. This paper fulfills this need by conducting a systematic literature review on mastery learning to answer the following research questions:

(1) how has mastery learning been implemented in undergraduate engineering courses from 1990 to 2021?
(2) what student outcomes have been reported for mastery learning implementations in undergraduate engineering courses?

Understanding Mastery Learning

From the earliest times, initiated individuals have undergone a process of learning from a master and have had to fulfil requirements to earn the title of 'master' (Leonard et al., 2008). The most modern and complete model for mastery learning is accredited to Bloom (1971) while John Carroll (1963) is recognized as providing the theoretical foundation. A mastery learning class implementation can be characterized as possessing three key features that distinguish it from a traditional class. These three key features are (1) the specification of clearly defined learning units tied to ML assessments, (2) the application of ML assessments and (3) the delivery of feedback on each ML assessment. These features serve as a definition for mastery learning and they have been derived from Bloom's theoretical description of ML (Bloom, 1971) and were applied in the implementation of ML in a number of undergraduate engineering courses (e.g., Armacost & Pet-Armacost, 2003; Bekki et al., 2012; Green, 2000; Halperin, 2020; Sangelkar et al., 2014). The first feature of ML is that the material to be studied is clearly divided in units of achievement, herein referred to as learning units that are tied to ML assessments. In typical ML implementations, students are tested and tracked as they move through the learning units. The second key feature of mastery learning is the type of assessment that a ML implementation provides to the student. These assessments can be homework, quizzes, exams, or parts of a projects. In these assessments, a benchmark for 'mastery' is defined and this is typically 70%, 80% or 90% of the maximum score the student can receive. If the student does not achieve 'mastery', they are allowed to repeat the assessment, i.e., do a 'retake', without receiving a penalty for failed attempts. The number of times the student is allowed to repeat the assessment depends on the particular implementation of ML, but in principle, and ideally, the student should be allowed to performed retakes as many times as it's necessary for the student to achieve 'mastery'. The ML process, equivalent to a ML assessment, is defined as the process from the moment the assignment is given to the students to the moment the retake process for that assignment is complete. The third and final key feature of a ML implementation is that the student is given feedback on each ML assessment so that they may improve their performance on the retakes. In practice, the level of feedback that a student receives can range from simple feedback indicating the correctness or incorrectness of an answer to deeper guiding feedback that helps the student improve a section of a learning unit.

Methods

The purpose of this investigation is to uncover how ML has been implemented in undergraduate engineering courses and the student outcomes that have been reported. Before beginning a formal systematic literature review, a high-level literature review was conducted to ascertain the quantity and the type of articles found on the topic of mastery learning implementations in undergraduate engineering courses (Borrego et al., 2014, 2015). The preliminary review yielded several sources that fit our scope, thus indicating there would be sufficient sources to warrant employing the systematic review. This paper used the methodology proposed by Borrego et al. (2014) for conducting systematic literature reviews: (1) deciding to do a systematic review; (2) identifying scope and research questions; (3) defining inclusion and exclusion criteria; (4) finding and cataloging sources; (5) critique and appraisal and (6) synthesis. Borrego et al. (2014) introduced the method for conducting systematic literature reviews in engineering education and adapted sources on systematic literature reviews originally meant for other fields.

Framing the research questions

The EPPI-Centre (2010), a center based in the University College of London focused on research synthesis and research use, advises systematic literature reviewers to conceptualize research questions appropriately as they will guide the rest of the systematic literature review process. In this article, we crafted the research questions to guide the investigation towards discovering the types of ways mastery learning has been applied in undergraduate engineering courses and towards understanding the student outcomes that had been measured in those courses. The research questions were framed using the PICO framework (population, intervention, comparison, outcomes; Borrego et al., 2014). The PICO framework helps ensure that the relevant parameters are used in the design of research questions and in the later stages of the process. In our use of the framework, the Population to be investigated were students in undergraduate engineering courses. The Interventions to be studied were courses where mastery learning was applied to homework, quizzes, exams, or projects. The Comparison group were courses of the same topic as the ML courses that employed a traditional grading system as a control group. However, studies without a control group were also included. The Outcomes to be studied were the positive, negative or neutral outcomes reported.

Search Strings

The titles and abstracts of an initial sample of papers that used a mastery-based approach were surveyed to understand the nomenclature. We encountered 'mastery-based testing,' 'mastery based assessment,' 'mastery grading,' and 'mastery learning.' It was determined that the root search strings to be used be 'mastery based' and 'mastery learning.' The search covered dates from January 1990 to September 2021.

We chose to use 7 databases to search for sources relevant to our systematic review, specifically, three subject databases (i.e., Education Full Text (EBSCO), Engineering Village, IEEE Xplore), two journal databases (i.e., Science Direct, ASEE PEER database), and two general databases (i.e., JSTOR, Scopus). The Google Scholar database was not included because it doesn't allow the investigator to read the sources' abstracts.

In most of the search strings, we used the root search strings 'mastery based' and 'mastery learning' and attached the keywords 'STEM,' 'science,' 'engineering,' and 'math.' This was done in order to focus our search to mastery learning approaches used for engineering courses and to address our research questions. The words 'STEM,' 'science,' and 'math' were also included so that courses that were labeled 'STEM,' 'science,' and 'math' but that focused on engineering were not accidentally omitted. Table 1 shows the search strings used in our search for sources.

Searching for the root term ‘mastery based’ in JSTORE and Science Direct databases yielded less than 25 sources each. After reviewing the titles and abstracts, we found that a number of sources were relevant to the aim of the systematic literature review and to the research questions. These smaller number of articles would be screened out of the review if the additional strings ‘STEM,’ ‘engineering,’ ‘science’ and ‘math’ were added to the root term ‘mastery based.’ To preserve the search results in JSTORE and Science Direct, we moved these articles to the next phase of our screening process – the title and abstract review. We adopted the following rule: for each database, if searching for the root terms ‘mastery based’ or ‘mastery learning’ or ‘mastery grading’ yielded less than or equal to 25 sources each, all sources were included in the title and abstract review; if it yielded more than 25 sources, the additional search words ‘STEM,’ ‘engineering,’ ‘science’ and ‘math’ were added to the search and those resulting articles were reviewed in title and abstract. The search for ‘mastery grading’ yielded less than 22 sources in each database, therefore all those sources were included in the title and abstract screening. The databases ASEE PEER and IEEE Xplore are engineering databases, therefore only the root phrases ‘mastery based’, ‘mastery grading’ and ‘mastery learning’ were used. The search terms ‘STEM,’ ‘engineering,’ ‘science’ and ‘math’ were not applied in ASEE PEER and IEEE Xplore since these datasets publish engineering/STEM focused articles.

Table 1. Search strings employed	
‘Mastery based’*	‘Mastery based’ AND Math
‘Mastery learning’	‘Mastery learning’ AND STEM
‘Mastery grading’	‘Mastery learning’ AND Science
‘Mastery based’ AND STEM	‘Mastery learning’ AND Engineering
‘Mastery based’ AND Science	‘Mastery learning’ AND Math
‘Mastery based’ AND Engineering	

* For all databases, searching for ‘mastery-based’ and ‘mastery based’ is equivalent.

Inclusion and exclusion criteria

The total number of articles that met the inclusion criteria in the title or abstract among all databases was n = 584. The first iteration of the screening process examined the title and abstract of each paper. Articles were removed from further review if they violated one of the 15 exclusion criteria. The exclusion criterions can be found in Figure 1. For example, articles were excluded if the study did not discuss the implementation and student learning outcomes of the ML course. If alternative methods were incorporated in the course (i.e., flipped classroom and project-based learning) the article was removed from further analysis. If the course was a Massive Open Online Course (MOOC), if it had online lecture components or if it was a mobile game learning system it was eliminated from the screening. If data for the study was collected for only part of the semester the study was eliminated from the list. If ML was applied to only a portion of a course, for example a laboratory, the study was removed from the list. If the study was performed on non-human subjects, like mice, the study was removed. Other criterions used to eliminate articles included: duplicate, population of study was outside the scope of investigation, article was a literature review, the focus of the study was a non-STEM course, etc. Journal manuscripts, practitioner articles, and complete conference papers were considered, and work-in-progress papers were excluded.

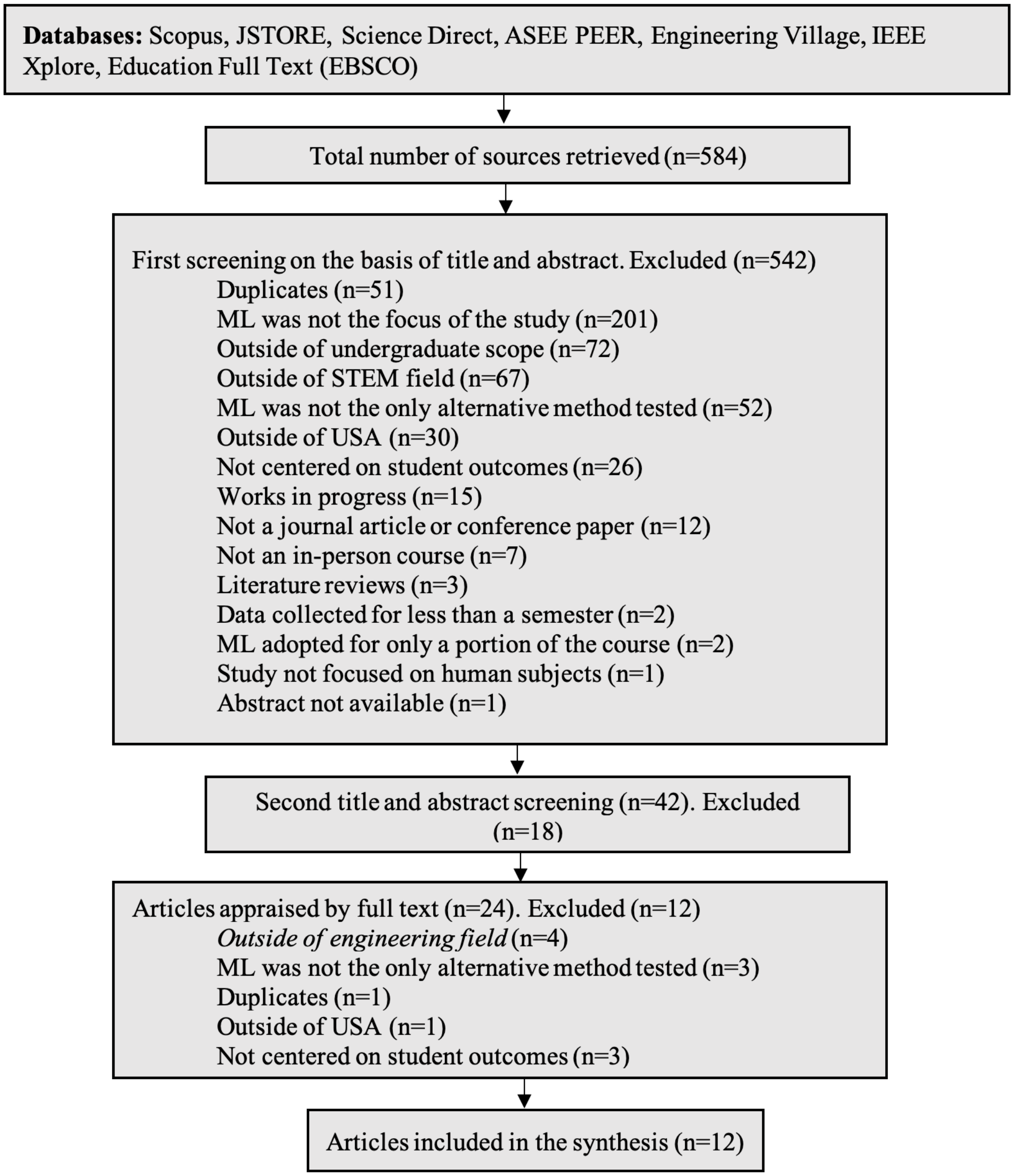

Figure 1. Flow chart of article screening procedure.

Cataloging sources

Figure 1 shows the article screening process followed. The process begun when sources were obtained through the 7 databases and ended when the 12 final articles to be synthetized were left. In the first title and abstract screening, 546 sources were screened out and 38 were left as sources that would go on to the next step in the screening process. The next step in the screening process was a secondary title and abstract screening. The inclusion and exclusion criteria followed was the same as for the first title and abstract screening step. A second title and abstract screening process was undertaken as a quality check to verify that sources that passed through the first screening process satisfy the inclusion/exclusion criteria. The secondary screening process excluded 18 sources. Twenty-four sources were left to undergo the full-text appraisal. In the full-text appraisal, the article was read in its entirety to ensure it met the inclusion/exclusion criteria. The exclusion criteria were similar to the criteria used in the title and abstract screening process. For this paper, one additional exclusion criterion was added to the exclusion criteria of the full-text appraisal: Outside of the engineering field. Four papers were excluded because they were unrelated to engineering classes and were related to mathematics and physics classes. The final number of papers that passed through the full-text appraisal was 12.

Findings

Implementation of mastery learning in engineering courses

After systematically examining articles focused on mastery learning, based on the inclusion and exclusion criteria, we found nine studies that applied a mastery learning approach in engineering courses (i.e., Armacost & Pet-Armacost, 2003; Bekki et al., 2012; Craugh, 2017; DeGoede, 2020; Kelley, 1999; Moore, 2016; Mukherjee & Cox, 1998; Ritz et al., 2020; Sangelkar et al., 2014). Three separate studies applied ML using web-based tools (i.e., Green, 2000; Leonard et al., 2008; Paull et al., 1999). Web-based implementations have the potential to eliminate difficulties when implementing the ML approach by automating the generation of retake tests through random number generation, the delivery of performance feedback and the grading of retakes. Table 2 provides an overview of the course evaluation categories where instructors applied a mastery learning approach.

Armacost and Pet-Armacost (2003) implemented ML in an Operations Research course in the Fall 2000 and Fall 2001 semesters. Specifically, ML was applied to two midterm exams and the content of each successive retake exam was made more difficult. The retake attempts were scheduled to be within one week or less than the previous retake. Bekki et al. (2012) implemented a ML system in three undergraduate courses: Engineering Statistics, LabVIEW programming, and Environmental Engineering. They divided the workload given to students through two instruments: evidence assignments and competency assignments. Evidence assignments were homework or in-class activities that prepared students to complete competency assignments. These evidence assignments were intended to provide practice on competencies and were not counted towards their final course grade. ML competencies, in the form of quizzes or exams, were based on instructional units that aligned with learning objectives or departmental outcomes. In Craugh (2017) ML was implemented in three sections of a Statics course across five midterm exams. Students were able to retake problems that hadn't reached a requisite level of competency. Subsequent retake problems were of lower difficulty and were worth fewer points. The final exam in each section was comprehensive and assessed using the traditional partial credit method. DeGoede (2020) implemented ML on a Vibrations Analysis course which included four ML exams each with a 'Proficiency' portion and a 'Mastery' portion. The 'Proficiency' portion of the exam assessed the core competency of the class unit and was designed with the intention to ensure that

Table 2. Evaluation metric where the mastery learning approach was applied						
Source	**Engineering Courses**	**Evaluation Metric**				
		Mid-terms	**Final Exam**	**Quiz**	**Home-work**	**Project**
Armacost and Pet-Armacost, 2003	Operations Research	**X**				
Bekki et al., 2012	Engineering Statistics, LabVIEW Programming, and Environmental Engineering	**X**		**X**		
Craugh, 2017	Statics	**X**				
DeGoede, 2020	Vibration Analysis	**X**				
Kelley, 1999	Engineering Graphics, Drafting, and Computer Aided Design			**X**	**X**	
Moore, 2016	Strength of Materials and Thermodynamics				**X**	
Mukherjee and Cox, 1998	Systems Analysis and Design Capstone Project					**X**
Ritz et al., 2020	Statics and Mechanics of Materials	**X**				
Sangelkar et al., 2014	Statics	**X**				
Web-based Implementation						
Green, 2000	Signals and Systems				**X**	
Paull et al., 1999	Electrical Engineering Technology Circuits				**X**	
Leonard et al., 2008	Circuit Analysis I-II	**X**				

all students had the prerequisite knowledge to navigate subsequent class units. The 'Mastery' portion of the exam required students to solve problems with uncommon conditions, interpret the results and predict future outcomes. The 'Proficiency' portion of the exam could be retaken on future exam dates and the 'Mastery' portion of the exam could be retaken on the final exam. Kelley (1999) implemented ML in Engineering Graphics, Drafting, and Computer Aided Design courses where they focused on the student completion of course objectives. Course objectives were evaluated through in-class quizzes or in-class assignments and, in principle, students could be evaluated an infinite number of times. There were no set number of times that a student maybe evaluated on an objective. In Moore's (2016) implementation, ML was applied to a Strength of Materials course and a Thermodynamics course. ML homework was assigned every week and the students were allowed to resubmit problems as many times as needed (students rarely needed more than two resubmissions). Mukherjee and Cox (1998) implemented ML in a systems analysis and design project course across 5 years. In the implementations, ML was applied to the deliverables of a phase of the project. After the first submission of a word document, the instructor would grade the deliverables and return the document with feedback. Students would then have the opportunity to return the document with the corrections added. This process would continue until the students achieved a perfect score for that phase. Ritz et al. (2020) implemented ML in a Statics and

Mechanics of Materials course where they had two ML midterms. Students were given two additional attempts to retake parts of the ML exam in order to improve their scores. Sangelkar et al. (2014) implemented a ML strategy in six sections of a Statics course with six ML midterm exams. The final exam for all sections was delivered and graded using traditional grading practices. Students could retake the midterm exams twice, however the points awarded were reduced after each successive retake.

There were three studies that explored ML through online implementations. Green (2000) implemented ML homework using the MATLAB Webserver in a Signals and Systems course. Homework assignments were individualized to students, problems were graded automatically, and instantaneous feedback was given after each problem set. Students were able to resubmit the homework an infinite number of times before the due date; however, the particular numbers in each homework question changed for every resubmission (Green, 2000). Paull et al. (1999) also implemented ML homework online in an Electrical Engineering Technology Circuits course. Homework problems were created, administered, and graded online. Students were able to practice solving problems related to the homework an infinite number of times; following the practice problems, they were expected to demonstrate mastery on a recorded homework set. The course had two sections; one section had to complete the homework through the Web, and the other section had to complete the homework manually, serving as a control group. Leonard et al. (2008) implemented a ML test method in a one-year sequence of courses Circuits I and II. The ML tests were generated, administered and graded online. The tests consisted of ten questions and a perfect score, analogous to achieving mastery, was required to pass the test. If the student failed a test, they had to retake a newly generated one and the test contained different questions.

Evaluating Student Learning Gains

From the 9 non-web implementation studies that were examined only 2 collected information regarding learning gains evaluated through close-ended survey questions (i.e., Armacost and Pet-Armacost, 2003; Moore, 2016). Moore (2016) and Ritz et al. (2020) collected information about students' learning gains through a comparison of the final exam grade with a control group, while Craugh (2017) compared the final exam grade between the ML section and the control group for students with low previous GPA. Of the online ML implementations, two studies reported on learning gains regarding grades and course passing rates (i.e., Paull et al., 1999; Leonard et al., 2008). In the following subsections, we report on student outcomes related to learning gains. Learning gains are broadly defined as gains measured through students' responses to survey questions regarding level of learning, gains measured by comparing final exam grades with a control group, and gains measured by comparing ML course grades or final exam grades with grades from previous courses that used traditional grading practices.

Evidence of learning gains

Two studies administered survey questions to evaluate students' perceptions of their learning gains (i.e., Armacost and Pet-Armacost, 2003; Moore, 2016), 2 separate studies (i.e., Moore, 2016; Ritz et al., 2020) compared final exam grades from a ML implementation with a control group, and one study (Craugh, 2017) compared final exam grades between mastery and traditional classes taught in the same semester for students with low previous semester GPAs. Craugh (2017) used a metric called Quality Point Rating (QPR) that is similar to GPA. Craugh (2017) reports that students that began the mastery courses with lower QPR had a better score on the final exam than students in the traditional classes that entered with similar QPR scores. The students with stronger QPR's did not benefit as much from the mastery learning approach. Interestingly, there were no studies that compared ML course grades with grades from traditional implementations of the same course taught in previous semesters.

Ritz et al. (2020) conducted an investigation that compared two Statics and Mechanics and Materials courses. The course taught using the traditional grading method served as the control group to compare against the course that was taught using a mastery learning system. The effectiveness of the mastery learning course compared to the traditional course was evaluated by comparing the grades on the final exam, which applied a partial credit grading technique. Ritz et al. (2020) concluded that the mastery learning implementation did not lead to statistically significant learning gains. However, the ML course did show a higher final exam grade than the control group. In an implementation that assigned ML only on homework assignments, but not on midterm exams, Moore (2016) compared the grade on a final exam from a traditional class to a ML class and found no significant difference between the two classes. However, in the same study, students reported that they learn better through the ML system through feedback collected using survey questionnaires. Evidence of learning gains, through students' perspectives captured via survey questionnaires, is also echoed in Armacost and Pet-Armacost (2003) study. While final exam grades did not provide a concrete measure of learning gains when applying a mastery learning approach to a course, students' self-reported assessment of their own learning provided preliminary evidence of the method's effectiveness.

Evidence of learning gains through online Mastery Learning implementations

Learning gains for the online ML implementations were analyzed in two studies (i.e., Paull et al., 1999; Leonard et al., 2008). Comparisons between the performance of mastery groups and non-mastery groups were drawn for grades and course passing rates. Leonard et al. (2008) found that 66% of students that underwent the traditional approach (before the implementation of the mastery approach) finished the one-year sequence; whereas 80% of students that underwent the mastery approach passed the sequence. The study further clarifies that most of this effect can be attributed to the performance of minority students who, before mastery, had a completion rate of 55% and after mastery a completion rate of 90%. In contrast to these results, Paull et al. (1999) found that the overall grades for the computerized and manual homework groups were almost exactly the same.

Student Evaluations of Mastery Learning

In this section, we describe student outcomes related to student evaluations of mastery learning reported through close-ended question responses (itemized surveys) and open-ended question responses. Of the 9 non-web ML implementations, 2 studies administered a set of close-ended survey questionnaires to understand students' experience with the mastery learning approach (i.e., Armacost and Pet-Armacost, 2003; Moore, 2016), 2 collected responses to open-ended questions centered around what the students liked and disliked about the pedagogical method (i.e., Kelley, 1999; Craugh, 2017) and 3 collected both closed-ended question responses and open-ended question responses about the ML approach (i.e., Bekki et al., 2012; Ritz et al., 2020; Sangelkar et al., 2014). Of the online ML implementations 1 study administered close-ended and open-ended survey questionnaires to students (i.e., Paull et al., 1999), and 2 of them discuss students' responses to only open-ended questions (i.e., Green, 2000; Leonard et al., 2008).

Students' evaluation of Mastery Learning using close-ended survey questions

Most authors did not administer the same survey instruments across studies. However, two studies administered similar survey questions that asked students if they perceived they learned better through an ML system and whether they preferred an ML approach over a traditional grading system. Moore's (2016) and Armacost and Pet-Armacost's (2003) survey results showed that most students agreed *they learned better* with the mastery learning system. Armacost and Pet-Armacost (2003) reported that "the results overwhelmingly supported the use of the system;" 75% of students in Fall 2000 and 67% of students in Fall 2001 strongly agreed that they learned better through an ML approach (p. 24). In a follow-up question, Armacost and Pet-Armacost (2003) asked students if the retests made it such that students "only learned how to take the [mastery learning] test better." All students, except one, disagreed or strongly disagreed with that question. When asking students, "which system do you feel you learn more with," Moore (2016) reports that most students responded that they learn "more with mastery" or "a lot more with mastery." In these studies, the students' self-evaluation was such that repeated testing did not merely teach them tricks on test-taking; rather, they reported learning the material better. There are also coinciding results about the preference of the mastery grading system over a traditional grading system or the inclination to do a mastery grading course again in Moore (2016) and Armacost and Pet-Armacost (2003) studies. Specifically, Moore (2016) reported that most survey respondents agreed that they prefer the mastery grading system over the traditional grading system. Armacost and Pet-Armacost (2003) reported that most students would like to participate in the mastery grading system again.

Most survey instruments were not replicated across studies and therefore, it is difficult to extract a clear consensus on students' perceptions on ML. However, 9 non-web implementations and 1 web-based study, as a group, report some results regarding students' perspectives and approaches to learning the course content. These results include the indication that approximately half the number of students collaborated more with the mastery learning approach (Moore, 2016). Approximately half of the students felt the mastery grading system was a more fair and accurate assessment of their understanding than traditional partial credit grading (Moore, 2016). As well, the ML approach did not seem to influence students' motivation to cheat (Moore, 2016). Armacost and Pet-Armacost (2003) also found that students reported that studying for the re-exams did not hurt preparation for other exams in the same ML class. Bekki et al. (2012), who implemented ML using competency assignments and evidence assignments, found that the students were satisfied with their understanding of the ML approach, the feedback they were provided, and the knowledge they were learning in the course. Paull et al. (1999) reports that 84% of students "felt that doing the homework on the internet would be beneficial," while only 22.6% of students "felt that the software was detrimental [to the completion of the homework] " (p. 10).

Sangelkar et al. (2014) reported that students did not appreciate the ML approach until they had advanced in their undergraduate education. Sangelkar et al. (2014) tracked students from the sections they were taught and asked, 1) if grades obtained in the ML were a fair evaluation of their understanding of the subject and 2) if they would recommend taking a ML Statics course to a friend. Students that had finished a Statics ML course and that were in their sophomore year responded with Neutral average response in a 5-point Likert scale from Disagree to Agree. In these same questions, students in their junior year (who had previously taken a ML Statics course) had higher scores than students in their sophomore year. When students in their junior year were asked if 'Mastery is a good way to learn statics' 38% agreed (Sangelkar et al., 2014).

Students' positive evaluation of Mastery Learning using open-ended questions

Five studies gathered student evaluation using open-ended questions at the end of the course (i.e., Bekki et al., 2012; Kelley, 1999; Craugh, 2017; Ritz et al., 2020; Sangelkar et al., 2014). All 3 web-based ML implementation studies collected answers to open-ended questions from questionnaires (i.e., Green, 2000; Paull et al., 1999; Leonard et al., 2008). A number of positive salient trends from students' evaluation were that they strategize how they study based on the retakes (Ritz et al., 2020), they "intellectually appreciated the concept" (Craugh, 2017, p. 7), and liked having the opportunity to improve their grades (Kelley, 1999). Additional sample comments reported in the studies show that students appreciated having multiple attempts to succeed (Bekki et al., 2012). Students' evaluation also suggested that the pedagogical approach supported their understanding of the material (Craugh, 2017). Students also stated that the ML approach exerted positive pressure to focus and learn the material and a shift away from trying to pass the class with only partial understanding,

> "At first, I didn't like the test taking set up, but then it really grew on me. I think it is a great way to evaluate students learning and it really helped having to retake certain problems. It made me focus and learn where I otherwise wouldn't have gone over it if I was just given partial [credit]" (Craugh, 2017, p. 6).

Some studies weighted the number of positive comments versus the number of negative comments about ML. Specifically, Bekki et al. (2012) and Kelley (1999) reported that they received more positive comments than negative comments regarding the mastery learning implementation, while Sangelkar et al. (2014) reported having received more negative comments about the ML implementation. Bekki et al. (2012) reported that "the majority of student responses indicated that they were happy with the approach and the efforts made by the instructors in implementing the approach" (p. 5). Kelley's (1999) focus group also revealed that "the consensus opinion from students was favorable toward mastery learning" (p. 10). Sangelkar et al. (2014) counted the instances a positive comment appeared in their open-ended question surveys. The question asked was, "What do you like or dislike about mastery learning method?" (p. 12). The top three positive comments were: "I can retake/multiple tries" (40% of positive comments), "I can solve problems correctly from the first time" (18% of positive comments), "Less material to study for each exam" (11% of positive comments) (p. 12).

Regarding the results from web-based implementations, Green (2000) describes that "most students appreciated the immediate feedback of the online assignments" (p. 14). Leonard et al. (2008) reported that at the end of the semester in Circuits I students felt stressed because they kept trying to reach perfection when taking the ML test (passing all questions in the test was required to pass the test) but that "students realized that the approach was working" (p. 5). By the end of the two-course sequence, Circuits I and II, students were convinced that the ML approach worked.

Students' negative evaluation of Mastery Learning using open-ended questions

Four studies reported negative evaluations of ML through open-ended questions (i.e., Bekki et al., 2012; Craugh, 2017; Kelley, 1999; Ritz et al., 2020; Sangelkar et al., 2014), while the remaining studies did not report negative evaluations. There were a few emerging themes in the negative feedback given by students in written student evaluations observed across studies. The first negative comment that was common across two studies is that some students thought the time it took to complete an assignment or test was too long due to the retakes (i.e., Kelley, 1999; Craugh, 2017). The second negative comment is that students felt they should be allowed to get partial credit on an assignment or exam – allowing them to get a lower grade on the assignment or exam without the need to get a 'mastery' grade (i.e., Kelley, 1999; Craugh, 2017). Students felt that they should have the opportunity to choose if they were finished with an assignment or exam even if they received a lower grade in order to focus on other projects or assignments. In Craugh's (2017) implementation, ML was applied to five class exams and students were able to retake problems that didn't reach the mastery level. The retake problems were less difficult on each retake and they were also worth fewer points. In the following student quote from Craugh (2017), a student describes their desire to be given the option to retake a class exam:

> "For test [regrades], if possible, I believe that students should be given the option whether or not to retake. For instance, if a retake conflicts with studying for another test or creates an otherwise greater burden for the student, the student should have the option to decline if they are fine with an 85 the first time and want to focus on their next test" (Craugh, 2017, p. 8).

There were other negative evaluations reported. Specifically, Kelley (1999) reported that students lack the motivation to work until they achieve a high grade on assignments and the lack of feeling comfortable with a new grading system. Some of the negative comments may be attributed to overly complicated mastery learning implementations. For example, Bekki et al. (2012) reported negative comments on student evaluations describing confusion and dissatisfaction with the assessment process. These comments may be connected with Bekki et al.'s (2012) complicated mastery learning implementation. Sangelkar et al. (2014) who coded students' written comments into categories of "like" and "dislike," found that 62% of the comments were unfavorable to the ML approach while 38% of the comments favored the implementation.

Although there were some patterns in the negative feedback received across studies, some of the negative feedback can be attributed to an overly complicated ML implementation. Nevertheless, based on the studies gathered in this systematic review there are more studies that report more positive comments than negative comments about ML implementations.

Discussion and Implications

The mastery learning process is applied from the moment the assignment is given to the students to the moment the retake process for that assignment is complete. When mastery learning is applied to midterms, the ML process is only conducted a few times, the number of midterms in a semester. The practice that comes with the exercise of ML is less than when ML is applied in the homework. Typically, there are a greater number of homework sets per semester when compared to the number of midterms per semester. Thus, students undergo a greater amount of practice by going through the ML process with ML homework which might be beneficial for their learning process. Of the studies that implemented ML, none used ML in the final exam. In most universities, after administering the final exam, the instructors have limited time available to submit the final grades. Most universities do not provide more classes, activities, or exams after administering the final exam. Therefore, if ML was applied to the final exam there would be no opportunities to administer ML final exam retakes. Only one study applied ML to a design project class (Mukherjee and Cox, 1998). Students were continuously given feedback on how to improve on the different phases of the project until a perfect score was achieved for each phase. In design project implementations, the instructor must provide individualized written feedback that can be lengthy. In contrast, in a homework, quiz, and/or exam ML implementation the instructor must, at minimum, only provide feedback about how the student failed to achieve a 'mastery' level.

There is a lack of closed-ended survey question replication among the studies. Most studies used a set of original questions, and few of the questions appeared in other studies. This leads to a breadth of survey results regarding mastery learning but it does not allow researchers to draw conclusions on survey questions that would apply to a large number of studies. Due to a lack of survey question replication among studies, there is also a lack of consensus regarding the opinion of students about mastery learning. The objective of systematic reviews is to provide a " 'bottom-line' statement regarding what the evidence supports and what gaps remain in our current understanding" (Cook & West, 2012, p. 950). We found that it was difficult to determine a bottom-line statement regarding the effectiveness of mastery learning since the data collected varied. It is recommended that future studies on ML in undergraduate engineering classes distribute surveys among its students that use similar questions as those found in the most salient studies discussed here. In this manner, future systematic reviews would be able to ascertain if there are similarities or differences in the answers students have given to the same questions across studies and draw more definitive conclusions regarding the students' perspective on ML implementations.

Of the 12 studies discussed in this systematic review, only three studies made statements regarding the magnitude of positive comments relative to negative comments received from open-ended survey questions (Bekki et al. (2012); Kelley (1999); Sangelkar et al., 2014). Specifically, 2 studies reported having received more positive comments than negative comments regarding mastery learning and 1 study reported having received more negative comments than positive comments. These results suggest that typically, there are more positive perspectives than negative perspectives on ML, and hence students have mostly a positive view about the ML approach. However, the evidence for this is not definitive. To strengthen the conclusion that students have a stronger positive perspective on ML, future studies should consider asking open-ended questions about mastery learning that elicit positive comments and negative comments; and count the positive comments versus the negative comments on ML. Suppose a larger number of future studies performed this research design. In that case, future systematic reviews on ML could make stronger conclusions regarding the relative magnitude of the positive comments versus the negative comments on ML and have a clearer picture of the perspective of students on ML.

Conclusion

This paper reports on a systematic review performed on mastery learning applied to undergraduate engineering classes from 1990 to 2021. Seven data bases were scanned, delivering a total of 584 sources of which 12 articles were synthesized. Most studies applied the ML approach to midterms. Some studies applied ML to quizzes and homework assignments and one study applied ML to projects. Several studies indicated that mastery learning had no effect on student's final exam grades. While other studies reported that students perceived an increase in their learning as a result of the ML approach. A clear consensus on the responses to close-ended survey questions could not be attained due to a lack of survey question replication; however, because studies employed different close-ended survey questions ample information about student perspectives on ML can be found.

Bibliography

Armacost, R. L., & Pet-Armacost, J. (2003). Using mastery-based grading to facilitate learning. *Proceedings - Frontiers in Education Conference, FIE*, *1*, T3A20-T3A25. https://doi.org/10.1109/FIE.2003.1263320

Averill, R., Recktenwald, G., & Roccabianca, S. (2018, June). Effect of assessment methods on performance in mechanics of materials. *ASEE Annual Conference & Exposition*.

Bekki, J. M., Dalrymple, O., & Butler, C. S. (2012). A mastery-based learning approach for undergraduate engineering programs. *Proceedings - Frontiers in Education Conference, FIE*. https://doi.org/10.1109/FIE.2012.6462253

Bloom, B. S. (1971). Mastery learning. In J. H. (Ed) Block (Ed.), *Mastery learning: theory and practice* (pp. 47–63). Holt, Rinehart and Winston.

Borrego, M., Foster, M. J., & Froyd, J. E. (2014). Systematic literature reviews in engineering education and other developing interdisciplinary fields. *Journal of Engineering Education*, *103*(1), 45–76. https://doi.org/10.1002/jee.20038

Borrego, M., Foster, M. J., & Froyd, J. E. (2015). What is the state of the art of systematic review in engineering education? *Journal of Engineering Education*, *104*(2), 212–242. https://doi.org/10.1002/jee.20069

Carroll, J. (1963). A model of school learning. *Teachers College Record*, *64*(8), 723.

Cook, D. A., & West, C. P. (2012). Conducting systematic reviews in medical education: A stepwise approach. *Medical Education*, *46*(10), 943–952. https://doi.org/10.1111/j.1365-2923.2012.04328.x

Craugh, L. E. (2017). Adapted mastery grading for statics. *ASEE Annual Conference & Exposition*.

DeGoede, K. (2020, June 22). A mastery-based learning model for an upper-level vibration analysis course. *ASEE's Virtual Conference*.

Evidence for Policy and Practice Information and Co-ordinating Centre (EPPI-Centre). (2010). *EPPI-Centre methods for conducting systematic reviews*.

Feldman, J. (2019). *Grading for equity: what it is, why it matters, and how it can transform schools and classrooms*. Corwin Press.

Green, R. A. (2000). Mastery learning with the MATLAB webserver. *ASEE Annual Conference*, 5.440.1-5.440.14.

Guskey, T. R., & Gates, S. L. (1985). A synthesis of research on group-based mastery learning programs. *Annual Meeting of the American Educational Research Association*, *69th*.

Halperin, A. (2020). Mastery-based testing in calculus with a final exam component. *PRIMUS*, *30*(8–10), 1017–1039. https://doi.org/10.1080/10511970.2019.1700575

Harsy, A. (2020). Variations in mastery-based testing. *PRIMUS*, *30*(8–10), 849–868. https://doi.org/10.1080/10511970.2019.1709588

Hjelmstad, K. D., & Baisley, A. (2020, June). A novel approach to mastery-based assessment in sophomore-level mechanics courses. *ASEE Virtual Annual Conference Content Access*.

Kelley, D. S. (1999, June 20). Mastery learning as a teaching methodology in engineering graphics. *ASEE Annual Conference*.

Kulik, C.-L. C., Kulik, J. A., & Bangert-Drowns, R. L. (1990). Effectiveness of mastery learning programs: A meta-analysis. *Review of Educational Research*, *60*(2), 265–299.

Kulik, J. A., Kulik, C. L. C., & Cohen, P. A. (1979). A meta-analysis of outcome studies of Keller's personalized system of instruction. *American Psychologist*, *34*(4), 307.

Leonard, W. J., Hollot, C. v., & Gerace, W. J. (2008). Mastering circuit analysis: an innovative approach to a foundational sequence. *38th Annual Frontiers in Education Conference*.

Malcom, S., & Feder, M. (2016). Barriers and opportunities for 2-year and 4-year STEM degrees: systemic change to support students' diverse pathways. In *Barriers and Opportunities for 2-Year and 4-Year STEM Degrees: Systemic Change to Support Students' Diverse Pathways*. National Academies Press. https://doi.org/10.17226/21739

Moore, J. (2016). Mastery grading of engineering homework assignments. *Proceedings - Frontiers in Education Conference, FIE*, *2016-November*. https://doi.org/10.1109/FIE.2016.7757584

Mukherjee, A. ;, & Cox, J. L. (1998). Effective use of mastery based experiential learning in a project course to improve skills in systems analysis and design. *The Journal of Computer Information Systems*, *38*(4), 46–51.

Paull, T. A., Jacob, J. M., & Herrick, R. J. (1999, June 20). Automated homework in electrical engineering technology. *ASEE 1999 Annual Conference*. http://www.clearcutsoft.com/TestPilot/.

Ranalli, J., & Moore, J. P. (2015, June). New faculty experiences with mastery grading. *ASEE Annual Conference & Exposition*.

Ritz, H., Dimiduk, K., & van Paridon, A. (2020, June 22). Effect of mastery-graded exams on student outcomes in statics and mechanics of solids course. *ASEE's Virtual Conference*.

Sangelkar, S., Ashour, O., Warley, R. L., & Onipede, O. (2014). Mastery learning in engineering: a case study in statics. *ASEE Annual Conference & Exposition*, 24.887.1-24.887.19.