Motivation and Knowledge: Pre and Post Assessment of MOOC participants from an Energy and Sustainability Project
Abstract

Understanding factors promoting or preventing participants’ completion of a massive open online course (MOOC) is an important research topic, as attrition rates remain high for this environment. Motivation and digital skills have been identified as aspects promoting student engagement in a MOOC, and they are considered necessary for success. However, evaluation of these factor has often relied on tools for which the psychometric properties have not been explored; this suggests that researchers may be working with potentially inaccurate information for judging participants’ profiles. Through a set of analyses (t-test, exploratory factor analysis, correlation), this study explores the relationship between information collected by administering valid and reliable pre and post instruments to measure traits of MOOC attendees. The findings from this study support previously reported outcomes concerning the strong relationships among motivation, previous knowledge and perceived satisfaction factors for MOOC completers. Moreover, this study gives evidence of the feasibility of developing valid assessments for evaluation purposes.

Keywords: MOOC assessment, exploratory factor analysis, assessment validity
Motivation and Knowledge: Pre and Post Assessment of MOOC Participants from an Energy and Sustainability Project

Since their emergence in 2008, massive open online courses (MOOCs) have ignited the academic community due to their potential concerning a variety of interests beyond presenting a flexible educational alternative (Gaebel, 2013). Ranging from college instructional purposes (e.g., blended learning; Rayyan et al., 2016) to international workforce training (Garrido et al., 2016), educators constantly evolve MOOC scopes moving forward educational content design and technological platforms (Zhang & Nunamaker, 2003). As a result, MOOC projects have become a feasible response to attend current educational challenges at a lesser resources and financial costs (Pegler, 2011).

However, beyond a merely educational response perspective; nowadays, MOOCs have potential as a massive research laboratory (Diver & Martinez, 2015) as well. By individualizing learning, this environment challenges dynamics well examined under traditional educative settings (Mazoue, 2013). For instance, unlike traditional courses, MOOCs’ characteristics not only determine the ways in which content is delivered (e.g., asynchronically, massively, etc.; Kilgore, Bartoletti, & Freih, 2015), but they also challenge what is known about students’ learning characteristics (e.g., learning and habit styles, interest in learning, etc.; Barcena, Martin-Monje, & Read, 2015). Moreover, given that MOOC are courses designed to reach needs sought by huge audiences (Kennedy, 2014), a continuous research approach is required to understand better teaching and learning characteristics present in this format. Therefore, researchers are contributing constantly to the literature by examining MOOCs’ technology, design, delivery conditions, or learning and assessment, among other aspects (Daradoumis, Bassi, Xhafa, & Caballe, 2013).
However, even with an increasing amount of research under execution to promote learning aspects, MOOC participants’ completion rates remain reported regularly as low (0.7–52.1%, with a median value of 12.6%; Jordan, 2015). This makes it necessary to examine what prevents or promotes an attendee’s completion of a MOOC, as completion rates challenge efforts to ensure a MOOC meets quality features for its educational content (Kilgore, Bartoletti & Freih, 2015) or design (Kerr, Houston, Marks & Richford, 2015).

In this regard, educational and psychological aspects have been re-examined to compare outcomes between traditional and MOOC learning settings (e.g., students’ characteristics, course design, etc.; Durksen, Chu, Ahmad, Radil, & Daniels, 2016). However, given that within a traditional setting, learner’s expectations are more standardized or courses completion rates can be a sign of student’s success (Littlejohn, Hood, Milligan, & Mustain, 2016), researchers must evaluate outcomes from this environment when working with MOOC attendees.

Yet, to evaluate participants’ performance (time spent, execution of tasks, etc.), examining MOOC completers has become a common strategy (Stevanovic, 2014), where research shows motivation and digital skills are features strongly supported by MOOC literature to predict learners’ performance (Pursel, Zhang, Jablokow, Choi, & Velegol, 2016; Xu & Yang, 2016).

Given that motivation is strongly related to student engagement (Shapiro et al., 2017), MOOC researchers have included this factor into their agenda. Now, educators deem motivation as important ingredient for participants’ self-regulated learning (Magen-Nagar & Cohen, 2017) and as a requirement to succeed when acquiring content from a MOOC (Barak, Watted, & Haick, 2016).
Although social motivation is an important aspect for traditional learners, inner factors are required to learn from MOOC (e.g., intrinsic and extrinsic motivations; Xiong et al., 2015). As MOOC’s scopes enable delivering education asynchronously and massively (Chen, 2013), keep examining motivation is still a fruitful direction for research (de Barba, Kennedy, & Ainley, 2016) as MOOCs reach massive and diverse audiences (Admiraal, Huisman & Pilli, 2015).

On the other hand, Digital skills are essential features to address in MOOC research, as technology is part of the MOOC environment by definition (Rivera & Ramírez, 2015). Moreover, these courses evolve continuously thanks to educational technology (Yuan & Powell, 2013). It has been found that people with high levels of digital skills choose to participate in MOOCs whereas people with lower levels opt for traditional training (Castaño-Muñoz, Kreijns, Kalz, & Punie, 2017). Thus, limited technology skills hamper participants’ opportunities to finish a MOOC as this format involves a high level of self-management of educational content (Onah, Sinclair, & Boyatt, 2014).

Among the required skills to attend a MOOC, searching and processing information and digital communication are central (Aesaert, Nijlen, Vanderlinde, & Braak, 2014). Thus, it is not surprising that researchers are interested in keep evaluating motivation and digital skills given their importance for MOOC education.

Although traditional assessments (e.g., scoring, providing feedback, etc.) are considered to examine learner’s motivation and digital skills, MOOC’s design prevent deploying these traditional practices given the magnitude of the audience a course reaches regularly (Admiraal, Huisman & Pilli, 2015). Even though validity aspects of traditional tools used to assess readiness towards e-learning remains uncertain (Farid, 2014), criterion-referenced (Dray, Lowenthal, Miszkiewicz, Ruiz-Primo, & Marczynski, 2011) and theoretical or empirical data can be used to
develop valid and reliable tools to explore factors contributing to or impeding students’ participation in MOOCs (Xiong et al., 2015).

As a MOOC grants a data enriched environment (Thille, Scheneider, Piech, Halawa & Greene, 2014), and that there is a need to reinforce tools used to evaluate motivation and digital skills traits, data from MOOC participants become an opportunity for researching purposes addressing such as concerns.

Thus, given that it is imperative to understand learning specific to the MOOC context (Littlejohn et al., 2016), and to continuously gather information about factors encouraging MOOC completion (Blackmore, 2014), this study examines participants’ motivation and digital knowledge characteristics by means of collecting data using a new set of pre and post assessments.

Thus, the objective of this study is to examine relationships between initial motivation and digital/previous knowledge participants reported as influencing their decision to attend a MOOC to similar content information resulting from a post assessment administered to MOOC completers. To accomplish this objective, procedures to 1) identify information among MOOC completers and noncompleters, 2) evaluate psychometric properties of the post measurement tool and 3) correlate initial and ending information from MOOC completers were executed.

**Method**

**Sample**

Participants \( n = 1,315 \), females = 589) from a MOOC titled “La reforma enérgetica y sus oportunidades” (Energetic reform and its opportunities; Tecnológico de Monterrey, 2017) comprised the dataset for this study. Their ages ranged from 15 to 77 years (mean = 30.88, standard deviation [SD] = 10.55), and they reported the following educational levels: high
school, 23%; associate’s degree, 9%; bachelor’s degree, 50%; graduate degree, 14%; and not reported, 4%. In terms of discipline, this pool reported having the following backgrounds: health, 1.75%; art and humanities, 3.35%; business, 12.77%; social sciences, 23.65%; science and engineering, 29.81%; and not defined, 28.66%. Most participants attended this MOOC from a Mexican location (97.5); the remaining locations included Argentina, Colombia and Ecuador.

For a second set of analyses, available information from participants who finished the mentioned MOOC were included ($n = 313$).

**Instrument**

For the first set of analyses, information collected using the second section of the “Encuesta inicial sobre intereses, motivaciones y conocimientos previos en MOOC” (Initial assessment for evaluate interests, motivation and previous knowledge; EIIMC-MOOC; Author, 2017c) was evaluated. This section collects information regarding participants’ reported motivation and previous knowledge related to attending this MOOC. The EIIMC-MOOC presents reliability coefficients of $\alpha = .898$ for the overall structure and $\alpha_1 = .872$, $\alpha_2 = .879$ and $\alpha_3 = .728$ for motivation, previous general knowledge (measuring digital skills) and previous specific knowledge factors, respectively (Author, 2017a).

For the second set of analyses, we used the “Encuesta final sobre intereses, motivaciones y conocimientos previos en MOOC” (Ending assessment for interests, motivations, and previous knowledge; EFMC-MOOC; Author, 2017d). The EFMC-MOOC is a mixed-format, 17-item tool designed to evaluate the changes in motivation and knowledge participants experience after attending a MOOC related to the topic of energy. Given that the EFMC-MOOC was conceived to post-evaluate participants’ motivation and knowledge, its second section emulates the EIIMC-MOOC tool in content and format. Examples of the items include “Este curso satisfizo las
necesidades de formación que me llevaron a inscribirme en él” (“This course satisfied the training needs that motivated me to enroll in it”; motivation and interests) and “Creo que este curso me permitió adquirir los conocimientos básicos de los contenidos estudiados” (“I believe this course allowed me to acquire basic knowledge from the content explored”; acquired knowledge). Experts in education and methodology have evaluated the EFMC-MOOC for content validity, and its format and content have been piloted to evaluate examinees’ comprehension (Author, 2017b). For this study, the second section of the EFMC-MOOC was examined for its psychometric properties (the first section collects demographics).

Procedure

The EIIMC-MOOC and EFMC-MOOC were administered at the beginning and end of the “La reforma enérgetica y sus oportunidades” (Energetic reform and its opportunities) MOOC using links embedded in the course. These links took participants to an online survey service where directions to answer and statements regarding authorizing the use of information collected and confidentiality were presented for each tool. Participation was voluntary, without incentive, and the time needed to complete the survey was approximately 30 minutes.

Analysis

Participants from the “La reforma enérgetica y sus oportunidades” MOOC were divided into two groups—participants who completed both tools (completers) and those who completed the initial tool only (noncompleters). The rationale for employing these groups was to create a proxy to consider participants finishing (group 2) and not finishing (group 1) the course. Thus, to identify profile differences and similarities, as a first set of analyses, a series of t-test analyses was conducted for the defined groups across scores for each factor (motivation, previous general knowledge, and previous specific knowledge) measured by the EIIMC-MOOC tool.
Next, the structure of the EFMC-MOOC tool was examined via exploratory factor analysis (EFA) using the axis factoring method including oblique rotation (direct oblimin); reliability was estimated via Cronbach’s alpha. Examining the EFMC-MOOC structure allowed the instruments’ scopes to be contrasted, as psychometric properties for the EIIMC-MOOC have already been reported (Author, 2017a).

Finally, as content validity for both instruments were already established by a panel of experts before examining the psychometric properties of the EFMC-MOOC tool, correlation analysis was conducted to evaluate associations between pre and post information collected from participants in group 2; to this end, scores yielded from the initial and ending tools were used as variables. All analyses were executed using SPSS 24.0 software (IBM Corp., 2016).

**Results**

**t-Test analyses**

Table 1 shows that on average, participants who finished the MOOC scored higher across variables (motivation, previous general knowledge, and specific knowledge) measured by the initial survey. However, although all mean scores presented significant differences when compared to scores from participants who did not finish the course, the results represented a low effect size ($r$ range of .097 to .223; see Table 2).

<table>
<thead>
<tr>
<th>MOOC Finished?</th>
<th>N</th>
<th>Mean</th>
<th>Std.</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>N</td>
<td>1004</td>
<td>19.55</td>
<td>6.086</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>313</td>
<td>20.88</td>
<td>4.712</td>
</tr>
<tr>
<td>General</td>
<td>N</td>
<td>1004</td>
<td>16.48</td>
<td>5.430</td>
</tr>
<tr>
<td>Knowledge</td>
<td>Y</td>
<td>313</td>
<td>17.68</td>
<td>3.837</td>
</tr>
<tr>
<td>Specific</td>
<td>N</td>
<td>1004</td>
<td>5.30</td>
<td>2.139</td>
</tr>
<tr>
<td>Knowledge</td>
<td>Y</td>
<td>313</td>
<td>5.99</td>
<td>1.702</td>
</tr>
</tbody>
</table>
Exploratory Factor Analysis

The descriptive statistics showed that the normality assumptions were met; the set of 13 items presented an absolute value smaller than 2.3 for skewness (mean of −1.39; range from −2.34 to −0.76), and kurtosis had a mean of 3.29 (range from -0.009 to 9.13). In the presence of large samples, absolute values greater than 3.0 and 10.0 indicate problematic skew and kurtosis indices, respectively (Kline, 2005).

The Kaiser–Meyer–Olkin (KMO) measure verified the sampling adequacy for the analysis; the result was .97, which is well above the acceptable limit of .5 (Kaiser, 1974). Bartlett’s test of sphericity, $\chi^2 (78) = 2123.559, p < .00$, indicated that correlations between items were sufficiently large for executing an EFA procedure.

An initial analysis was run to obtain eigenvalues for each factor in the data. Two factors had eigenvalues over Kaiser’s criterion of 1. In combination, they explained 52.18% of the variance (see Table 3).
This criterion is a good indicator for the number of factors that are tenable to retain when considering a combination of sample size (>250), and the average retained communality is .51 or higher (Field, 2009). Table 4 shows the item communalities extracted for this solution.

**Table 4. Communalities for EFMC-Mooc Sample**

<table>
<thead>
<tr>
<th>Item</th>
<th>Initial</th>
<th>Extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.437</td>
<td>0.448</td>
</tr>
<tr>
<td>2</td>
<td>0.523</td>
<td>0.579</td>
</tr>
<tr>
<td>3</td>
<td>0.643</td>
<td>0.620</td>
</tr>
<tr>
<td>4</td>
<td>0.456</td>
<td>0.424</td>
</tr>
<tr>
<td>5</td>
<td>0.485</td>
<td>0.456</td>
</tr>
<tr>
<td>6</td>
<td>0.358</td>
<td>0.270</td>
</tr>
<tr>
<td>7</td>
<td>0.502</td>
<td>0.454</td>
</tr>
<tr>
<td>8</td>
<td>0.517</td>
<td>0.656</td>
</tr>
<tr>
<td>9</td>
<td>0.501</td>
<td>0.538</td>
</tr>
<tr>
<td>10</td>
<td>0.418</td>
<td>0.399</td>
</tr>
<tr>
<td>11</td>
<td>0.597</td>
<td>0.658</td>
</tr>
<tr>
<td>12</td>
<td>0.574</td>
<td>0.577</td>
</tr>
<tr>
<td>13</td>
<td>0.669</td>
<td>0.705</td>
</tr>
</tbody>
</table>

Extraction Method: Principal Axis Factoring.
The scree plot showed a clear inflexion that would justify retaining two factors (Figure 1). Thus, given the large sample size, convergence of the scree plot, and Kaiser criterion found on this solution, two factors were retained in the final analysis.

![Scree Plot](image)

**Figure 1. Scree Plot for the EFMC-MOOC Sample**

A clear pattern matrix was obtained for this two-factor solution (see Table 5). The items that clustered on the same components suggested that factor 1 represents a motivation and interest dimension (6 items), while factor 2 represents gained knowledge (4 items).
Reliability analysis estimated via Cronbach’s method presented $\alpha = .898$ for the structure. The values were $\alpha_1 = .829$ and $\alpha_2 = .882$ for factors 1 and 2, respectively.

**Correlations**

In terms of the correlation results obtained when pre and post information was obtained from participants who finished the MOOC, there were significant ($p < .01$ level) outcomes across all factors examined. Motivation presented a higher correlation when examined with factors taken from the final tool ($r = .606$ and $r = .506$ for factors 1 and 2, respectively). As for the other initial factors, previous general and specific knowledge correlated moderately significantly with final factors 1 and 2, although previous specific knowledge presented a weaker relationship (see Table 6).
Discussion

MOOC environments are becoming an important setting for exploring learners’ characteristics. Accordingly, the results from this study support efforts to continue investigating such characteristics, especially to understand the participants’ motivation, knowledge (previous and acquired) and levels of satisfaction; this research line is important because once a completers’ profile is identified, MOOCs can be personalized to engage attendance more effectively as a strategy to reduce dropout rates (Alario-Hoyos, Pérez-Sanagustin, Kloos, Parada, & Muñoz-Organero, 2014).

When examining the initial information, the scores for motivation and previous general and specific content knowledge factors were higher for the completers group compared with the noncompleters group. It should be mentioned that these outcomes also showed low effect sizes, suggesting that the results need to be interpreted cautiously; however, they are in agreement with the literature reporting that completers obtain significant higher ratings, as they have confidence

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Factor 1</strong></td>
<td>Pearson Correlation</td>
<td>.691**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>313</td>
</tr>
<tr>
<td><strong>Factor 2</strong></td>
<td>Pearson Correlation</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>313</td>
</tr>
<tr>
<td><strong>Motivacion</strong></td>
<td>Pearson Correlation</td>
<td>.606**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>294</td>
</tr>
<tr>
<td><strong>Previous general knowledge</strong></td>
<td>Pearson Correlation</td>
<td>.496**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>296</td>
</tr>
<tr>
<td><strong>Previous specific knowledge</strong></td>
<td>Pearson Correlation</td>
<td>.363**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>301</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
Note: factor 1 = profesional development; factor 2 = technology skills.
in their ability to complete MOOCs successfully (Barak et al., 2016). Moreover, it is notable that the scores were consistently significant across all factors, although the categories for grouping attendees (completers vs. noncompleters) did not account for heterogeneous background profiles. Thus, future analysis to differentiate attendees’ profiles should also consider reviewing other types of information (e.g., educational levels, work training, etc.) about participants to evaluate differences by subcategories as well.

As for the structure of the EFMC-MOOC, the results support the claim that this tool meets the initial validity and reliability standards. The statements of the items loading on each factor allow the interpretation that this tool measures participants’ levels of satisfaction about the gains obtained after attending the MOOC. This satisfaction level can be evaluated by a two-factor structure involving 1) professional development gains and 2) technology skills growth. These factors correlate highly, but are they are well differentiated ($r = .737$), and together, they explain 52% of the variance. This is consistent with the findings reported in literature when exploratory analyses are executed. In terms of reliability, the EFMC-MOOC shows internal consistency for the overall structure and across factors. An advantage of examining the psychometric structure of an instrument relates to the viability of interpreting students’ scores properly, for instance, to identify students at risk (Farid, 2014). In traditional education, administering pre and post assessment tools with similar content is a regular activity to evaluate learning; however, for MOOC environments, this activity is still developing (Chudzicki, Chen, Zhou, Alexandron, & Pritchard, 2015). Accordingly, the present results align with such efforts. Moreover, developing reliable measures provides opportunities to current efforts to track and understand participants’ changes in behavior and performance occurring across MOOC attendance (Aiken et al., 2014; Perna et al., 2014). Future research projects could include using
valid tools as formative assessments to track such as changes, as it is desirable to have immediate measures rather than a delayed measure of situational interest (de Barba et al., 2016).

In terms of the pre and post information derived from attendees finishing the MOOC, all scores from factors measured initially correlated significantly to final scores. The results showed a consistent moderate association across variables. Like in a previous report about the role motivation plays in perceived learning (Horzum, Kaymak, & Gungoren, 2015), the motivation factor measured in this study appeared to be the stronger variable associated with perceived satisfaction levels for attending a course. In contrast, the previous specific knowledge variable correlated less with to final information, and although prudence recommended when interpreting previous knowledge self-evaluation scores (Lui & Li, 2017), this finding agrees with reports asserting that this factor not only relates to engagement, but is also a strong predictor for success in a MOOC (Kennedy, Coffrin, & de Barba, 2015).

Overall, the findings from this study are consistent with the previous literature focussing on the need to understand attrition factors and motivational transition across MOOCs (Xu & Yang, 2016). Accordingly, it has also been suggested that pedagogical models should consider the technology practices involved (e.g., digital skills) to engage participants continuously to increase retention (Petronzi & Hadi, 2016). The combination of factors evaluated in this study (motivation, knowledge, satisfaction level) follows suggestions about not relying on behavioral aspects exclusively, but instead, including cognitive elements, as both aspects are related to MOOC engagement. Thus, they both increase the probability of completing a course (Li & Baker, 2016).

Finally, examining potential relationships among information collected pre and post attending a course and comparing initial profiles of completers and noncompleters may have
benefits in terms of orienting MOOCs to the work market, since a solely academic-oriented objective can detract from participants’ learning, as transfer of knowledge is not guaranteed (Sanchez-Acosta, Escribano-Otero, & Valderrama, 2014). Thus, future research should consider how motivation and previous knowledge result when MOOCs target different objectives, as in the applied project supporting participants from this MOOC. Moreover, research data emerging for such research should also consider an open access perspective, as by nature, MOOCs comprise open-access learning materials. Thus, the results and tools derived from this type of courses should align to this perspective to ensure that they are innovative (McGreal, Mackintosh, & Taylor, 2013).
Conflict of Interest Declaration

The author(s) declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Author (2017d).


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