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Finding Competent Reviewers for Online Courses

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Short Research Paper

Finding Competent Reviewers for Online Courses

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Abstract: Identifying competent reviewers who can contribute helpful reviews for online courses is an imperative task for online learning platforms and course instructors. Online learners value reviews of recent course experience, as such a proactive approach to soliciting and incentivizing reviews from competent reviewers is needed. This research proposes two performance-based reviewer competence indicators, i.e., reviewers' prior helpfulness and specialization, and tests their predictive power on reviewers' contributing helpful online course reviews. A sample of 36,825 reviews and their reviewers on a leading MOOC platform in China was analyzed. Results show that both reviewers' prior helpfulness and specialization predict the helpfulness of their review contribution. The predictive power of reviewers' prior helpfulness is susceptible to situational conditions, including learners/reviewers' working status and course learning performance, whereas that of reviewer specialization is relatively consistent. This research enhances the understanding of performance-based reviewer competence assessment, particularly in the online learning context. Its results can be directly applied to identify potential reviewers and solicit helpful online course reviews.

Keywords: review helpfulness, reviewer competence, prior performance, online learning, performance-based measures

1. INTRODUCTION

The proliferation of online learning in the past decade and the surge of Massive Open Online Courses (MOOCs) since 2012 worldwide have significantly expanded the accessibility of education to the general population [1, 10, 17]. Until October 2020, more than 30 MOOC platforms have been launched in China. These platforms host over 34,000 MOOCs with 540 million learners [2]. Over 150 million university students have received credits from MOOCs [2]. With a large number of online courses available, prospective learners often face significant difficulties in choosing high-quality and suitable courses. Therefore, they rely heavily on online course reviews for informed decision-making.

Online course reviews are a common feature of online learning platforms. Online course reviews are different from traditional course evaluations/feedbacks in educational institutions, which are solicited confidentially at the end of each semester for the use of the program and course instructors. Online course reviews on online learning platforms are similar to online product reviews on commercial platforms in both format and purpose. In general, they consist of a numeric rating and comments by learners who have taken the course or anyone who wants to share information. They are listed on a course webpage for any interested parties to access.

As prospective learners rely on course reviews to make informed course decisions, they highly value the recency and timeliness of reviews that project the latest course experience. Consequently, identifying potential reviewers and soliciting high-quality and helpful course reviews proactively and promptly is of great importance for online course providers and online learning platforms to support and satisfy the information needs of prospective learners.

Identifying potential reviewers who can contribute helpful course reviews entails an understanding of

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reviewer competence indicators and their relations to reviewers' review contributions. That is, what reviewer attributes can predict useful review contributions? However, little research has addressed this question. Extant literature on online reviews has examined reviewer information as peripheral cues in reader's review elaboration [3, 4, 18]. That is, when reviewer information, such as gender [3], identity [4], profile image [5], and expertise [6, 7], are presented along with reviews, they affect review readers' judgment on the review helpfulness. These peripheral cues are not reviewer competence indicators in that the later points to reviewers' intrinsic ability to contribute helpful reviews. In the limited research on the subject, Du et al. [8] suggest that past review helpfulness is a strong indicator of reviewer competence in contributing helpful reviews.

To gain further understanding on reviewer competence in the online course contexts, this research posits reviewers' prior review helpfulness [7] as well as their specialization as two competence indicators and tests their predictive powers on the helpfulness of review contribution. In addition, we examine the boundary conditions of the relationship based on learners/reviewers' working status and course performance.

Empirical analysis on 36,825 reviews from 24,491 reviewers on a leading MOOC platform in China indicates that both reviewer prior review helpfulness and their review specialization are useful reviewer competence indicators, predicting their review performance. Interestingly, the predicting results of reviewer prior helpfulness are more susceptible to the varying conditions of contextual factors including reviewers' working status and course performance. Its predicting power is stronger for learners/reviewers who have a full-time job and perform well in the course. Specialization, on the other hand, stays more consistent in indicating reviewer competence. Its association with reviewer competence does not vary by reviewers/learners' working status and course performance.

2. BACKGROUND

Based on audience' helpfulness votes, a large body of research has studied factors that affect the perceived helpfulness of online customer reviews [11-13, 18, 19]. The research has largely taken a perspective of readers' information processing to understand how readers evaluate perceived review helpfulness through various available information. Dual-process theories, such as the elaboration likelihood model, are commonly applied to explain the effects of identified information factors [11]. Factors affecting the argument quality of a review such as review depth, content sentiment, and linguistic style [11-13, 19] are central factors involved in message elaboration. Reviewer information that is provided to the audience along with reviews, such as reviewer gender [3], identity [4], profile image [5], experience [14, 15], and expertise [6, 7], are source cues or peripheral factors for simplified inferences on the value of the message.

The crowd-based review quality assessment mechanism employs a result-oriented approach by relying on readers to vote for the helpfulness of reviews. The approach is effective but can be redundant and time-consuming. That is, a large number of reviews of a wide variety of quality and helpfulness are provided to readers; the voting process takes time and effort; the helpfulness results are prone to biases [16]. A proactive approach is to identify reviewers who can contribute helpful reviews and solicit and recommend reviews from them. However, little research has examined reviewer competence and indicators. Among a few exceptions, Mathwick and Mosteller [9] identified three types of reviewers with different egoistic motives of contributing reviews, including indifferent independents, challenge seekers, and community collaborators. They suggest that reviewers of different types can benefit from tailored review environments for review contribution [9]. Du et al. [8] examined reviewers' performance-based measures and found that past review helpfulness is a strong indicator of reviewer competence in contributing helpful reviews.

3. RESEARCH FRAMEWORK

This research explores two performance-based reviewer competence indicators, namely reviewer prior helpfulness and reviewer specialization. Reviewer competence concerns their ability in generating helpful reviews. Reviewer prior helpfulness refers to the general level of helpfulness of a reviewer as reflected in prior review postings. Reviewer specialization refers to the extent of course categories a reviewer's opinions are valued for. It relates to the breath of the reviewer's competence. Reviewers of high specialization receive a high share of helpfulness votes from their reviews on courses of a similar type. Reviewers of low specialization are valued for their reviews in multiple course categories.

We posit the two performance-based reviewer competence indicators can predict the quality of their future review contributions. We propose the following hypotheses:

***H1a**: Reviewer prior helpfulness predicts the helpfulness of their incoming reviews on online courses.*

***H1b**: Reviewer specialization predicts the helpfulness of their incoming reviews on online courses.*

Additionally, we posit that contextual factors such as learners/reviewers' working status and learning performance may alter the predicting power of reviewer prior helpfulness and specialization on review helpfulness. We propose the following hypotheses:

***H2**: The prediction powers of reviewer prior helpfulness and specialization on online course review helpfulness vary across learners/reviewers with different working status.*

***H3**: The prediction power of reviewer prior helpfulness and specialization on online course review helpfulness varies with the learning performance of a reviewer in a course.*

4. METHODOLOGY

4.1 Data

We obtain a propriety dataset from a leading MOOC platform in China. The MOOCs on the platform can open as separate sessions repeatedly. The dataset contains all 1,355,280 course reviews for 5,821 MOOCs on the platform from May 2014 to Feb. 2021. Course reviews on the focal MOOC platform are presented on the course webpages, on which the number of registered learners of each course session, the number of all course reviews, and the average numeric rating of all course reviews are presented. Each course review consists of a numeric rating and a short textual comment posted by learners who have registered for the course. Meanwhile, the reviewer's nickname and avatar, the date of review posting, and the registered course session of the reviewer are also publicized. Moreover, the learner/reviewer will receive a course certificate if he/she earns a score that is higher than the required one.

To test our hypotheses, we construct the dataset for analysis in the following way. First, following prior studies [23], we keep course reviews that have received at least one vote. This results in a dataset of 179,205 reviews (i.e., 13.22% of the total reviews posted). Second, to test the impacts of reviewers' prior helpfulness, we eliminate the first course review of each reviewer. Then, we remove the course reviews produced by reviewers who do not report whether they are "Professional" or "Student". Finally, because it takes time for course reviews to accrue helpfulness votes, we remove relatively new course reviews that were posted within 60 days of data retrieval to ensure that each course review has sufficient time to accumulate helpfulness votes [24]. The final dataset for analysis contains 36,825 course reviews from 24,491 reviewers.

4.2 Variables

Table 1 presents the definitions and operationalizations of the dependent variable, independent variables, moderator, and control variables.

Table 1. Definition and operationalization of variables

Variable	Definition and operationalization
Dependent variable	
ReviewHelpfulness	The helpfulness of a course review; measured by the number of helpfulness votes a review receives.
Independent variables	
ReviewerPriorHelpful	Reviewers' prior helpfulness; measured by the average number of helpfulness votes per review a reviewer received before posting a focal review.
ReviewerSpecialization	Reviewer specialization; measured by the Herfindahl-Hirschman Index (HHI) of the helpfulness votes received by a reviewer across course disciplines.
Moderators	
Professional	A dummy variable with the value of 1 denoting working learners and the value of 0 denoting learners without ongoing work.
LearningPerformance	A learner/reviewer course performance; measured by a dummy variable with the value of 1 for learners who finish a course and receive the course certificate, and 0 otherwise.
Control variables	
ReviewExtremity	The extremity of a course review is measured by a dummy variable with the value of 1 for reviews with rating 1 or 5, and 0 otherwise.
ReviewValence	Review positivity is measured by a dummy variable with the value of 1 for reviews with rating 4 or 5, and 0 otherwise.
ReviewLength	The length of a course review; measured by the number of Chinese characters in a review.
ReviewInconsistency	The extent to which a review rating differs from the average rating of a course; measured by the absolute difference between the numeric rating of a course review and the average rating of all reviews for the course.
ReviewAge	Review age; measured by the number of days between the review posting date and the data retrieval date.
CourseLoad	Course load; measured by the average number of lecture videos required to learn by the course in each week within the class duration.
CoursePopularity	The popularity of a course; measured by the number of reviews it receives.
CourseSatisfaction	Learners' course satisfaction toward a course; measured by the average numeric rating of all reviews it receives.

4.3 Empirical model

The regression equation used in our study is specified in equation (1). Because the dependent variable, *ReviewHelpfulness*$_i$ is a count variable of an over-dispersion nature, the negative binomial model is used in the analysis [20, 21]. Natural logarithm transformation is taken when a variable is highly skewed.

$$\begin{aligned} ReviewHelpfulness_i \; = \; & \beta_0 + \beta_1 LogReviewerPriorHelpful_i + \beta_2 ReviewerSpecialization_i + \\ & \beta_3 LogReviewerPriorHelpful_i \times Professional_i + \beta_4 ReviewerSpecialization_i \times \\ & Professional_i + \beta_5 LogReviewerPriorHelpful_i \times LearningPerformance_i + \\ & \beta_6 ReviewerSpecialization_i \times LearningPerformance_i + \beta_7 Professional_i + \\ & \beta_8 LearningPerformance_i + \beta_9 ReviewExtremity_i + \beta_{10} ReviewValence_i + \\ & \beta_{11} LogReviewLength_i + \beta_{12} ReviewInconsistency_i + \beta_{13} LogReviewAge_i + \\ & \beta_{14} CourseLoad_i + \beta_{15} LogCoursePopularity_i + \beta_{16} CourseSatisfaction_i + \\ & \beta_{17-18} ReviewYear_i + \beta_{19-29} ReviewMonth_i + \beta_{30-35} ReviewDoW_i + \\ & \beta_{36-58} RClassNo_i + \beta_{59-69} CourseDiscipline_i + \varepsilon_i \qquad (1) \end{aligned}$$

5. RESULTS AND ANYLYSES

5.1 Descriptive analysis

Table 2. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Median	Max.
ReviewHelpfulness	36,826	2.919	13.410	1	1	1,445
ReviewerPriorHelpful	36,826	1.171	10.726	0	0	1,195
ReviewerSpecialization	36,826	0.823	0.267	0.115	1	1
Professional	36,826	0.309	0.462	0	0	1
LearningPerformance	36,826	0.275	0.447	0	0	1
ReviewExtremity	36,826	0.901	0.298	0	1	1
ReviewValence	36,826	0.946	0.226	0	1	1
ReviewLength	36,826	29.203	43.239	5	15	500
ReviewInconsistency	36,826	0.390	0.605	0	0.231	3.950
ReviewAge	36,826	521.586	254.652	60	500	1.106
CourseLoad	36,826	4.868	3.380	0	3.927	32.500
CoursePopularity	36,826	789.539	1,941.914	1	296	28,063
CourseSatisfaction	36,826	4.760	0.169	2.538	4.785	5

Table 2 presents the descriptive statistics of the variables in the study. The mean of the dependent variable, *ReviewHelpfulness*, is 2.919. That is, a course review in the dataset for analysis receives about 3 helpfulness votes. The mean of *ReviewerPriorHelpful* is 1.171, indicating that the reviewers in the MOOC platform received an average of about one helpfulness vote per review. The mean of *ReviewerSpecialization* is 0.823, which reveals that the reviewers in general are of low specialization. They post reviews and receive helpfulness votes across a wide range of course disciplines. The mean of *LearningPerformance* is 0.275. In other words, 27.5% of the course reviews in our dataset were posted by reviewers who have earned the certificate for the course they reviewed for. Because a learner may receive a course certificate only when he/she has passed the course, the ratio shows that the pass rate among course reviewers is significantly higher than the reported low pass rate in all learners [28]. The mean of *Professional* is 0.309, indicating that 30.9% of the reviewers are working professionals. It shows that MOOCs are not only popular among students but are well accepted among working professionals. The mean of *CourseLoad* is 4.868, i.e., on average, learners are required to watch nearly 5 course videos per week in a course.

5.2 Empirical analysis

Table 3. Estimation results

DV: ReviewHelpfulness	(1)	(2)	(3)	(4)
Log#ReviewerPriorHelpful	0.166***	0.157***	0.156***	0.030
	(0.008)	(0.010)	(0.010)	(0.030)
ReviewerSpecialization	0.056**	0.035	0.051*	0.211**
	(0.022)	(0.027)	(0.028)	(0.086)
Log#ReviewerPriorHelpful		0.029*		0.019
×Professional		(0.018)		(0.018)
ReviewerSpecialization		0.061		0.059
×Professional		(0.045)		(0.045)
Log#ReviewerPriorHelpful			0.039**	0.040**

DV: ReviewHelpfulness	(1)	(2)	(3)	(4)
×LearningPerformance			(0.018)	(0.018)
ReviewerSpecialization ×LearningPerformance			0.015 (0.045)	0.017 (0.045)
Professional	-0.052*** (0.013)	-0.052*** (0.013)	-0.079* (0.040)	-0.079* (0.040)
LearningPerformance	-0.213*** (0.014)	-0.273*** (0.040)	-0.213*** (0.014)	-0.266*** (0.041)
ReviewExtremity	0.152*** (0.019)	0.152*** (0.019)	0.152*** (0.019)	0.152*** (0.019)
ReviewValence	-0.460*** (0.050)	-0.459*** (0.050)	-0.462*** (0.050)	-0.457*** (0.050)
Log#ReviewLength	0.363*** (0.006)	0.363*** (0.006)	0.362*** (0.006)	0.362*** (0.006)
ReviewInconsistency	0.076*** (0.019)	0.076*** (0.019)	0.076*** (0.019)	0.078*** (0.019)
Log#ReviewAge	-0.235*** (0.038)	-0.234*** (0.038)	-0.234*** (0.038)	-0.231*** (0.038)
CourseLoad	0.025* (0.013)	0.025* (0.013)	0.025* (0.013)	0.092** (0.046)
CoursePopularity	0.120*** (0.005)	0.120*** (0.005)	0.120*** (0.005)	0.121*** (0.005)
CourseSatisfaction	-0.131*** (0.038)	-0.130*** (0.038)	-0.133*** (0.038)	-0.135*** (0.038)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y
Class no FE	Y	Y	Y	Y
Course discipline FE	Y	Y	Y	Y
lnalpha	-0.502*** (0.010)	-0.503*** (0.010)	-0.503*** (0.010)	-0.504*** (0.010)
#observations	36,825	36,825	36,825	36,825
Log likelihood	-73,713.12	-73,711.33	-73,710.64	-73,692.33

Note: * p<0.1; * p<0.05; *** p<0.0

Table 3 presents the results of regression analyses. Model 1 shows that the parameter estimation of reviewers' prior helpfulness and specialization are both significantly positive. Thus, H1a and H1b are strongly supported.

Models 2 to 4 include interaction terms of situational factors and reviewer competence indicators to test H2 and H3. As shown in Models 2 and 4, the parameter estimations of the interaction term between learners' working status (i.e., professional) and reviewer prior helpfulness re significantly positive, but those of the interaction term between professional and reviewer specialization are insignificant. This indicates that reviewer prior helpfulness is a stronger predictor of review performance for working learners than for non-working learners, but the prediction power of reviewer specialization remains consistent across learner types about their working status. H2 is partially supported.

As shown in Models 3 and 4, the parameter estimations of the interaction term of learning performance and reviewer prior helpfulness are significantly positive, but those of the interaction term between learning performance and reviewer specialization are insignificant. This indicates that reviewer prior helpfulness is a stronger predictor of review performance for learners with course certificates than for those without, but the prediction power of reviewer specialization remains consistent across learner types with and without course certificates. H3 is partially supported.

6. DISCUSSIONS AND CONTRIBUTION

This research proposes and explores reviewers' prior review helpfulness and review specialization as key reviewer competence indicators and provides evidence on their predictive power on the quality of review contribution. Moreover, we examine the boundary conditions of the relationships based on learners/reviewers' working status and course performance. Our findings indicate that both reviewers' prior helpfulness and specialization are useful reviewer competence indicators. The predicting results of reviewer prior helpfulness are susceptible to the varying conditions of situation factors. It is a more effective predictor for learners/reviewers who have a full-time job and perform well in the reviewed course. Meanwhile, specialization stays more consistent in indicating reviewer competence. Its predicting power does not vary by reviewers/learners' working status and learning performance in the reviewed course.

This research makes several contributions. It advances the understanding of reviewer competence by delineating and validating two performance-based indicators and providing evidence of their predicting power on reviewer performance in review contribution. It also probes the conditions that affect the predicting power of reviewer competence indicators on review helpfulness. Furthermore, it is one of the first to study online course reviews, which is an important topic in the surging e-learning trend but has been neglected in prior IS research. The knowledge from this research can be directly applied by online learning platforms in identifying competent reviewers and soliciting and recommending reviews for online courses.

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