Surveying the Motivations of Groups of Learners in Highly-Technical STEM MOOCs

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***Abstract*— Highly technical STEM MOOCs have recently become widely available, but little is known about the motivations of the various groups of learners participating. In this work, we perform a detailed survey of 1,624 learners to examine their motivations in detail. These learners exhibited overall high levels of intrinsic motivation, but varied in their extrinsic motivation, according to their current position as students, workers, or unemployed individuals. Students generally reported the highest levels of extrinsic motivation compared to other groups (p<0.001). The results from this analysis indicate that additional factors about learners in each group, such as their course participation and performance, should be examined in future work to help better understand the various needs of those enrolling in highly technical STEM MOOCs.**

Keywords—MOOCs, motivation, learners

I. Introduction

Massive open online courses (MOOCs) have rapidly become a popular trend in online education worldwide. The term MOOCs refers to online courses open to large numbers of students, with the materials freely available in an online environment. MOOCs are typically free of tuition fees, hard prerequisites, and requirements for participation in the course, and therefore create an easy and investment-free option for accessing educational materials on a variety of topics [2], ranging from introductory-level to highly-advanced technical courses. Due to the open nature of MOOCs, those who enroll are free to enter, participate in, and leave courses as they deem appropriate.

Learners are free to enroll in a MOOC whether or not they intend to complete or even participate in the course; most students do not complete all or even most elements of their courses [2]. It is therefore reasonable to assert that completion rates are inaccurate and arguably even inappropriate indicators of MOOC success [3]. Not surprisingly, this ambiguity has brought about challenges for the evaluation of MOOCs and has rendered many traditional course evaluation techniques irrelevant. Some researchers have suggested that MOOC completion rates are only relevant when interpreted alongside learners' goals [3[. In other words, MOOC completion rates are only meaningful for students who had intentions of completing a course and then either did or did not see it through to the end. For students who never intended to complete a course, their completion is not an indicator of whether or not they got what they wanted from their course experience or an indicator of the quality of the MOOC; treating it as such is misleading. We further argue that whether or not course completion is an accurate index of MOOC quality may only be relevant when considered through the perspectives of both learner intentions and MOOC course design. In other words, if learners enroll in a MOOC because they intend to complete the course, it is important to understand the factors that contribute to their completion of or attrition from the course, in order to adjust the course in a way that promotes completion. On the other hand, if learners enroll in a MOOC just to access the information it contains, it may prove more effective (for both students and instructors) to simply post the materials in an open online space, sans the other course-like elements.

Because learners enrolled in MOOCs may choose to fully participate in all aspects of the course, skim the materials for information they find most relevant to their needs, or drop out entirely at any point in the course, researchers have begun to investigate MOOC learners' reasons for enrolling in the first place and have reported reasons that include: entertainment, interest in the course topic, and professional development [1]. Additionally, patterns of learners' usage of course material (i.e. clickstream or "back end" data) is beginning to be used in efforts to better understand users' intentions (author et al., under review). Still, much remains unknown about the specific motivations of the various types of learners who enroll in MOOCs, and particularly, the intentions of those who enroll in highly-technical STEM MOOCs. Overall, the task of evaluating MOOCs is much too intricate and nuanced for traditional means of course evaluation. In order to develop more fitting indices of MOOC quality it is crucial to better understand the intentions and needs of those who are enrolling. Addressing the deficiency in our understanding of MOOC learners is crucial to both designing more effective MOOC pedagogies and ultimately helping the learners succeed, regardless of their intentions or goals [4]. With the number of MOOCs and online learners continually increasing, understanding learners becomes increasingly necessary to ensure the future success of MOOCs in general.

The purpose of the present study is to understand the composition of learners enrolled in highly advanced nanotechnology-related MOOCs. The guiding hypothesis for this research is that within highly-technical MOOCs, there are underlying groups of learners with various motivations and intentions, based on their current employment or informational needs.

II. INSTRUCTIONAL DESIGN OF MOOCS

Tailoring both content and delivery to the needs of learners, known as instructional design, is a vital component of instruction. Smith and Ragan define instructional design as a "systematic and reflective process of translating principles of learning and instruction into plans for instructional materials, activities, information resources, and evaluation" [6]. Further, Smith and Ragan assert that understanding learners' needs and goals is not only necessary but central to successful instructional design and ultimately effective teaching [6]. Without a comprehensive understanding of the learners, regardless of educational platform, instruction cannot be appropriately designed to meet their needs and ultimately produce the desired outcomes for both learners and instructors.

The lack of knowledge about the specific needs of various MOOC learners presents a sizable problem for MOOC designers and instructors [7]. What we do know about MOOC learners is that most are well-educated, employed, and living in developed parts of the world [4]. With regard to course participation rates, researchers have reported average retention rates of between 5% and 15%, indicating that the overwhelming majority of those enrolling in MOOCs do not complete the courses for one reason or another [2,8].

Although various characteristics of MOOC learners have been identified, little is known about what motivates them to engage with the course materials in the ways that they do—a point deemed significant by multiple researchers [4,9]. Because many MOOCs are designed to attract massive numbers of learners from a variety of backgrounds, and because enrollment is free of requirements, learner goals are not often assessed as part of the enrollment process [3]. Coursera, one of the larger platforms for MOOCs, has recently incorporated a question about intended use of the course to the participant registration survey, but how this information is used (and more specifically, how it is used in terms of MOOC design) remains unknown. Further, as little as is known about MOOC learners as a whole, even less is known about those enrolled in highly-technical STEM MOOCs more specifically. Currently, MOOCs are not targeted at a specific user. They are, by definition, open and attract diverse groups of learners, from high school students to university faculty. Some learners flip through the material like they would a textbook; few want to actually sequentially participate in all aspects like in a traditional course. Understanding the various groups of learners is essential to being able to design MOOCs in ways that effectively support learning for as diverse a collection of learners as MOOCs attract. The present study examines the existence of underlying groups of learners within those enrolled in advanced nanotechnology-related MOOCs as a means of exploring the motivations of learners enrolled in a highly-technical MOOC.

III. MOTIVATION FOR LEARNING

Instructional research suggests that whether a learning environment is successful is largely dependent upon whether learners can learn what they want to learn when they want to learn it [5]. In other words, an individual's motivation to engage in learning is a major factor in the success of a learning experiences. Fischer also adds that while educational materials are currently accessible to much of the world's population, utilizing those materials in a way that actually results in measurable knowledge gain requires a motivated and effective learner [5].

From decades of research on educational motivation, we know that individuals are driven to act by differing forces in various situations, suggesting that motivation is a multi-faceted and fluid construct. Ryan and Deci posited that when it comes to learning, people possess varying amounts of both internal and external motivations when making decisions about their behaviors [10]. Self-Determination Theory explains these contrasting reasons as intrinsic and extrinsic motivation [11]. Given that MOOCs attract such massive groups of learners, it is important to understand the various motivating factors at work.

Intrinsic motivation refers to one's innate desire to engage in a particular activity and is considered to be free of external pressures or incentives. In other words, if one is intrinsically motivated to engage in learning, they engage because they have an inherent inclination to learn and participate in endeavors to help them do so. Those who are intrinsically motivated to learn value increasing their own knowledge and skills for their own sake, and therefore engage in learning opportunities without requiring pressure or incentives by external influence. Ryan and Deci write that decisions motivated by intrinsic factors are ones that "emanate from one's sense of self" [10]. For this reason, intrinsic motivation is regarded as more conducive to higher levels of performance, creativity, and persistence than is extrinsic motivation [10.12].

Though activities driven by intrinsic motivation often result in the highest quality outcomes, many of the learning activities in which people engage are not motivated entirely by intrinsic factors [10]. In general, many of our decisions are often (at least partially) driven by external pressures or rewards. Ryan and Deci explicitly state that being entirely intrinsically motivated to engage in learning becomes increasingly difficult as social demands and roles "require individuals to assume responsibility for non-intrinsically interesting tasks"—a point that is likely to be particularly applicable to those employed in rapidly changing and competitive technical fields [10]. Motivating factors extraneous to one's innate desires are referred to as extrinsically motivating. In contrast to intrinsic motivation, extrinsic motivation causes one to engage in learning in an effort to achieve a particular outcome for which learning serves as the means. These desired outcomes may include achieving social approval, earning a desired grade in a course, fulfilling a professional requirement (i.e. professional development or certifications), or avoiding consequences for not engaging in the learning opportunity. Intrinsic and extrinsic motivations are not mutually exclusive and are thought to exist (to varying degrees) within all learners. In other words, individuals differ in their levels of each orientation of motivation, possibly having more of one type of motivation than the other for engaging in various behaviors related to learning. In some instances, a single individual's learning may be primarily motivated by intrinsic factors, such as genuine interest, while in other situations, learning may be almost entirely motivated by an extrinsic factor (e.g. supervisor request, position requirements, etc.).

IV. METHODS

a. Setting, Participants, and Data Collection

The present study focused on learners from four [blinded for review] courses. [Blinded] is an online instructional platform established by [blinded], supported in part by the National Science Foundation (NSF). The continually evolving nature of nanotechnology constantly renders traditional course textbooks obsolete [13], and most current material is only available through updates such as conference proceedings. [Blinded] addresses this issue by offering short (typically 5 weeks in length) MOOCs developed by experts from across the field of nanotechnology. The center in collaboration with EdX present information on most recent developments, they are well-equipped to disseminate advanced STEM-related content to the masses. Researchers administered a voluntary survey during the first week of three [nanotechnology center] courses: Fundamentals of Nanoelectronics, Bioelectricity, and Organic Electronic Devices. Survey responses for the three courses were combined, and after cleaning data for incomplete responses, a total of 1624 learners were included in the present study sample.

b. Survey

The survey gathered information on learners' demographics, prerequisite background, level of education, employment status, their expectations for course participation, personal goals for the course, and levels of intrinsic and extrinsic motivation for learning. The survey included seven forced-choice items related to learners' backgrounds (i.e., education level, employment status) and goals for the course (i.e., intended participation and learning goals), seven Likert-style items from the Intrinsic and Extrinsic subscales of the Motivational Learning Styles Questionnaire [14] and five constructed response items regarding learners' primary fields of study/work, what directed them to the course, and what they hope to gain from enrolling. The intrinsic motivation subscale was intended to measure the extent to which learners were motivated by internal factors to engage in the course, including an innate interest in learning new information and an inherent desire to be challenged. In contrast, the external motivation subscale assessed the extent to which learners were motivated by extraneous factors, such as social pressure to participate or the desire to surpass others. Respondents rated each of the subscale items on a 7-point Likert scale that ranged from "Not at all like me" to "Very much like me". The text of the surveys differed slightly between courses, as to remain relevant to each course's specific content.

c. Data Analysis

As not all survey respondents completed the survey in its entirety, the data were first assessed to determine the nature of missing points of data. The missing data were determined to be Missing Completely At Random (MCAR), meaning that we could discern no patterns of incompleteness and could therefore conclude that the missing data do not indicate issues with the survey or any patterns of learner behavior. Incomplete survey attempts were deleted due to the categorical nature of the items.

To better understand particular underlying groups of learners that may exist within these MOOCs, we decided to focus on differences that may exist between groups of learners with various employment statuses, as these differences are likely to influence the needs, time constraints, and motivations of various learners. We divided respondents into four groups: those who were working full-time (n = 502), those who were working full-time and also part-time students (n = 265), those who were full-time students (n = 626), and those who were not working (n = 231). An open-response item asked participants to indicate their primary field of work or study, and responses were analyzes through content analysis. One researcher used an *a priori* coding scheme using U.S. Bureau of Labor occupation categorizations to categorize all responses, and a second researcher applied the same coding scheme to a subset of responses (10%) in order to establish interrater agreement. Analyses showed a 95.3% rate of agreement with a Cohen's kappa of 0.92. The vast majority of respondents (1,358) reported working in STEM fields, including Architecture, Engineering, Life Sciences, Computer, and Mathematics fields.

V. RESULTS

a. What do learners hope to do with what they learn in the MOOCs?

One survey item asked learners what they intend to do with the information they learn from the course; possible responses were 1) gain a broad understanding of the topics, 2) gain a deep understanding of the material, or 3) be able to apply the information to their work. A chi-square test of independence revealed significant differences between these four groups in what they hope to do with what they learned (χ^2(6, N = 1624) = 39.53, $p < .001$). The majority of those working full-time, working full-time and also part-time students, and full-time students reported wanting to be able to apply the information they learned in the MOOC, whereas those who reported being unemployed were almost evenly divided between wanting to apply the information, wanting a deep understanding of topics, and just wanting a broad understanding of the course topics. Table I provides frequencies and percentages of each response for each group.

TABLE I. DESIRED LEVEL OF UNDERSTANDING MATERIAL

Employment/ Student Status	**Desired level of understanding**		
	Broad	*Deep*	*Application -level*
Working full-time	113 (22.5%)	160	229

		(31.9%)	(45.6%)
Working full-time/ Part-time student	71 (26.8%)	68 (25.7%)	126 (47.5%)
Full-time student	113 (18.1%)	175 (28%)	338 (54%)
Not working	75 (32.5%)	81 (35%)	75 (32.5%)

b. How do learners hope to perform (grades) in the course?

A chi-square test of independence was performed to examine the relation between employment status and goals for course grade outcomes. The relation between these variables was significant, meaning that the four groups did differ in their desires for grade outcomes in their respective courses (χ^2(6, N = 1624) = 14.56, $p < .05$). Full-time students had a greater desire than other groups to obtain a high grade in the MOOC. Table II provides frequencies and percentages of responses about desired grade outcomes for each group.

TABLE II. DESIRED GRADE OUTCOMES

Employment/ Student Status	**Desired Grade Outcome**		
	High Grade	*Passing Grade*	*Not concerned*
Working full-time	193 (38.4%)	76 (15.1%)	233 (46.4%)
Working full-time/Part-time student	106 (40%)	46 (17.4%)	113 (42.6%)
Full-time student	293 (46.8%)	98 (15.7%)	235 (37.5%)
Not working	83 (35.9%)	39 (16.9%)	109 (47.2%)

c. What motivates learners to engage in the course?

Regression analyses revealed no significant likelihood that groups differ in intrinsic motivation (F(3, 1620) = 1.698, $p > .01$). Analyses did, however, suggest a significant likelihood that the groups differ in extrinsic motivation (F(3, 1620) = 8.813, $p < .001$, $\eta_p^2 = .016$), with full-time students and full-time workers who were also part-time students reporting higher levels of extrinsic motivation. Table III shows the means and standard deviations of both intrinsic and extrinsic motivation for all four groups of learners.

TABLE III. MEANS AND STANDARD DEVIATION OF MOTIVATION STYLES

Employment/ Student Status	**Motivation**	
	Intrinsic	*Extrinsic*
Working full-time	5.79 (±0.98)	3.36 (±1.7)
Working full-time/Part-time student	5.77 (±1.0)	3.57 (±1.67)
Full-time student	5.78 (±1.03)	3.81 (±1.75)
Not working	5.62 (±1.06)	3.28 (±1.7)

VI. DISCUSSION

A. Key Findings

Respondents working full-time report extrinsic motivation levels very similar to respondents who are not working at all, and both of these groups reported lower extrinsic motivation than respondents who were full-time or even part-time students. Of all respondents, full-time students reported the highest levels of extrinsic motivation, which seems plausible, as they presumably experience increased pressure to engage in learning. This also suggests that professionals enrolling in highly-advanced technology-related MOOCs are not doing so directly because of professional requirements. Respondents who reported being unemployed reported the lowest levels of extrinsic motivation, which makes sense, as learners in this group likely have no explicit educational or professional requirements to participate in the MOOCs they are enrolled in. Levels of intrinsic motivation were as high for non-workers as for full-time workers, full-time workers who were also part-time students, and full-time students, suggesting that MOOC learners who were unemployed are just as internally motivated to engage in the courses as those who are currently working or studying in the field.

This research also suggests that pre-course surveys could be utilized as a pedagogical tool for MOOCs more broadly, and allow MOOC providers to anticipate learner needs and tailor courses to engaged learner. Prior research has also suggested the use of pre-course surveys for adapting courses to learners with various needs and intentions [15]. Pursel and colleagues found that learners who completed the pre-course survey were more likely to complete the course, which provides compelling support for adjusting courses to aid those students in particular. For example, they might benefit from private forums allowing them to interact directly with one another and to "avoid much of the 'noise' that takes place in large forums". This adapted structure would also allow instructors to have a more direct line of communication with students who are dedicated and likely to complete the course. Our research adds to this line of work by quantifying the importance of intentions and motivations for the course among the survey respondents. Being "surrounded" by learners with highly similar motivations and intentions for the same MOOC could be even more helpful to both learners and instructors, as such a structure would allow for tailored communication, instruction, feedback, or course design, thus maximizing their chances of successful course completion.

Also, as previously mentioned, regression analyses reveal no significant differences between workers and students in intrinsic motivation. Though there were statistically significant differences in extrinsic motivation, effect sizes were rather small, suggesting that these differences are not incredibly meaningful. This may be partially due to the way in which we assessed motivations for engaging in the courses. Perhaps focusing on the internal and external reasons why learners were motivated to engage is not the most appropriate way of assessing motivation in highly technical MOOCs. In light of these results, we have decided to explore other sources of motivation for MOOC learners.

Of the many motivational theories present in educational psychological literature, Expectancy Value-Cost (EV-C) models [16] could help explain STEM MOOC learner motivations. EV-C proposes that the two main components of motivation to engage in a task are: (1) having an *expectancy* that one will be successful in the task and (2) perceiving *value* in engaging in the task. Expectancy, which is linked to previous achievement-related outcomes (e.g., grades), refers to the extent to which one feels that he or she can be successful in a given task. Value, which is linked to factors like innate interest and future plans related to the current task, reflects the extent to which one feels that a task is worth doing [17,18]. When people value something, and students in particular, they are more likely to engage in the task [19]. Expectancy and value are typically positively related to achievement and persistence in educational settings [20].

EV-C models also take into account the *cost* of engaging in a task. Researchers have found cost to be negatively related to expectancy and value, but also learning outcomes [19]. Within MOOCs specifically, for learners who are employed full-time, the cost of fully participating in a MOOC may be higher than the perceived value or their expectancy of success in the course (i.e., learners may be able to find the information they want by simply skimming and not fully participating). This cost-benefit analysis may be at the center of professionals' attrition from MOOCs. In other words, it may be the case that professional MOOC learners do not experience sufficient expectancy and value to overcome the inherent costs (i.e., time) of participation.

EV-C models, like the intrinsic and extrinsic motivation framework, are centered in individuals' internal beliefs. The results of the present study found high levels of intrinsic motivation across all learners, and we therefore agree that an individual-centered approach to motivation is more appropriate for these classes of learners. In order to understand learners' academic choices, we have to understand what they are thinking and considering while they decide [21]. Future research should include evaluations of motivation through an EV-C framework.

B. Limitations

The low response rate to the survey is indicative of a self-selection bias. Over 22,000 students were initially enrolled in the three courses, but only 1,624 completed responses were received after learners were solicited for the survey. About twenty-percent of learners that submitted responses did not complete at least half of the items and were therefore excluded entirely from analysis. We therefore only had data from a small percent of all learners enrolled in the three MOOCs, which may not be fully representative. To have a better picture of the broader student population enrolling in MOOCs, we may need to either obtain a higher response rate or adjust the survey weightings. The former may be achieved through adjusting the pre-survey timing, frequency, or incentivization, or through web-design such as A/B testing, where some portion of the course-taking population must complete survey questions to continue with the course. For the latter, we may consider weighting survey data based on known demographics for the respondents, as compared to the learner population as a whole, as is commonly done in political polling [22].

In addition, the surveys assess learner motivation from a perspective that may not be the most suitable for this particular learning environment, and therefore motivation may not have been captured in enough detail or in the proper context to fully explain why these groups of learners engaged to the extent that they do.

Finally, it would be ideal to link the survey data directly back to individual learner data. This would enable us to determine the extent to which motivation affects course participation and performance.

VII. Conclusions

In this study, we find that the learners in highly technical STEM MOOC courses generally exhibit overall high levels of intrinsic motivation, but vary in their extrinsic motivation, according to their current position as students, workers, or unemployed individuals. Students generally report the highest levels of extrinsic motivation compared to other groups ($p<0.001$), which is an eminently reasonable result in the context of any course. Overall, these results are part of a larger effort to increase the body of knowledge related to learners who enroll in highly advanced and technical MOOCs. The results from this particular analysis suggest that other factors about learners, such as their course participation and performance, should also be examined in order to better understand the specific needs of the groups of learners enrolling in highly technical STEM MOOCs.

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