IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 1, 2020, accepted August 8, 2020, date of publication August 20, 2020, date of current version September 11, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3018132

Influence of MOOCs eWOM on the Number of Registrations and Completions

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This work was supported in part by the Chinese National Social Science Fund Thirteenth Five-Year Plan Education Topic under Grant BFA180064, in part by the Shanghai Philosophy and Social Sciences Project under Grant 2016BGL002, and in part by the Post-Graduate Education Reform Project of Tongji University under Grant ZD1903018.

ABSTRACT MOOCs (Massive Open Online Courses) users continue to rise in number globally, and accordingly, the electronic word of mouth (eWOM) for MOOCs is an important source of information for MOOCs learners, but research on the effects of MOOCs eWOM is still lacking. Therefore, from the perspective of group size and group recognition in the MOOCs online review forum and the internal relationships in the MOOCs course learning forum, this paper studies the influence mechanism of MOOCs eWOM on the number of registrations and completions. First, according to the literature review, based on the number of online reviews, the online rating valence and eWOM publishers in the MOOCs online review forum, as well as the number of posts and the number of teaching assistants in the MOOCs course learning forum, research hypotheses are proposed in this study to construct a conceptual model. Second, Coursera is the typical MOOCs platform that is selected as the research object to obtain data from November 2018 to August 2019. Third, after preprocessing the data, on the basis of the Hausman test, the corresponding fixed effect of an econometric model is established, and Stata is used to process the data to verify the research hypotheses. Finally, according to the research conclusions related to eWOM, to improve the number of registrations and completions of MOOCs, development suggestions are proposed for MOOCs platform providers and MOOCs course providers, as well.

INDEX TERMS Educational technology, management information systems, online communities/ technical collaboration.

I. INTRODUCTION

MOOCs (Massive Open Online Courses), as an emerging Internet education model, represents a new stage in the development of open education resources for students worldwide. MOOCs is a self-driven Internet education model [1]. This education model, on the one hand, gives students free time and course arrangements and provides the possibility for personalized learning; on the other hand, there is a sharp contrast between the higher MOOCs course registrations and the lower completion volume, which becomes the main problem that affects the learning effectiveness of MOOCs [2].

The MOOCs platform provides both the online review forum and the course learning forum. MOOCs learners and MOOCs instructors can communicate and interact through the MOOCs forum. More and more MOOCs learners are willing to take the initiative in sharing the MOOCs learning experience on the MOOCs platform and tend to search for the MOOCs learning experience shared by other MOOCs learners; thus, social learning becomes one of the characteristics of MOOCs [3].

The MOOCs platform provides online review functions, and thus, it will use electronic word of mouth (eWOM) for their audience. The online review function has become an important source for consumers to obtain product information and reduce product uncertainty. Consumers increasingly rely on eWOM to make purchase decisions [4]. Similarly, the online review function of a MOOCs platform has become an important source for MOOCs learners to obtain course information and thus reduce the uncertainty of the course selection. MOOCs learners use MOOCs eWOM to evaluate the quality of the MOOCs and make decisions for MOOCs registration and learning.

The impact of eWOM on the purchasing behavior of consumers has received widespread attention. Studies have shown that eWOM has an enormous impact on product

The associate editor coordinating the review of this manuscript and approving it for publication was Justin Zhang.

sales [5]. In the field of MOOCs, with the worldwide development of MOOCs, the number of MOOCs learners continues to rise globally. Many studies discuss the learning behavior of MOOCs learners from the perspectives of the motivation of learners and the courses provided by the MOOCs platform [7]. Research on the effect of MOOCs eWOM on the number of registrations and completions is still lacking. Therefore, from the perspective of eWOM, this article explores the impact mechanism of MOOCs eWOM on MOOCs registration and completions, which can provide a theoretical basis for improving the effectiveness of the MOOCs.

II. LITERATURE REVIEW

To gain a comprehensive understanding of our research question, a literature review is conducted. The first section summarizes MOOCs related research to justify eWOM in this specific domain. In the following sections, we review recent studies of eWOM to introduce how it works under information asymmetry.

A. MOOCs RESEARCH

Large scale is the first attribute of MOOCs. Anyone connected to the Internet can register for MOOCs, gain access to MOOCs resources, interact with MOOCs learning peers, and exchange knowledge and share knowledge with MOOCs learning peers [8]. Openness is the second attribute of MOOCs, which is reflected in free access, sharing and collaboration [9]. Learners can choose to register for MOOCs and participate in MOOCs learning for free [10], [11]. At present, Coursera, edX and Udacity are three internationally well-known MOOCs platforms, each of which is associated with well-known higher education institutions. Among them, Coursera is an international MOOCs platform, and it provides comprehensive courses.

For the research on MOOCs, 2012 acted as a turning point. Most of the research before 2012 was based on the relevant educational theories, studying the impact of MOOCs on higher education organizations from the perspective of the curriculum; thus, it lacked research on the quality of MOOCs and MOOCs learning behaviors [12]. After 2012, with increasing of internationalization and diversification of MOOCs, social network theory, self-determination theory and activity theory were gradually applied for in-depth exploration of MOOCs [13]. Correspondingly, the research theme was transferred to the participation of MOOCs learners, MOOCs completions and the role of social networking platforms in MOOCs learning [14].

With the worldwide development of MOOCs, the number of users on MOOCs platforms has been increasing gradually, but there are few MOOCs learners who actually complete the courses. The majority of the MOOCs course completion percentages is less than 10%, and the overall average completion percentage is approximately 5% [15]; thus, the motivation of learners has become the research focus of MOOCs [16]. Researchers conducted extensive discussions from the perspective of both individual MOOC learners and the MOOC educational environment.

From the perspective of individual MOOC learners, researchers mainly study the learning motivation and strategies of learners [17]. Through a questionnaire survey, it was found that the main motivation for learners to have MOOCs is learning interest [18], followed by the requirement of career development [19]. Learning interest is the prerequisite for learning MOOCs. It was found that the learning motivation level and the knowledge level can be used to predict the probability of learners completing the course [20]; and compared with learners who do not use a MOOCs learning forum, the number of completed learners who use the MOOCs learning forum is higher [21]. From the perspective of the MOOCs educational environment, the MOOCs platform as an open education platform can provide learners with personalized courses. MOOCs learners can interact and communicate in a MOOCs course learning forum. Research has found that the number of postings in a MOOCs course learning forum has a positive impact on the course completion rate [22]; the openness and reputation of the MOOCs curriculum have a significant positive impact on the willingness of learners to continue learning. The better the reputations of the MOOCs are, the stronger the willingness of a learner to continue learning [10].

Therefore, MOOCs as an online education platform, MOOCs online review information and MOOCs learning discussion information constitute MOOCs eWOM, but there is little research on MOOCs eWOM and its impact.

B. eWOM RESEARCH

The presence of eWOM is widely considered to be one of the most important factors that affects consumer behavior and the most important source of information for consumers in making purchasing decisions.

eEWOM is especially important for intangible products, which are difficult to evaluate for consumer choices; for example, in tourism or hotels, the overall satisfaction of the consumers will affect the behavioral decisions of others [23]. This circumstance has made eWOM becomes a more reliable medium [24].

eWOM can provide consumers with all of the information related to the use, characteristics and sales of goods or services [25], [26]. Consequently, eWOM has become one of the most influential sources of information on the Internet, and it has great marketing value to enterprises, which makes eWOM a hot research topic [27], [28].

In the research on the publishing motivation of eWOM, social relationship motivations have the greatest impact on the eWOM of consumers [25]. Based on the theory of social transactions, it is found that the degree of effort that consumers need to give to obtain favorable rewards negatively affects the consumers' willingness to praise [29]–[31].

Taking eWOM publisher's profile picture as a research object, it was found that eWOM publisher's profile picture can significantly improve a consumers' evaluation of the usefulness of online reviews [32]. In addition, the network centrality of the reviewers in the group will affect other consumers' evaluations of the usefulness of their reviews [33].

According to the relevant literature in the education field, reputation is a research hotspot similar to eWOM, and eWOM is the reputation in the mobile Internet era [34]. Reputation in the education field can be understood as eWOM possessed by a university, a teacher, or a course, which shows the degree of public recognition. The research on eWOM in the education field mainly focuses on two aspects: one aspect is the reputation influence and the other aspect is reputation management.

Relating research on reputation influence in the education field has found that the reputation of university professors will affect students' course selection behavior. The reputation of professors has a positive influence on students' decision-making in course selection. The better the professor's reputation, the greater the intention of the students' course selection [35]. University reputation has a significant positive impact on the decision-making process for individuals to choose universities [36]. Students prefer to choose universities with high reputations. Based on these considerations, a questionnaire survey is used to find that the reputation has a positive impact on the image of the university, which then will have a positive impact on the student loyalty and satisfaction [37]. Therefore, the effective dissemination of eWOM plays a positive role in the building of college brands in higher education.

University reputation is a cognitive result and emotional response in the brain caused by factors such as university spirit, university behavior, school operating facilities, and social contributions. Reputation management has become a new topic for university development. Modern universities are socially embedded and are no longer a closed group. Therefore, reputation management is especially important in the construction of colleges and universities. Reputation management in colleges and universities has three dimensions, i.e., performance records, moral standards and professional quality [38].

In the education field, eWOM is manifested by reputation, and reputation has an impact on students' decision-making behavior in course selection and school selection. Most of the current reputation researches in the education field focuses on the reputation influence of teachers or universities. With the increasing numbers of learners in the MOOCs platform, information asymmetry is widespread, and MOOCs eWOM is an important source of information that affects learners' autonomous learning decisions. Therefore, under an information asymmetry situation, the impact of MOOCs eWOM on learners' course selection and learning behavior is especially important, but there are few related studies.

C. ASYMMETRIC INFORMATION SITUATION

Asymmetric information means that in market economic activities, all types of people have different understandings of the relevant information. In the market, the seller understands all types of information about the commodity better than the buyer. The party with more information can benefit from the market by delivering reliable information to the information-poor party [39]. With the rapid development of the Internet, producers are no longer the only source of commodity information, eWOM has become an important part of commodity information. Consumers are both users and producers of commodity information. Thus, eWOM has greatly reduced the information asymmetry between producers and consumers and has become an important reference for consumers when choosing commodities.

Due to the prevalence of information asymmetry, the actual value of goods purchased by consumers could be lower than the expected value. Therefore, each purchase decision made by consumers will bear certain risks, which are embodied in six dimensions, i.e., finance, function, physical, psychological, social and time [40].

Under an asymmetric information situation, after perceiving the risks, consumers will tend to use certain clues as the basis for judging the value of commodities to reduce their perceived risks [41]. The perceived value that clues bring to consumers is divided into the predictive value and the confidence value. Clues are divided into intrinsic cues and extrinsic cues. Among them, internal cues refer to some information inherent in the product itself and are not affected by external factors; external cues refer to additional information about the product, which will change over time. When consumers judge the value of commodities, internal clues of commodities are difficult to obtain; therefore, when there are few internal clues, consumers are inclined to rely on the external cues of commodities, and use easy-to-obtain information about commodity eWOM as external cues [42], for example, product sales, product ratings and online review information. Consumers strive to be consistent with most people by following the information from them to reduce the information asymmetry, lower the perceived risk, and ultimately influence purchase decisions.

Group size, group recognition, and intragroup relations are important factors that affect the spread of eWOM [43]. The number of online reviews represents the group size for popular products, and it has an awareness effect in eWOM communication; the online rating valence reflects the group recognition of the product and thus plays a persuasive effect in eWOM dissemination [44]. The intragroup relationship is divided into strong relationships and weak relationships. Strong relationships refer to the relationship between individuals with similar social and economic characteristics within the group. People with strong relationships within the group better understand the needs of eWOM searchers; therefore, the strong relationships within the group are more likely to stimulate the spread of eWOM information, and the spread of eWOM in a strong relationship community is faster [45]. Strong relationships focus on influence and trust, which measure the spread depth of eWOM. A weak relationship refers to the relationship between individuals with large differences in social and economic characteristics within the group. There are multiple small groups within one group; a weak relationship is a bridge between these small groups, and it plays a bridging role in the spread of eWOM effectively. Thus, weak relations focus on the scale and measure the spread breadth of eWOM [45].

D. SUMMARY OF THE LITERATURE REVIEW

Because MOOCs are the experiential product, it is difficult for learners to measure the quality of a course through the basic information on the course, such as, the duration time or number of materials, and thus, potential MOOC learners will choose the appropriate course through MOOCs eWOM. A MOOCs platform provides the online review forum and the course learning forum, respectively, displaying MOOCs reviews and ratings, MOOCs learning knowledge and learning experience, thereby forming MOOCs eWOM. eWOM as an external clue that can have a significant positive impact on consumers' purchasing intentions. Therefore, in a MOOCs platform, eWOM as an external clue to MOOCs will also affect the decision making of learners in MOOCs registration and completion.

Although the research on the impact of eWOM has been extended to the education field, under an asymmetric information situation, the research on MOOCs eWOM is lacking. Therefore, considering the asymmetric information, from the group size and group recognition of a MOOCs online review forum, as well as the group internal relationships in the MOOCs learning forum, this paper studies the influence mechanism of MOOCs eWOM on the registration and completion of MOOCs.

III. THEORETICAL BASIS AND RESEARCH HYPOTHESES

A. RESEARCH HYPOTHESES

1) INFLUENCE OF THE NUMBER OF MOOCs ONLINE REVIEWS

Online reviews in eWOM are built on the basis of information sharing, in such a way that the product achieves the widely known effect, which represents the interactive effect and spread of eWOM. It was found that the greater the number of online reviews, the more attention is paid to the product by people, and the higher the consumer's enthusiasm is to transfer the product eWOM. Therefore, the potential consumers are more likely to know the product, which in turn can lead to an increase in sales [44].

It was found that the number of online reviews has a significant impact on the consumers' purchasing decisions, and indirectly affects the pricing of product vendors [46]. Using the data from the website, it was found that the number of reviews has a significant positive effect on the movie box office; in other words, the larger the number of movie reviews, the higher the box office receipts [47].

There are similar conclusions in other industries. It was found that the more reviews that are provided for online catering, the higher the catering sales will be [6]. Through quantitative analysis of the real data on the website, it was found that the larger the number of product reviews, the larger the corresponding product sales are, and the number of product reviews will significantly affect the product sales [48].

By further studying the impact of online reviews on new product sales, it was found that regardless of whether it is a search product or an experience product, the greater the number of online reviews there is, the higher the consumer's perceived shopping value will be to stimulate the consumer's shopping behavior, and then, the larger the corresponding product sales; therefore, the number of reviews has a positive effect on the sales of the goods [49]. Due to the asymmetric information, potential MOOCs learners will follow the information of online reviews in the MOOCs review forum published by other learners to reduce the uncertainty of the MOOCs. Therefore, this paper proposes the following research hypotheses.

H1 The number of MOOCs online reviews positively affects the number of MOOCs registrations

H2 The number of MOOCs online reviews positively affects the number of MOOCs completions

2) INFLUENCE OF THE MOOCs ONLINE RATING VALENCE

The rating valence refers to the consumer's evaluation of products, which is measured by using the average or praise ratio of online ratings [50]. The rating valence provides consumers with information about the product quality and affects the consumers' willingness to buy. The influence of the rating valence is mainly reflected in its persuasive effect. When a product has a higher average online rating or a larger proportion of favorable reviews, it can affect the potential consumers' perception of the product and eventually convince the potential consumer to purchase the product [36].

The study of the effect of the online rating valence on the sales found that the online rating valence has a significant effect on the sales. For example, by measuring the impact of the online user reviews on a movie box office in a specified market area, it was found that the online rating valence is the most important influencing factor [47]. Research also determined that the higher the online rating valence of the products is, the higher the sales of the corresponding products [44]. When studying the dissemination eWOM, it was found that the higher the online ratings on the product are, the stronger the dissemination eWOM effect [51].

Due to the asymmetric information, potential MOOCs learners will follow MOOCs online rating information published by other MOOCs learners in the MOOCs review forum to reduce the uncertainty of the MOOCs, and then, they will choose the appropriate MOOCs for registration and learning. Therefore, this paper proposes the following research hypotheses.

H3 The MOOCs online rating valence positively affects the number of MOOCs registrations

H4 The MOOCs online rating valence positively affects the number of MOOCs completions

3) INFLUENCE OF MOOCs ONLINE REVIEW PUBLISHERS

From the perspective of the credibility of eWOM publishers to study the impact of the credibility of eWOM publishers on product sales, it was found that the number of professional reviews can increase the likelihood of users making a purchasing decision and indirectly improve the sales by enhancing the user activity [52]. The credibility of online review publishers, for example, the enthusiasm, participation, experience, reputation, ability and sociality, affects the number of customers [53].

Taking Airbnb as the research object, it was found that high-quality online reviews will make online review publishers more trustworthy, which will then affect the consumers' subsequent decisions [54]. It was found that the credibility of online review publishers will influence the consumer information adoption through the mediating role of perceived risk, which in turn affects consumer decision-making [55]. Therefore, the higher the credibility of eWOM publishers, the greater the impact that they will have on eWOM. Online reviews with higher credibility and professionalism can make eWOM more persuasive, which in turn will have a greater impact on the number of consumers of the product.

After they finish learning the course and passed the final test, MOOCs learners become completed learners of courses they registered for; otherwise, MOOCs learners are uncompleted learners of the courses they registered for. In the MOOCs online review forum, online reviews can be divided into reviews by MOOCs completed learners and reviews by MOOCs uncompleted learners according to whether or not the MOOC learners have completed the courses that they registered for. Obviously, since MOOCs completed learners have longer exposure to the course and a more comprehensive understanding of the course, they can provide online reviews of higher credibility and professionalism than the MOOCs uncompleted learners. Therefore, this paper proposes the following research hypotheses.

H5 The effect of the number of MOOCs online reviews by completed learners on the number of course registrations is stronger than that of uncompleted learners

H6 The effect of the number of MOOCs online reviews of completed learners on the number of course completions is stronger than that of uncompleted learners

H7 The effect of the MOOCs online rating valence of completed learners on the number of course registrations is stronger than that of uncompleted learners

H8 The effect of the MOOCs online rating valence of completed learners on the number of course completions is stronger than that of uncompleted learners

4) INFLUENCE OF THE MOOCs LEARNING FORUM

MOOCs learners enter into the learning stage after registering for the course. Then, the course learning forum is open to the MOOCs learners, providing an important learning and communication platform for the MOOCs learners and, thus, becoming an important part of MOOCs eWOM.

As the information maintainer of the MOOCs learning forum, the teaching assistant is responsible for solving the doubts of the learners and has strong credibility and influence in the forum, which reflects the strong relationship within the MOOCs learning forum group. The learners who have large differences in the MOOCs learning forum constitute multiple small groups, which reflects the weak relationship within the MOOCs learning forum group. The relationships within the group measure the dissemination effectiveness of eWOM. This study selects the number of teaching assistants to measure the strong relationship of eWOM in the MOOCs learning forum, and the number of learner posts to measure the weak relationship of eWOM in the MOOCs learning forum. According to the study of MOOCs, the better the reputation of the course, the stronger the learning continuance of the learners, and thus, the higher the number of MOOCs completions might be [10]. Therefore, this paper proposes the following research hypotheses.

H9 The number of learner posts in the MOOCs learning forum positively affects the number of MOOCs completions

H10 The number of teaching assistants in the MOOCs learning forum positively affects the number of MOOCs completions

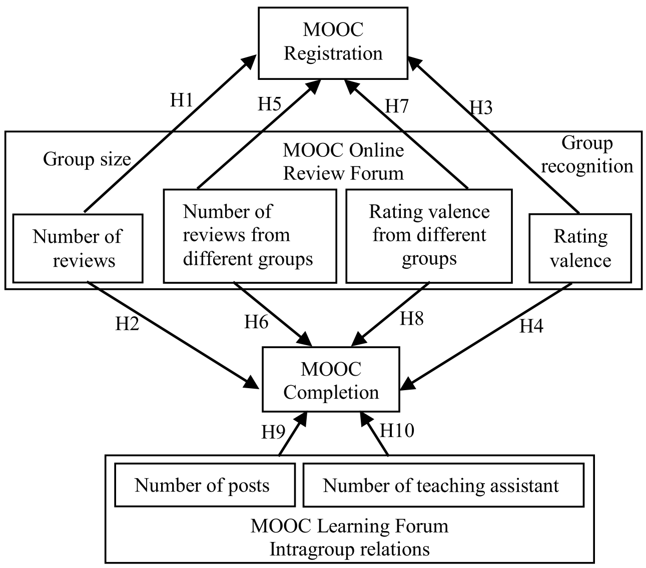

FIGURE 1. Effect of eWOM on MOOCs registrations and completions.

B. CONCEPTUAL MODEL BUILDING

Based on the above research hypotheses, the conceptual model of the effect of eWOM on MOOCs registrations and completions is constructed as shown in Figure 1. Both the number of online reviews and the online rating valence affect the number of MOOCs registrations and completions. In addition, the internal relations of the group, i.e., the number of learners' posts and the number of teaching assistants in the MOOCs learning forum affect the number of MOOCs completions.

IV. DATA ACQUISITION AND VARIABLE DEFINITION

A. MOOCs PLATFORM SELECTION

This article chooses the Coursera platform as the research object for the following reasons.

First, according to the latest statistics from Class Central (www.classcentral.com), the number of registered users in Coursera has reached 30 million in 2019, and Coursera has collaborations with the top universities in the world to provide a wide variety of courses.

Second, in Coursera, the courses are divided into 11 categories. At the same time, each category is divided into different subcategories, to make a total of 45 subcategories. There are more than 3,000 courses that cover many fields.

Third, Coursera provides more teaching languages (including subtitles) for learners from different countries with different languages around the world, which allows learners to break from the constraints of the teaching language.

Fourth, in addition, the Coursera platform strictly divides online reviews into completed learner reviews and uncompleted learner reviews, according to whether the learner has completed the course.

Therefore, this study selected MOOCs on the Coursera platform as the research object.

B. DATA COLLECTION

This study accesses the data of 68,486 courses from November 2018 to August 2019 on the Coursera platform. Taking half a month as a time dimension, a total of 20 time dimensions for the data are obtained.

The obtained data includes three parts of MOOCs, i.e., basic information on courses, information from online review forums and information from course learning forums. The basic information on the courses includes the time length of the course, the number of materials and the category of the course. The online review information includes the online rating valence and the number of online reviews of the MOOCs, and the online rating valence and the online reviews of the MOOCs are provided by completed learners and uncompleted learners, separately. Learners must give their corresponding course ratings when posting their course reviews, but they can choose not to post course reviews after the course's rating. The MOOCs course learning forum is open only to MOOCs learners who registered for courses. Each MOOCs learner can post and reply in the course learning forum to communicate and discuss the course learning; at the same time, a different number of teaching assistants of each course is set up in the course learning forum to respond to questions from learners.

The following steps are applied to preprocess the acquired data. First, null values and incomplete original data are deleted. Second, the basic information of the course is calculated for each time dimension, in which the time length of the course is defined as the week length, and the number of course materials is defined as the number of documents that help in the course learning, including videos and reading materials. Third, the weighted average online ratings by the MOOCs completed learners and uncompleted learners are calculated, and they range from 1 to 5. Fourth, courses opened on the Coursera platform in different time periods are not exactly the same, and the Coursera platform opens new courses one after another, which means that there is no guarantee that each course will appear in each time dimension; thus, the original data as the unbalanced panel data must be converted to balanced panel data. Consequently, 43,480 balanced panel data are obtained in 20 time dimensions with 2,174 course samples in each time period.

C. DESCRIPTIVE STATISTICAL ANALYSIS OF DATA

Taking the data of the 2,174 course samples in the 20th time dimension as an example, the course category, the number of courses, the percentage, the number of participants for online ratings and the average number of participants for online ratings are shown in TABLE 1, and correspondingly, the descriptive statistics of the basic course information is shown in TABLE 2.

TABLE 1. Illustrations of course samples.

Course category	Number of Courses	Percentage	Number of participants for online ratings
Arts and Humanities	229	10.53%	86233
Business	576	26.49%	280278
Computer Science	388	17.85%	374968
Data Science	209	9.61%	598400
Information Science	49	2.25%	73230
Language Learning	79	3.63%	48453
Health	236	10.86%	82469
Mathematics	48	2.21%	16475
Personal development	85	3.91%	76588
Physical Science and Engineering	123	5.66%	60109
Social Science	152	6.99%	64736

In Table 2, according to the classification criteria on the Coursera platform, the 2,174 course samples can be divided into 11 categories. The business category has the largest number of courses, with a total of 576 courses that accounts for 26.49%, and the average number of participants for the online ratings is 487. The number of courses in the data science category is 209, and the number of courses in the information science category is 49, which accounts for less than 12% of the total courses, but the average number of participants for the online ratings is 2,863 and 1,526, respectively, which shows that these courses are very popular.

TABLE 2. Descriptive statistics of basic information on the course.

Variable	Average	Std.	Min	Max
Number of course registrations	810.46	3815.27	3.00	114984.00
Number of course completions	568.74	2798.19	1.00	68802.00
Duration time	17.15	9.54	2.00	94.00
Number of materials	69.22	39.65	0.00	456.00
Online rating valence	4.61	0.24	2.5	5
Online rating valence by uncompleted learners	4.59	0.28	2.50	5.00
Online rating valence by completed learners	4.64	0.24	1.00	5.00
Number of online reviews	146.96	713.87	0	27373
Number of online reviews by uncompleted learners	47.31	203.62	0.00	7565.00
Number of online reviews by completed learners	128.20	647.63	0.00	19808.00
Number of posts in learning forum	655.56	3261.41	0.00	138744.00
Number of teaching assistants in learning forum	8.53	7.84	0.00	126.00

TABLE 3. Definition and description of research variables.

Variables	Symbols	Descriptions
Explained Variable	$LnAllNum_{ij}$	Number of registration of course i at time j
	$LnComNum_{ij}$	Number of completion of course i at time j
Explanatory Variables	$RaVal_{ij}$	Online rating valence of course i at time j
	$ComRaVal_{ij}$	Online rating valence of course i at time j by completed learners
	$UnfRaVal_{ij}$	Online rating valence of course i at time j by uncompleted learners
	$LnCmNum_{ij}$	Number of online reviews of course i at time j
	$LnComCmNum_{ij}$	Number of online reviews of course i at time j by completed learners
	$LnUnfCmNum_{ij}$	Number of online reviews of course i at time j by uncompleted learners
	$LnPostsNum_{ij}$	Number of posts of course i at time j in learning forum
	$LnAssiNum_{ij}$	Number of teaching assistants of course i at time j in learning forum
Control Variables	$LnTime_{ij}$	Duration time of course i at time j
	$LnMaNum_{ij}$	Materials amount of course i at time j

MOOCs learners can make online reviews and ratings of a course only after registering for the course. In Table 2, the average of the MOOCs online rating valence is higher, which could be due to the self-selection bias of the learners [56]; learners who are very satisfied with the course are willing to make ratings more than the unsatisfied learners. Although the minimum and maximum values of the online rating valence are 2.5 and 5, respectively, the standard deviation of the online rating valence is less than 0.3, which indicates that the distribution of the online rating valence is relatively uniform with few degrees of dispersion.

D. DEFINITION OF RESEARCH VARIABLES

The definition and description of research variables in this paper are divided into three categories: explained variables, explanatory variables and control variables, as shown in Table 3.

Compared with the online rating valence, the standard deviations of the other variables are large, for example, the standard deviation of the number of registrations, the number of completed learners and the number of postings in the course learning forum are all above 2000, which indicates that these indicators vary greatly in different courses. To reduce the data fluctuation within the variables and the data fluctuation between different variables, this study conducted a logarithmic conversion of these research variables [57]. After the logarithmic transformation, the regression coefficient measures the effect of the rate of change of the independent variable on the rate of change of the dependent variable.

The explained variables are also called dependent variables, and they include the number of course registrations and the number of course completions. The explanatory variables are also called independent variables, and they include variables in the MOOCs online review forum and variables in the MOOCs learning forum.

Variables in the MOOCs online review forum include the number of online reviews, which is used to measure the group size of the learners, and the online rating valence, which is used to measure the group recognition of the learners. Considering the credibility of eWOM publishers, learners in the MOOCs online review forums are divided into completed learners and uncompleted learners, to differentiate the number of reviews and the online rating valence by the completed learners, and the number of online reviews and the online rating valence by the uncompleted learners, respectively.

Variables in the MOOCs learning forum are divided into the number of learner posts, which is used to measure the weak relationship within members in the MOOCs learning forum, and the number of teaching assistants, which is used to measure the strong relationship within members in the MOOCs learning forum.

Considering the potential heterogeneity of other nonresearch variables [57], this study introduced two variables that are related to the nature of MOOCs as control variables: the duration time of the course in each time dimension, and the number of course materials in each time dimension.

V. ECONOMETRIC MODEL AND DATA ANALYSIS

The econometric model, which was first used in the economic research field, refers to the equation of the quantitative relationship between a phenomenon and its main factors. Because of the powerful capabilities for processing the panel data and time series data, the econometric model is gradually being applied by scholars in other research fields.

A. MULTICOLLINEARITY TEST

According to the explained variables, namely, the number of course registrations and course completions, Stata software

TABLE 4. Stepwise regression results of three models.

Variables	Model 1 Registration	Model 1 Completion	Model 2 Registration	Model 2 Completion	Model 3 Registration	Model 3 Completion
Materials amount (LnMaNum)	0.613*** (10.58)	0.650*** (9.61)	0.176*** (6.21)	0.125*** (3.21)	0.162*** (6.32)	0.101*** (3.02)
Course Duration (LnTime)	0.398*** (25.70)	0.419*** (23.16)	0.150*** (19.53)	0.138*** (14.44)	0.121*** (16.40)	0.085*** (9.67)
Number of reviews (LnCmNum)			0.740*** (334.63)	0.775*** (225.98)		
Online rating valence (RaVal)			0.272*** (19.53)	0.410*** (21.39)		
Number of reviews by completed learners (LnComCmNum)					0.471*** (182.83)	0.581*** (171.04)
Number of reviews by uncompleted learners (LnUnfCmNum)					0.291*** (94.79)	0.220*** (54.20)
Online rating valence by completed learners (ComRaVal)					0.166*** (15.04)	0.310*** (22.35)
Online rating valence by uncompleted learners (UnfRaVal)					0.155*** (16.31)	0.130*** (10.05)
Number of posts in learning forum (LnPostsNum)				0.051*** (26.94)		
Number of teaching assistants in learning forum (LnAssiNum)				-0.003 (-0.74)		
P value	0.000	0.000	0.000	0.000	0.000	0.000
R square	0.0014	0.0014	0.9144	0.8612	0.9047	0.8222

***p<0.001, **p<0.01, *p<0.05

is used to calculate both the variance expansion coefficient VIF1 of the research variables involved in the research hypotheses H1 to H4, H9 and H10. Stata software is also used to calculate the variance expansion coefficient VIF2 of the research variables involved in the research hypotheses H5 to H8. The calculation results are shown in Table 4. The variance expansion coefficients of all of the variables are far less than 10, which indicates that there is no multicollinearity among these variables [57].

B. ECONOMETRIC MODEL CONSTRUCTION

There are two main models for processing panel data in econometric research, i.e., the fixed-effect model and random-effect model. In practice, the choice of a fixed effect model or a random effect model should follow the Hausman test [57]. By using the Stata software, the variables involved in the number of course registration and the number of course completion were respectively subjected to the Hausman test and had a P value of less than 0.01. Therefore, this study selected the fixed effect model.

First, only the control variables were added as a benchmark model to build a fixed-effect model, model 1, with explained variables of the number of registrations and the number of completions, as shown in Eq.1, where $i = 1, 2, \ldots, N$ represents the course, $j = 1, 2, \ldots, N$ represents the time dimension, μ_i is the fixed effect of taking the course as a unit without changing with time, α_0 is the intercept term, and ε_{ij} is the residual.

Eq.1

$$\mathrm{LnAllNum}_{ij} = \alpha_0+\alpha_1\mathrm{LnMaNum}_{ij}+\alpha_2\mathrm{LnTime}_{ij}+\mu_i+\varepsilon_{ij}$$
$$\mathrm{LnComNum}_{ij} = \alpha_0+\alpha_1\mathrm{LnMaNum}_{ij}+\alpha_2\mathrm{LnTime}_{ij}+\mu_i+\varepsilon_{ij}$$

Second, according to the research hypotheses H1 to H4, H9 and H10, on the basis of model 1, explanatory variables, including the number of online reviews and the online rating valence in the online review forum, and the number of posts and the number of teaching assistants in the course learning forum are added to build a fixed effect model, model 2, as shown in Eq.2.

$$\begin{aligned}\mathrm{LnAllNum}_{ij} &= \alpha_0 + \alpha_1\mathrm{LnMaNum}_{ij} + \alpha_2\mathrm{LnTime}_{ij}\\ &\quad + \alpha_3\mathrm{RaVal}_{ij} + \alpha_4\mathrm{LnCmNum}_{ij} + \mu_i + \varepsilon_{ij}\\ \mathrm{LnComNum}_{ij} &= \alpha_0 + \alpha_1\mathrm{LnMaNum}_{ij} + \alpha_2\mathrm{LnTime}_{ij}\\ &\quad + \alpha_3\mathrm{RaVal}_{ij} + \alpha_4\mathrm{LnCmNum}_{ij}\\ &\quad + \alpha_5\mathrm{LnPostsNum}_{ij} + \alpha_6\mathrm{LnAssiNum}_{ij}\\ &\quad + \mu_i + \varepsilon_{ij}\end{aligned}$$

Last, according to research hypotheses H5 to H8 on the basis of model 1, the explanatory variables in the online review forum by completed learners and by uncompleted learners are added to build a fixed effect model, model 3, as shown in Eq.3.

$$\begin{aligned}\mathrm{LnAllNum}_{ij} &= \alpha_0 + \alpha_1\mathrm{LnMaNum}_{ij} + \alpha_2\mathrm{LnTime}_{ij}\\ &\quad + \alpha_3\mathrm{ComRaVal}_{ij} + \alpha_4\mathrm{UnfRaVal}_{ij}\\ &\quad + \alpha_5\mathrm{LnComCmNum}_{ij}\\ &\quad + \alpha_6\mathrm{LnUnfCmNum}_{ij} + \mu_i + \varepsilon_{ij}\\ \mathrm{LnComNum}_{ij} &= \alpha_0 + \alpha_1\mathrm{LnMaNum}_{ij} + \alpha_2\mathrm{LnTime}_{ij}\\ &\quad + \alpha_3\mathrm{ComRaVal}_{ij} + \alpha_4\mathrm{UnfRaVal}_{ij}\\ &\quad + \alpha_5\mathrm{LnComCmNum}_{ij}\\ &\quad + \alpha_6\mathrm{LnUnfCmNum}_{ij} + \mu_i + \varepsilon_{ij}\end{aligned}$$

C. REGRESSION RESULTS OF THE MODELS

By using the Stata software, the data of 20 time dimensions is input into econometric models, and the stepwise regression method was used for analysis. The analysis results of the stepwise regression of three models are shown in Table 4.

The analysis results of Model 1, Model 2 and Model 3 show that the control variables have a significant positive effect on the number of MOOCs registrations. In terms of the fitting degree, the fitting degree R square in model 1 for the number of registrations and the number of completions are both 0.0014.

Adding explanatory variables on the basis of Model 1, the fitting degree R square in Model 2 are 0.9144 and 0.8612, which shows that the explanatory variables of the number of online reviews and the online rating valence in the online review forum have an important influence on both the number of MOOCs registrations and the number of MOOCs completions. Moreover, explanatory variables in the course learning forum have an important influence on the number of MOOCs completions.

Adding explanatory variables on the basis of Model 1, the fitting degree R square in Model 3 are 0.9047 and 0.8222, which shows that explanatory variables of the number of online reviews and the online rating valence by both completed learners and uncompleted learners in the online review forum have an important influence on the number of MOOCs registrations and the number of MOOCs completions.

1) INFLUENCE OF eWOM ON THE NUMBER OF MOOCs ONLINE REGISTRATIONS

According to the analysis results of Model 2, the regression coefficient of the number of online reviews is 0.740 ($p < 0.001$), which means that for every 1% increase in the number of online reviews, the number of MOOCs registrations will increase by 0.740%, which indicates that the number of online reviews affects the number of MOOCs registrations; therefore, the research hypothesis H1 is supported. Moreover, according to the analysis results of Model 3, it can be found that the coefficient of the number of online reviews by the completed learners (0.471, $p < 0.001$) is significantly larger than that of uncompleted learners (0.291, $p < 0.001$), which indicates that the number of online reviews by completed learners has a greater influence on the number of registrations in MOOCs. Therefore, the research hypothesis H5 is supported.

According to the analysis results of Model 2, the regression coefficient of the online rating valence to the number of registrations in MOOCs is 0.272 ($p < 0.001$), which means that for every 1% increase in the online rating valence, the number of registrations in MOOCs will increase by 0.272%, which indicates that the online rating valence positively affects the number of MOOCs registrations, therefore, the research hypothesis H3 is supported. Moreover, according to the analysis results of Model 3, it can be found that the coefficient of the online rating valence by completed learners (0.166, $p < 0.01$) is significantly larger than that of uncompleted learners (0.155, $p < 0.01$), which indicates that the online rating valence by completed learners has a greater influence on the number of MOOCs registrations. Therefore, the research hypothesis H7 is supported.

2) INFLUENCE OF eWOM ON THE NUMBER OF MOOCs ONLINE COMPLETIONS

According to the analysis results of Model 2, the regression coefficient of the number of reviews is 0.775 ($p < 0.001$), which means that for every 1% increase in the online rating valence, the number of completions will increase by 0.775%, which indicates that the number of online reviews positively affects the number of MOOCs registrations; therefore, the research hypothesis H2 is supported. Moreover, according to the analysis results of Model 3, it can be found that the coefficient of the number of online reviews by completed learners (0.581, $p < 0.001$) is significantly larger than that of uncompleted learners (0.220, $p < 0.001$), which indicates that the number of reviews by completed learners has a greater influence on the number of MOOCs completions. Therefore, the research hypothesis H6 is supported.

According to the analysis results of Model 2, the regression coefficient of the online rating valence to the number of MOOCs completions is 0.410 ($p < 0.001$), which means that for every 1% increase in the online rating valence, the number of MOOCs completions will increase by 0.410%, which indicates that the online rating valence positively affects the number of MOOCs completions; therefore, the research hypothesis H4 is supported. Moreover, according to the analysis results of Model 3, it can be found that the coefficient of the online rating valence by completed learners (0.310, $p < 0.01$) is significantly larger than that of uncompleted learners (0.130, $p < 0.01$), which indicates that the online rating valence by completed learners has a greater influence on the number of MOOCs completions. Therefore, the research hypothesis H8 is supported.

According to the analysis results of Model 2, the regression coefficient of the number of posts in the learning forum to the number of MOOCs completions is 0.051 ($p < 0.001$), which indicates that the number of posts in the course learning forum positively affects the number of MOOCs completions. Therefore, the research hypothesis H9 is supported. The regression coefficient of the number of teaching assistants in the learning forum to the number of completions is −0.003 ($p > 0.05$), which indicates that the number of teaching assistants does not have a significant effect on the number of completions in MOOCs. Therefore, the research hypothesis H10 is not supported, which means that the pure number of teaching assistants cannot affect the number of completions in MOOCs, and teaching assistants can only fully exert their influence by actively participating in answering questions in the learning forum.

VI. CONCLUSION

With the development of the Internet, increasingly numerous consumers search eWOM for related products through the Internet. A large number of studies have shown that eWOM has an important impact on product sales. MOOCs use the Internet as a carrier to form eWOM during courses delivery. Based on this aspect, this study mainly discusses the impact of MOOCs eWOM on the number of registrations and completions, selects the Coursera platform as the research object to obtain the research data, and constructs an econometric model to validate the research hypotheses proposed in this paper. Among the 10 proposed hypotheses, only 1 hypothesis is not supported; therefore, the following conclusions can be drawn.

First, the number of online reviews in the MOOCs online review forum has a positive effect on the number of registrations and completions of the courses, which shows that the number of MOOCs online reviews has an awareness effect. When the number of online reviews for a course is greater, this finding indicates that the scale of learners is larger and the awareness effect is stronger, which has attracted the attention of many potential MOOCs learners; as a result, and the enthusiasm of MOOCs learners in spreading eWOM of the course is so high that the potential MOOCs learners are more likely to know about this course. Accordingly, the number of course registrations increase, which in turn promotes MOOCs learners to complete the course due to the awareness effect.

Second, the online rating valence in the MOOCs online review forum has a positive effect on the number of registrations and completions of the courses, which shows that the MOOCs online rating valence has a persuasive effect. When a course has a relatively high rating valence, which indicates that the learner's recognition of this course is higher, and the persuasion effect is stronger, which on the one hand can lead potential MOOCs learners to change their attitudes, thereby persuading potential MOOCs learners to register for the course and on the other hand can make the registered MOOCs learners believe that this course is useful and be persuaded to complete this course, this circumstance will eventually lead to an increase in the number of registrations and completions of the course.

Third, the influence of the number of online reviews and the online rating valence by MOOCs completed learners has a stronger influence than that of the uncompleted learners, which indicates that when accessing eWOM information, the credibility of eWOM publishers is accounted for by potential MOOCs learners and the eWOM information from completed learners is more trustful. MOOCs completed learners and uncompleted learners are two different groups of eWOM publishers. Compared with uncompleted learners, MOOCs completed learners have a more comprehensive understanding about the course because of having a longer exposure to the course. Therefore, eWOM information from MOOCs completed learners have higher credibility, and potential MOOCs learners are more inclined to believe eWOM from MOOCs completed learners.

Four, the number of posts in the MOOCs learning forum has a positive impact on the number of completions of courses, which indicates that the more MOOCs learners communicate in the learning forum, the higher their enthusiasm for learning, which can more effectively spread eWOM through weak relations in the course learning forum and drive more learners to complete the course. However, the number of teaching assistants in the MOOCs learning forum does not have a significant positive effect on the number of completions of the course, which means that teaching assistants can only play a strong role only if they actively participate in interacting with learners in the MOOCs learning forum.

VII. IMPLICATIONS AND FUTURE RESEARCH

A. THEORETICAL IMPLICATIONS

The low completions of MOOCs are the main problem that affects the effectiveness of MOOCs. Many studies have explored this problem from the perspectives of the motivation of MOOCs learners and the curriculum of MOOCs platforms, but there is very little research from the perspective of eWOM. In the research of eWOM, most of the research objects are e-commerce platforms. Thus, from the perspective of eWOM, this study takes the MOOCs platform as the research object to explore the impact of MOOCs eWOM from the MOOCs online review forum and MOOCs learning forum on the number of MOOCs registrations and completions, which enriches the relevant research in the field of MOOCs, and expands the related research in the field of eWOM as well.

The number of online reviews is used to measure the awareness effect, and the online rating valence is used to measure the persuasion effect. This study uses the econometric model to analyze the data from the Coursera platform. The results show that the number of online reviews and the online rating valence in the MOOCs online review forum have a significant positive effect on the number of MOOCs registrations and completions, thus confirming the awareness effect and the persuasion effect of the number of online reviews and the online rating valence, respectively. Thereby, a theoretical basis for the in-depth study of eWOM of MOOCs is provided.

In the current research on eWOM, more attention is paid to eWOM displayed by online reviews. The MOOCs platform not only provides the online review forum but also provides the course learning forum. The course learning forum becomes an important communication platform for learners and instructors, which is conducive to creating a good online learning environment. Therefore, this study introduces the number of learner posts and the number of teaching assistants to measure the internal relationship in the course learning forum. This study confirms that the number of learner posts in the MOOCs learning forum has a significant positive effect on the number of MOOCs completions, but the number of teaching assistants has no significant effect on the number of MOOCs completions. Thus, research on MOOCs eWOM is expanded from the perspective of intragroup relations.

B. MANAGERIAL IMPLICATIONS

1) SUGGESTIONS FOR MOOCs PLATFORM PROVIDERS

Because the number of online reviews in the MOOCs online review forum has a significant positive effect on the number of registrations and completions of MOOCs, and that MOOCs completed learners have a higher awareness effect than MOOCs uncompleted ones, it is recommended that the MOOCs platform set up a corresponding reward mechanism to encourage MOOCs learners, especially MOOCs completed learners, to post online reviews. Then, MOOCs platforms reward MOOCs learners based on the validity of the online reviews, such as the length of the online reviews, the number of likes and whether the learner is a MOOCs completed learner, for the purpose of encouraging MOOCs learners to publish useful online reviews.

Because the number of learner posts has a significant positive effect on the number of completions of MOOCs, which reflects the spread of eWOM, it is recommended that the MOOCs platform encourages learners to participate in the MOOCs learning forum, for example, by providing the circle of friends and friends adding function, in such a way that learners can specify friends when posting. On the one hand, it can strengthen the social learning in MOOCs learning, and on the other hand, it can help MOOCs learners get attention and reply from others in time, thereby, promoting MOOCs learners to discuss and communicate in the MOOCs learning forum. Consequently, the learning enthusiasm of MOOCs learners can be enhanced with respect to completing the course.

2) RECOMMENDATIONS FOR MOOCs PROVIDERS

In the MOOCs platform, the number of registrations and completions of MOOCs is ultimately affected by the quality of the course. The online rating valence of the course is an intuitive feedback on the quality of the course. The number of weekly teaching hours and the number of learning materials are the manifestation of the course content. Therefore, it is recommended that the MOOCs provider, on the one hand, continuously enrich the course content, improve the teaching plan, and set the teaching hours reasonably, and on the other hand, improve the MOOCs teaching capability and teaching level, thereby improving the quality of the course.

Because the number of teaching assistants in the MOOCs learning forum has no significant effect on the number of completions of MOOCs, it is recommended that MOOCs providers should not simply increase the number of the teaching assistants in the MOOCs course learning forum and urge the teaching assistants to actively communicate and interact with learners, for example, respond to learner questions promptly, and fully use the influence of the strong relationship in the MOOCs course learning forum.

C. FUTURE RESEARCH

As one representative MOOCs platform, Coursera is selected as the research object of this study. Therefore, a comparative analysis of data on different MOOCs platforms and a discussion on whether the influence of eWOM on different MOOCs platforms are consistent will be further research directions of this study.

Because MOOCs learners will be affected by eWOM from the MOOCs online review forum via the group size and group recognition. This study uses the number of online reviews in the MOOCs online review forum and the number of posts in the learning forum, respectively, and there is no in-depth discussion of specific text information, such as the text length and sentiment attributes. Therefore, future research will dig deep into the content analysis to further explore the influence mechanisms of MOOCs eWOM.

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