

Surveying Motivation and Learning Outcomes of Advanced Learners in Online Engineering Graduate MOOCs

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Abstract—This research Work-In-Progress presents a survey of advanced learners’ motivation in highly-technical advanced engineering MOOCs. Advanced engineering courses as MOOCs are increasingly prevalent in graduate and professional learning and are gaining importance for credentialing and accredited degrees. However, these courses are open to the public as well as formal learners, making it difficult to generalize experiences for all. To understand what prevents advanced learners from reaching their goals and to better support them in meeting goals, there is a need for more sensitive tools to measure motivation. We have revised the Expectancy-Value-Cost scale and examined its functioning on pilot data to begin looking at validity evidence for using the revised scale with professional engineers. We analyze motivations, intentions, and course ratings of learners from two online MOOCs who are enrolled in formal degree programs at a four-year institution, learners completing a MOOC master’s degree, and independent learners. We also perform bivariate correlation of motivation items to test the performance of the instrument. Preliminary results show high motivation for all learner groups, but greater differences between independent and formal learners, with formal learners reporting a wider range of costs.

Keywords—*distance education, open and flexible education, open educational resources and practices*

I. INTRODUCTION

In the past decade, there has been an increasing number of advanced MOOCs for graduate and professional education. Courses have been adopted by traditional four-year universities and are organized into Master’s and MicroMasters programs via these platforms [1]. In 2020, Class Central reported more than 800 microcredentials across five global platforms, such as Specializations, Professional Certificates, Nanodegrees, or MicroMasters [2]. Nearly 47% of these credentials are in technology, engineering, or science areas [2].

Because these courses provide learners access to advanced engineering knowledge, they have the potential to impact development of professional skills in engineering education. As online education with MOOCs becomes more recognized with credentials and incorporated into formal degree programs, there is a need to assess their learning value and professional impact. Ensuring learners are motivated to participate in professional MOOCs depends on understanding the audience and their training needs [3].

Since advanced engineering courses are hosted on MOOC platforms, they are open to the public as well as formal learners. Demographics such as country of origin, gender, or

digital skill level may interact to influence motivation and learning access [4]. This makes it difficult to generalize which learning experiences are beneficial for all, since each has a unique background and professional goals. While factors such as engagement and motivation have been abundantly studied to differentiate between learners’ achievement [5], few studies have examined differences in these factors for emerging populations of professional and graduate learners.

New courses and degree programs are evaluated based on evidence of learning for all groups of learners who take them, including online students in MOOC-based graduate university degrees, learners in professional or certification programs, or those taking a course independently. This paper addresses the emerging group of graduate learners.

II. LITERATURE REVIEW

A. MOOCs for Professional Education

Independent learners have been represented in research as attracted by the openness of high-quality learning, able to personalize his or her learning in an environment with thousands of other like-minded learners, and as motivated to learn with a professional or personal goal in mind [6]. They may be managing careers, families, or other educational responsibilities, making flexible learning a priority for professional learners due to multiple competing demands. Adult learners are often motivated by lifelong learning and an intrinsic value for subject material which open education can provide [7], [8]. They may also seek certificates, degrees, or badges from a MOOC as evidence of their achievement, and to demonstrate to employers or interviewers that learning will translate into job skills [9].

Professional and advanced learners are seeking practical outcomes from courses to enhance their careers. Support for independent education is an important factor for success which many employees do not receive [10]. However, modern workplaces require employees to be constantly updating their skills. Whether in employer support to balance work and learning, or as corporate-provided MOOCs to train employees in company-defined skills [11], this support can be valuable in creating a supportive environment for professional learning.

In contrast, there is very little research into the success of MOOC-based online Master’s or professional degrees. As this new learning design continues to be implemented in graduate and postgraduate science, technology, engineering, and mathematics programs around the world, it is important to

understand these learners individually with unique goals, motivations, and obstacles to learning.

B. Expectancy-Value-Cost Theory of Motivation

Expectancy-Value-Cost theory represents three dimensions of motivation that explore how learners perceive learning goals and their own ability to reach them [12]. Expectancy asks the question, “Can I do the task?” and is defined as the belief in one’s abilities to perform the necessary work to reach a goal. It measures ability beliefs regarding what they can do now, and expectancy beliefs about future performance. High expectancy will motivate learners to engage in activity to help them reach a goal. Value asks the question “Do I want to do the task?” and is defined as how important the goal is to attain. It measures the value of learning in terms of utility to achieve goals, intrinsic value for its own sake, and attainment value to grow as an individual. High value also represents high motivation. Cost asks the question “What will it cost me to do this task?” and is defined as the obstacles that make it difficult to reach a goal. It measures tangible costs, such as time or money, as well as psychological, emotional, or effort costs invested in the task. High cost will decrease motivation as learners are hindered by obstacles from performing Expectancy and Value activities to reach the goal.

This motivation theory is relevant to MOOC research because courses are open access and learners are driven to participate by their own personal and professional goals. It also balances internal and external factors affecting learning and includes the costs which independent and professional learners very often face. However, there may be differences between independent learners driven by intrinsically valuing content with fewer costs, and formal Masters or MicroMasters learners committed to a multi-course sequence and may be more driven by achievement with greater cost.

C. Practicing Engineering Expectancy-Value-Cost (PE-EVC) Scale

Our past research has demonstrated the functioning of the Expectancy-Value-Cost (EVC) scale in advanced engineering MOOCs [13]. We found it sensitive enough to differentiate among learners on the Cost dimension, but the scale showed a ceiling effect for Expectancy and Value dimensions, as participants consistently responded with the highest response values for all items [13]. High endorsement of Expectancy and Value items reflects the theoretical connection between the two constructs, and the relatively recent addition of the Cost dimension [12].

Based on these results, the Practicing Engineering EVC scale (PE-EVC) has been updated to with more specific wording relevant to a MOOC context. Substituting “content” for “material” in E1 focuses on learning concepts over completing materials, as MOOC learners tend to drop out of courses. Success is defined in E2 as meeting personal learning goals. Modifying words such as “know,” “believe,” and “think” were removed, to more directly assess students’ thoughts about their abilities. Value items pinpoint what about the course is valuable and why. A fourth item has also been added to the cost dimension from the original survey on time investment (see item 10 in Table I). Responses are scored on a Likert-type scale from 1 (Strongly Disagree) to 6 (Strongly Agree). Cost items are reverse scored since low cost translates to high motivation in the EVC theory.

TABLE I. PE-EVC SCALE REVISIONS COMPARED TO ORIGINAL

Item Description		
	Original	Revised
E1-E3	<ol style="list-style-type: none"> 1. I know I can learn the material in this course. 2. I believe I can be successful in this course. 3. I am confident that I can understand the material in this course. 	<ol style="list-style-type: none"> 1. I can learn the content in this course. 2. I can meet my learning goals in this course. 3. I can understand the material in this course.
V1-V3	<ol style="list-style-type: none"> 4. I think this course is or will be important. 5. I value this course. 6. I think this course is or will be useful. 	<ol style="list-style-type: none"> 4. This course is important for my goals. 5. I value the subject material of this course. 6. I think this course will be useful to me.
C1-C3	<ol style="list-style-type: none"> 7. Because of other things that I do, I do not expect to have time to put into this course. 8. I think I will be unable to put in the time needed to do well in this course. 9. I think I may have to give up too much to do well in this course. 	<ol style="list-style-type: none"> 7. This course requires too much time. 8. Other things that I do prevent me from giving time to this course. 9. I will be unable to put in the time needed to succeed in this course. 10. I may have to give up too much to do well in this course.

The focus of this paper is on addressing the need for better understanding of motivation in MOOC contexts based on practical barriers and needs. We use the PE-EVC to assess learners’ motivation, and relate it to their self-reported learner status, course engagement intentions, and learning goals from the pre-course survey.

III. METHODS

A. Data Collection

Participants for this study were recruited from six advanced engineering MOOCs offered through the edX platform. Semiconductors Fundamentals lasted for 6 weeks, Nanophotonic Modeling for 5 weeks, Fundamentals of Current Flow for 5 weeks, Fundamentals of Transistors for 7 weeks, Fiber Optic Communications for 5 weeks, and Introduction to Quantum Transport for 5 weeks. They are offered by a large four-year institution which also includes them as part of a formal online Master’s degree. All six courses were taught with similar pedagogies of video lectures, group discussion boards, practice problems, weekly quizzes, and midterm and final exams.

TABLE II. TOTAL PARTICIPANTS BY ANALYSIS STAGE

	Ind.	Micro	MS
Pre-Course Survey	261	24	29
Motivation Survey	65		
Pre-Course & Motivation Match	18	2	13

Note: “Ind.”= Independent, “Micro”= MicroMasters, “MS” = Masters.

As a part of the course plan, learners were invited to take three surveys during the course. Upon enrollment, they received the pre-course survey which asked their learning goals, anticipated course engagement, intended use of course

content, learner status, and demographics. After the first week, learners received the motivation survey revisiting learning goals and asking the ten PE-EVC motivation items. After the course ended, learners received the post-course survey of their satisfaction with course content and delivery, and suggestions for improvement. Participation was voluntary and learners were not compensated in any way. Data from the two surveys were analyzed independently, then matched for learners who completed both pre-course and motivation surveys. Table II shows total responses by learner enrollment group for each stage of survey analysis. Given the declining response rate of learner enrollment and survey responding in general, we chose to only administer the motivation survey once at the beginning of the course.

TABLE III. DEMOGRAPHICS BY LEARNER STATUS

	Ind.	Micro	MS
Gender (n=102)			
Male	58	10	9
Female	14	3	6
Nonbinary	2	0	0
Student Status (n=105)			
Full-time student	33	5	3
Part-time student	9	3	14
Not a student	34	4	0
Employment Status (n=109)			
Employed full-time	40	10	14
Employed part-time	7	1	0
Not employed	28	2	4
Retired	0	0	0
Other	3	0	0
Highest Completed Level of Education (n=109)			
High school or pre-college	12	0	0
Some college education	2	2	0
Associate's degree	1	0	0
Bachelor's degree	25	11	14
Master's degree	22	0	3
PhD	15	0	0
Other	1	0	1

Note: "Ind."= Independent, "Micro"= MicroMasters, "MS" = Masters.

Respondents were primarily male (75%), and independent learners (72% - 73%) (see Table II). The majority of all three groups were employed full-time (59%) or not employed (31%). Masters students were primarily part-time students (82%), while independent and MicroMasters learners were either full-time students (Ind. = 43%, Micro = 42%) or not students (Ind. = 45%, Micro = 33%). A Bachelor's degree was the most reported level of education for all learner groups (Ind. = 32%, Micro = 85%, MS = 78%).

B. Data Analysis

This study examines the intentions across learner groups by analyzing frequency of responses to two pre-course survey items, "What are your learning goals for this course?" and "How many hours will you dedicate each week to this course?" Motivations by learner group are also investigated by matching learners who completed both the pre-course survey and the motivation survey, and calculating the average reported Expectancy, Value, and Cost within each group.

To examine the performance of the PE-EVC in this learning setting, a Spearman rank-order correlation was used to test the relationships of items within each dimension and across dimensions. Highly correlated items within and across dimensions may or may not support the existing factor structure of the instrument.

IV. RESULTS

A. Learner Intentions

The majority of learners had optimistic learning goals for the course, with most intending to successfully learn all or most content (Ind. = 76%, Micro = 93%, MS = 100%) (see Table III). Independent learners were willing to skip some parts of the course compared to learners in formal programs. Independent learners had the widest variety of anticipated hours dedicated to the course, with the most planning 3-5 hours per week (34%). Most MicroMasters and MS learners were more willing to commit time with at least 7-9 hours per week or more (Micro = 61%, MS = 39%).

TABLE IV. INTENTIONS BY LEARNER STATUS

	Ind.	Micro	MS
What are your learning goals for this course? (n=137)			
Successfully learn all or most content	78	14	19
Become familiar with most topics, but not necessarily do all parts of the course	20	1	0
Become familiar with some of the topics, but not all of the content	5	0	0
How many hours will you dedicate each week to this course? (n=119)			
Less than 3 hours per week	8	1	0
3-5 hours per week	30	3	2
5-7 hours per week	13	1	3
7-9 hours per week	16	8	7
More than 9 hours per week	8	0	4
Not sure	13	0	2

Note: "Ind."= Independent, "Micro"= MicroMasters, "MS" = Masters.

B. Item Correlation

We performed a Pearson product-moment correlation on the ten PE-EVC items to test the scale's internal consistency across the three dimensions. Figure 1 shows the correlation coefficients and significance levels. Expectancy and Value items were correlated and significant within and across dimensions. Cost items were also significantly correlated within the dimension.

	E1	E2	E3	V1	V2	V3	C1	C2	C3	C4
E1										
E2	0.492**									
E3	0.624**	0.265*								
V1	0.543**	0.505**	0.259*							
V2	0.545**	0.477**	0.358**	0.738**						
V3	0.603**	0.548**	0.288*	0.560**	0.567**					
C1	-0.131	0.033	-0.234	0.042	-0.051	0.070				
C2	0.048	0.041	0.021	0.016	0.067	-0.080	0.445**			
C3	-0.109	-0.153	-0.113	-0.235	-0.338**	-0.151	0.409**	0.455**		
C4	-0.225	-0.083	-0.299*	-0.138	-0.206	-0.022	0.501**	0.384**	0.541**	

Fig. 1. Correlation coefficients for PE-EVC items. *p values significant at $\alpha = 0.05$. **p values significant at $\alpha = 0.01$.

Given the reverse scoring of Cost items, a negative correlation between these questions and the remaining six is desirable. Figure 2 shows significant negative correlations of C3 with V2 ($r = -0.338$) and C4 with E3 ($r = -0.299$). However, other Cost items do not significantly correlate, positively or negatively, with any Expectancy or Value items.

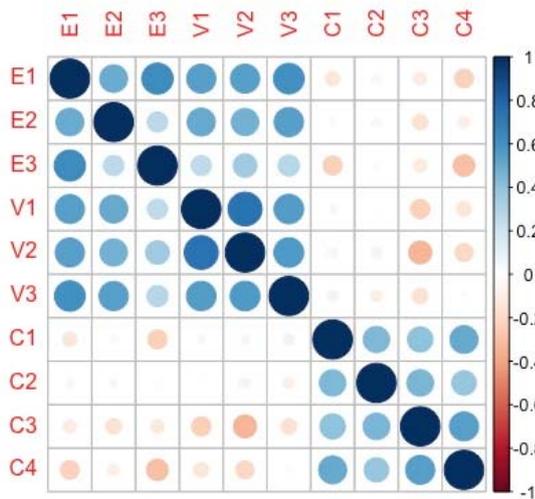


Fig. 2. Map of correlation direction and strength for PE-EVC items.

C. Motivation by Learner Status

To examine motivation differences among independent, MicroMasters, and MS learners, we compare average scores for each PE-EVC dimension across all groups. Figure 3 indicates that Expectancy and Value motivation averages were highest for MicroMasters learners, but that all three enrollment groups perceived Cost similarly. Masters students also indicated higher positive expectations and greater value of the course on average compared to independent learners.

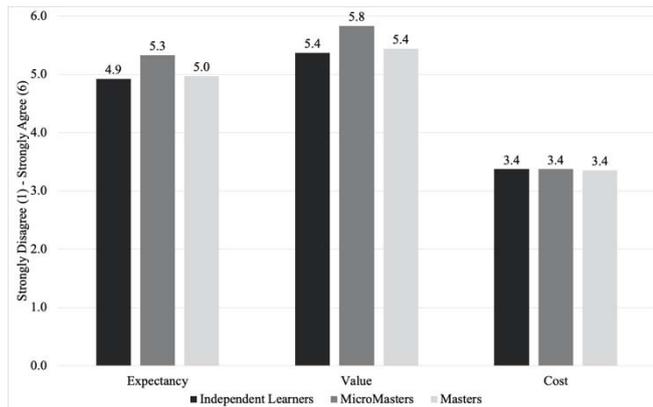


Fig. 3. Average motivation scores by learner enrollment status.

V. DISCUSSION

Independent learners and formal Master’s learners were more likely to have an advanced college degree than MicroMasters learners. This could suggest that they are adding to existing expertise with advanced learning, rather than seeking a formal MOOC-based degree. As the majority of Master’s students were also enrolled full-time, this learning path could be more suited to professional learners than others.

While the P-EVC scale showed good performance across Expectancy and Value dimensions and within Cost dimensions, further revision may be necessary to increase the

negative correlation between Cost items and the rest of the instrument. In addition, results show a strong correlation between Expectancy and Value items. As in previous research [13], learners tended report both high expectancy of success and strong value of course content. A limitation of correlation analysis is its inability to measure learners’ underlying construct of motivation, compared to tests such as Item Response Theory. Future research with a larger survey sample will perform item-level analysis to investigate the theoretical overlap between Expectancy and Value.

Continuing work will include more data from courses offered by the same university in this analysis, continuing to observe differences in motivation and intentions by learner status. We will also perform more advanced psychometric analyses on the PE-EVC scale to test its performance. Finally, we plan to test the scale’s connection to course activity by modeling predictiveness of motivation scores to engagement, interaction, and achievement.

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