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Exploring values affecting e-Learning adoption from the user-generated-content: A consumption-value-theory perspective

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Abstract:

The aim of this study is to utilise the user-generated content from social-media platforms and merchandise websites to explore various values affecting behavioural intention in context of e-Learning services from the consumption-value-theory perspective. This study has utilised a novel mixed-method approach based on natural language processing (NLP)-techniques for the both the qualitative and quantitative analysis. This study has used user-generated content of Coursera (an e-Learning service) consisting of online reviews from Coursera-100k-dataset and tweets about Coursera. Some of the important themes generated from the thematic based analysis of tweets are "value addition", "course content", "topic cover", "reliability of course", "course quality", "enjoyed course", "recommend the course", "value for money", "facilitator skills", etc. Results of the empirical study reveal that offers and deals, emotional connect, facilitator quality, course reliability, platform innovativeness, and compatibility are important predictors of behavioural intention. This study concludes with the various limitations and future directions.

Keywords:

e-Learning services; Consumption Value Theory (CVT); Latent Dirichlet Allocation (LDA); Natural Language Processing (NLP)-based approach; Topic-Modeling; User Generated Data.

Introduction

The advancement of technological innovations has led to the growth of various electronic services (better known as e-Services) like, food-delivery, hotel-booking, online-learning, etc. which has not only changed the way people used to live but has also made life easier. Over the years e-Learning services, which refers to the process of taking up courses over digital platforms (Gao, Wu, & Wu, 2018), have become a medium to enhance career growth (Ray, Bala, & Dasgupta, 2019). Some leading global e-Learning platforms are, Coursera, Udemy, Udacity, etc. (Kalish, 2019). The global e-Learning market is expected to reach $398.15 billion by 2026 (Costello, 2019). Despite the benefits of using e-Learning services, like, convenience, flexibility, etc. (Li, Asimiran, & Suyitno, 2018), retaining users in e-services is a huge challenge (Panigrahi, Srivastava, & Sharma, 2018). A good understanding of the values that affects user's decisions behind the choice of e-Learning services can help to solve various issues. For exploring customer perspectives, researchers have usually used traditional research methods (qualitative or quantitative or mixed-method approaches). However, the traditional research methods in most cases are limited by the sample size and the spread of the sample population (Boddy, 2016; Delice, 2002; Deziel, 2018).

The present era has witnessed a growth of various social-platforms like, Facebook, Twitter, etc. (Simon, Goldbergb, & Adinia, 2015). Social-media platforms enable users to openly exchange information online through exchange of user-generated content (Simon et al., 2015). Online-customer-reviews are also available in company websites and other related pages (Chatterjee, 2019). These user-generated data contains customer perspectives and a proper analysis can reveal deeper insights (Siering, Deokar, & Janze, 2018). Rohm, Stefl, & Clair (2018) have stated that in the e-Learning industry, firms need to keep a note of the latest consumer demands. Hence, understanding user-generated-content will provide a much wider perspective usually unavailable through traditional research approaches. Few studies have attempted to explore techniques to utilise the user-generated content for examining factors in the model of interest. Kunimoto and Saga (2014) and Saga and Kunimoto (2016) have used hierarchical Latent Dirichlet Allocation (hLDA) and structural equation modeling (SEM) for finding keywords based on a selected topic of interest. However, the study suffers from accuracy issues. Additionally, the emotional aspects of textual data were not captured in the study. Ray and Bala (2019b) attempted to utilise natural language processing (NLP)-based techniques to determine the factors affecting adoption of e-services utilising an SEM based analysis. However, the study has used a pre-defined corpus of words. Hence this study is not generalizable. This study attempts to address these research gaps.

While the business problem is to understand the values that affect user's decision from the online posts, the scientific problem is to formulate an approach to utilise the user-generated content for both qualitative thematic analysis as well as quantitative path model analysis. To address these two main research gaps, namely, exploring consumption values from user-generated content in context of e-Learning services, and second to formulate a technique to utilise the user-generated content in traditional-research approaches for reducing the limitations related to sample size and the spread of the sample population. This study attempts to utilise the user-generated content for exploring the various values that affect user's decisions using a mixed-method NLP-based approach.

The study is novel in that it has developed the dataset for the path-model from the user-generated content (consisting of online user reviews from Coursera 100k dataset (ref: Coursera)). This study has utilised a NLP-based approach by using a Latent Dirichlet Allocation (LDA) technique to perform topic-modeling on the user-generated data for both the qualitative thematic based analysis as well as for generating the dataset for path-model. The user-generated content consists of online reviews and user comments/tweets from Twitter. Results of the thematic-based analysis of the social media feeds generated the themes "value addition", "course content", "easy to understand", "easy to follow", "topic cover", "course reliability", "course quality", "enjoyed course", "recommend the course", "videos to watch", "good deals", "value for money", "facilitator skills", and "discussion forum". The empirical analysis revealed that offers and deals, emotional connect, facilitator quality, course reliability, platform innovativeness, and compatibility are important predictors of behavioural intention.

The section following this discusses the existing literature on e-Learning services, online reviews and NLP-based approach to form path-models. In Section 3, we have constructed the conceptual research model and framed the hypotheses to be tested. Section 4 discusses the methodology followed in this study followed by the results and discussion in Section 5 and Section 6 respectively. Finally this study concludes with the limitations, implications, and future directions.

Literature Review

This study attempts to utilise the user-generated data for exploring the various values that affect user's intention to take up courses from a particular e-Learning platform. To discuss the literature review, we have formed three subsections, namely, the online user generated content, the e-Learning platforms, and the consumption value theory.

Online User-generated Content

The penetration of internet and the smartphones had led to people posting comments/views about the services on social-platforms, like, Facebook, Twitter, company webpages, etc. These posts and reviews may influence the intention of potentially new prospects to use the services of a particular service-provider (Chatterjee, 2019). Extracting useful information from this user-generated data can solve various strategic issues for a service-provider. This information can be utilised by companies to influence customer buying behaviour through different strategies like, pricing and promotions (Ajorlou, Jadbabaie, & Kakhbod, 2016).

Extracting social-media-feeds and online-customer-reviews is a web-mining process. It involves three main operations: getting data from social-platforms; parsing, integrating, and storing the cleansed data; and analysing the cleansed data to extract information relevant to our objectives (Crooks, Croitoru, Stefanidis, & Radzikowski, 2013). Stopping and stemming are done in the cleansing phase to remove unimportant words and considering the 'root' words from the text to be analysed (Chatterjee, 2019). Text-mining can be used in extracting valuable information from user-generated content. One technique to perform text-mining is topic-modeling. Topic-modeling constructs a structure of topics from a group of documents utilising the concept that the document group that constitutes the corpus belongs to the specific topic (Kunimoto & Saga, 2014; Saga & Kunimoto, 2016). Topic-modeling can be performed by various techniques like, latent semantic indexing (LSI) (Kunimoto & Saga, 2014), latent dirichlet allocation (LDA) (Blei, Ng, & Jordan, 2003), hierarchial LDA (hLDA) (Blei, Griffiths, & Jordan, 2010), etc. Both LDA and LSI are similar in that they have the latent variables presented in a probabilistic way (Blei et al., 2003). Kunimoto and Saga (2014) had used hLDA to develop path-model from user-generated data. However, in hLDA, the main topic constitutes the root of the tree of infinite height and the hierarchical structure branches off endlessly. So, this technique had accuracy issues and was not able to explore factors of importance properly. The emotional aspects of textual comments were also not captured properly. Extant literature has often ignored exploring the 'emotional aspect' (Siering et al., 2018) from customer reviews. Additionally, extant literature has hardly focused on utilising both customer reviews (Chatterjee, 2019). Text-mining also finds wide application in sentiment and emotion analysis and is often referred to as opinion-mining (Barnaghi, Ghaffari, & Breslin, 2016). Utilisation of topic-based sentiment analysis in the contexts like, e-commerce, e-Learning, tourism, etc. (Popescu & Etzioni, 2007; Chatterjee, 2019) is still new. There are only a handful of studies that have attempted to explore techniques to utilise the user-generated content for examining factors in the model of interest. Kunimoto and Saga (2014) and Saga and Kunimoto (2016) used hLDA and SEM to construct path models on a selected topic of interest. However, the study suffers from accuracy issues. Ray and Bala (2019b) used NLP-based techniques using a predefined corpus to explore the factors affecting adoption of e-services utilising through SEM based analysis. The use of the pre-defined corpus makes the study not so generalizable. Exploring techniques to utilise the abundant user-generated data for understanding the factors of interest in various conceptual frameworks and in various contexts is still in its nascent stage. This study tries to address these gaps by utilising topic-modeling and text analytics to explore factors of importance in a chosen framework. For this study, we have chosen the e-Learning services to explore the values that customers value more.

E-Learning Services

Researchers over the years have analysed the factors that affect usage of e-Learning services from various directions, like, analysing the importance of social interactions on technical elements to improve e-mentoring systems (Headlam-Wells, Gosland, & Craig, 2006), using a task-fit model to understand retention of students in massive online open courses (Huang, Zhang, & Liu, 2017), understanding the influence of factors like, system-quality, perceived ease-of-use and system functionality on usage-intention (Li, Duan, Fu, & Alford, 2011), and analysing the importance of system response and system functionality of the e-Learning website on customer's continuance intention (Liao, Liu, Pi, & Chou, 2011). Pentina and Neeley (2007) in another comparative study between traditional and online ways of learning found that factors like performance expectancy, financial risks and societal status affects the decisions to choose between traditional and online ways of learning. Researchers Emerson and MacKay (2011) found that students who took classroom-based classes performed better than those who took online lessons. Griff and Matter (2012) investigated adaptive learning and found that it works best when the goals are properly aligned to objectives. Parahoo, Santally, Rajabalee, and Harvey (2015) in context of online higher education found that factors like university reputation, facilities and student-student-interactions influence satisfaction. Robinson (2016) found that factors like innovativeness and support-services influence decisions of using online courses.

Though, previous researchers have tried to understand customer behaviour in the use of e-Learning services using different approaches like, qualitative-based approach (Waheed, Kaur, & Qazi, 2016), quantitative-based approach (Li & Tsai, 2017), mixed-method approach (Chatterjee & Juvale, 2015), opinion-mining (Tewari, Saroj, & Barman, 2015) and even sentiment analysis (Zarra, Chiheb, Faizi, & El Afia, 2016), there are limited studies that have utilised the online-customer-reviews/comments. This study is the first that have attempted to analyse the user-generated data from e-Learning platforms using NLP-based approaches to build path-models.

Consumption-value-theory (CVT)

Understanding customer perspectives and the factors that affect the customer satisfaction and the adoption of various innovations is an important market research task (Rana & Dwivedi, 2016; Dwivedi, Rana, Janssen, Lal, Williams, & Clement, 2017; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019;). Sheth, Newman, & Gross (1991) developed CVT for capturing the various value-oriented elements that influence customers' behavioral choice. CVT uses five different values namely: functional, emotional, social, epistemic, and conditional (Sheth et al., 1991, pp. 160-163). Over the years, CVT has been used for explore consumer's behavioural choices in various contexts, like, using smartphones

(Bodker, Gimpel, & Hedmanm, 2009), etc. Understanding consumer values helps e-Services to establish an interactive engaging experience with the consumers and prevent switching to a competitor service (Wong, Chang, & Yeh, 2019). In this present study, CVT has been used to understand the users' behaviour with respect to e-Learning services for the following reasons. First, there is a research need for understanding the various values that affect customer behaviour in case of e-Learning services (here in this study, Coursera). Understanding customer behaviour with respect to the different consumption values in the e-Learning context will help to explore consumer perspectives better and our study is the first NLP-based study in this regard. Second, Choe and Kim (2018) have stressed the importance of CVT in capturing the multidimensional consumer-values. Hence, we have used CVT in this study.

Conceptual Model and Hypotheses development

This study has utilised nine independent variables grouped under various values, namely, functional values (compatibility, convenience), conditional values (offers & deals), quality values (course quality, facilitator quality, reliability of course), emotional values (emotional connect) and epistemic values (topic cover, platform innovativeness), and one dependent variable (intention to use the e-learning service) variables. The proposed model is depicted in Figure 1.

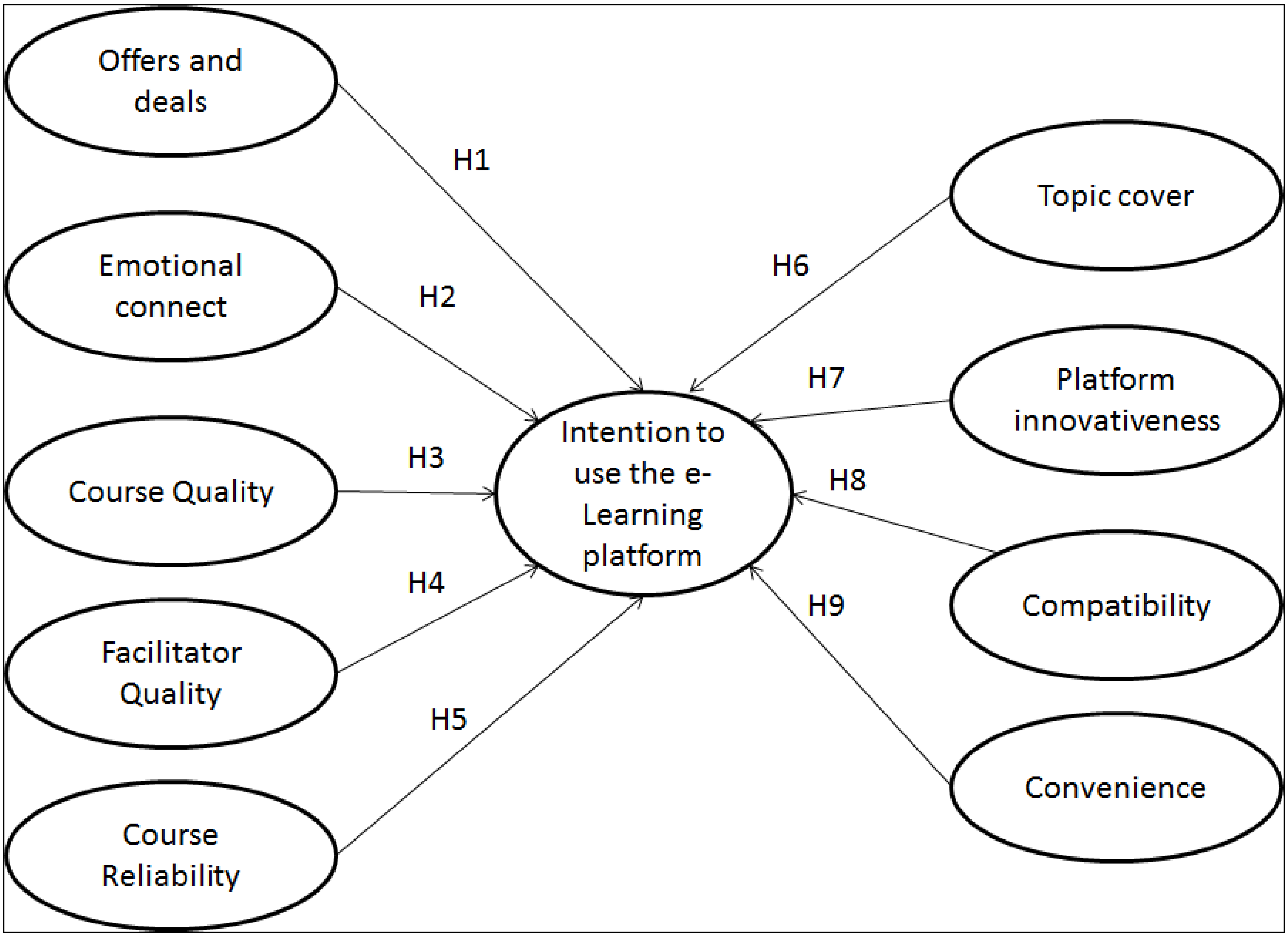

Figure 1. Proposed conceptual model (Source: Adapted from Sheth, Newman, and Gross, 1991)

Conditional values

Conditional values describe the various utilities, like, offers, discounts, etc. that an individual gets at specific situations. Researchers have found conditional values and customer intentions to be positively related in contexts like, purchase of organic food (Qasim, Yan, Guo, Saeed, & Ashraf, 2019), online shopping (Suman, Srivastava, & Vadera, 2019), etc. Choe & Kim (2018) found that price value has a positive influence on customer attitude. In context of e-Learning services, by conditional benefits we feel that when a customer gets better offers/discounts they will take up the course of interest from that particular provider. Companies like Coursera also use other strategies, like, fee-based model to attract students to take up more useful certificates on completion of courses (Fain, 2013), thus providing price value. Thus, based on the findings by earlier scholars, we suppose:

H1: Offers and deals (conditional values) have a positive influence on intention to use the e-Learning platform.

Emotional values

Emotional values refer to the various emotional aspects that an individual derives from a particular service (O'Donohoe & Turley, 2007; Chang, Hsu, & Lan, 2019; Lim, Teh, & Ahmed, 2016). In case of e-Learning services, we feel that emotional values can be measured by how much a customer enjoys the course and loves the service provided. Earlier researchers have found emotional values and usage-intention to be positively related in various scenarios like, consumption of organic food (Qasim et al., 2019), customer's purchase intention (Asshidin, Abidin, & Borhan, 2016), local food consumption (Choe & Kim, 2018), accepting public information technologies (Hsu et al., 2010), etc. In context of e-Learning services, we also feel that higher the emotional connect, the more the customer will be interested to use the service. Hence, in line with the findings of earlier researchers, we hypothesise:

H2: Emotional connect (emotional values) and usage-intention are positively associated.

Quality values

Quality values refer to the various standards, uniformity related to the product. Choe and Kim (2018) in context of food consumption among tourists defined quality values as taste/quality of food, dining experience, etc. In context of e-Learning services, Li et al. (2011) observed that course quality and usage-intention are positively associated. Yang, Shao, Liu, and Liu (2017) in context of MOOCs found that course quality has a convincing influence on retention intention. Liao et al. (2011) found that course quality and course flexibility has a significant impact on continuance intention.

Dağhan and Akkoyunlu (2016) stated that information quality acts upon customer's intention to use online platforms. Ali, Yaacob, Endut, and Sulam (2018) found that information quality significantly affects user's intention to use social-media for academic purposes. The course content, the rigour of course, the assignments, the examples, etc. provided in the course add to the course quality. Researchers Albelbisi and Yusop (2019) found that there is a significant influence of course quality on self-regulated learning skills. Users will generally opt for a course which has a good course quality and hence we hypothesise:

H3: Course quality (quality values) has a positive influence on intention to use the e-Learning platform.

A facilitator's way of course delivery and his/her ability to deliver the course content by making it interesting influences the user's intention to take up particular courses. This is another reason why some courses have higher subscriptions over other similar courses. Earlier researchers have also found a relationship between facilitator quality and the listener's performance (Paulus, Larey, & Ortega, 1995; Higginbotham & Myler, 2010; Berkel et al., 2018). Thus in line with earlier research works, we also suppose:

H4: Facilitator quality (quality values) has a positive influence on intention to use the e-Learning platform.

Course reliability refers to the validity and authenticity of the course certificate. Additionally it also related to the course content delivered, i.e., whether the course content is relevant, whether the course taught will be applicable in modern day scenarios, whether the course will help in career growth, etc. Researchers in recent times have voiced their concern about trust related to online based services (Belanger & Carter, 2008; Seufert, 2012; Hashim & Tan, 2015; Silic, Barlow, & Back, 2018; Chin, Harris, & Brookshire, 2018). Recently Ray et al. (2019a) have also found a positive relationship of authenticity on interest to take up a particular course. Thus, we propose:

H5: Course reliability (quality values) has a positive influence on intention to use the e-Learning platform.

Epistemic values

Epistemic values are related mainly to the customer's curiosity, knowledge and novelty (Choe & Kim, 2018). Earlier researchers have noted that epistemic values and usage-intention are positively associated in various scenarios, like, tourism (Choe & Kim, 2018), mHealth services (Lee, Han, & Jo, 2017), etc. In case of e-Learning services, new interesting concepts in a course, the novel techniques taught in the course, the unique examples taught in a course, etc. are related to the epistemic values. Using e-Learning services can provide epistemic values and users regard this as the ability to learn something new and valuable. Thus, we propose:

H6: Topic cover (epistemic values) has a positive influence on the intention to use the e-Learning service

Epistemic values also deals with the novel, unique offerings in the platform from the technical point of view which can help the user. Researchers Wang and Huang (2014) have argued that the service content of the platform is equally important as the platform design. Several other researchers (Zhang, Yin, Luo, & Yan, 2017; Shao, 2018) in context of MOOCs have also lend their support on a good platform design.

. **H7:** Platform innovativeness (epistemic values) has a positive influence on the intention to use the e-Learning service

Functional values

Functional values generally deals with the functional aspects of the service platform (website or application). Li et al. (2011) and Liao et al. (2011) in context of e-Learning services found a strong influence of system quality, perceived ease-of-use, system's response and system functionality on usage-intention. A service-provider providing better services will attract more customers. Researchers have found that functional values have a positive impact on usage-intention in various contexts like, purchase of organic products (Qasim et al., 2019), using self-service technologies (Jia, Wang, Ge, Shi, & Yao, 2012), accepting technologies (Hsu, Chen, & Wang, 2010), etc. Earlier researchers have found that factors like ease of use, usefulness, compatibility issues, etc. affect customer's intention to adopt certain technologies (Davis, Bagozzi, & Warshaw, 1989; Venkatesh, Morris, Davis, & Davis, 2003; Hsu & Wu, 2011). Compatibility refers to the fact that the e-Learning platform and the courses taught in that platform can be accessed from any device. Earlier researchers have found a positive relationship between compatibility and usage intention in various contexts like, intention to adopt mobile banking (Al-Jabri & Sohail, 2012; Lin, 2011), mobile commerce (Wu & Wang, 2005), online shopping (Chen, Gillenson, & Sherrell, 2002), etc. Thus in line with earlier research works, we propose:

H8: Compatibility (functional values) has a positive influence on the intention to use the e-Learning services.

. Convenience refers to the ease of use of the e-Learning platform. If the courses can be accessed at any-time and easily without much technical glitches of the platform, it will make more customers adopt the course. Earlier researchers have found that convenience has a positive influence on intention in contexts like, use of video games (Bassiouni, Hackley, & Meshreki, 2019), mobile payment services (Gao & Waechter, 2015), tourist revisit intention (Wong & Zhao, 2014), etc. Thus in line with earlier research works, we propose:

H9: Convenience (functional values) has a positive influence on the intention to use the e-Learning services.

Research Methodology

The main objective of this study is to explore the factors that affect user's choice of various online courses from the consumption value theory (CVT) stance by utilising the user generated content available in various online platforms. Hence, we have used an NLP-based approach in this study. Web-mining was utilised for extracting the text from the service-provider (in our case Coursera) platforms, like, Coursera webpages, Tweets, etc. Text-mining is performed to reveal the important information from the text. Topic-modeling, sentiment-analysis and emotional-analysis of the textual-data were also done for extracting relevant scores from the user-generated data.

Since the study is both purposive as well as probabilistic in nature, we have adopted a mixed-method approach. But the uniqueness of this study is that we have utilised an NLP-based approach for performing both the qualitative as well as the quantitative based analysis. The study is divided into two phases. In the first phase, we have utilised the NLP-based analysis to extract important themes from social-media pages using a content analysis based approach. Based on the themes generated, the conceptual model was formed and was tested quantitatively using an SEM based approach. The data for the quantitative based analysis was generated from the online reviews posted in Coursera. We have used the Coursera 100k dataset for our research purpose. The steps followed for performing the analysis are discussed in depth in the following sub-sections.

Sample Size

For analysing the user-generated content, we have used Coursera 100k dataset (contains 139581 reviews) (ref: Coursera) containing 1lakh user reviews. We have also extracted 1442 tweets from Twitter using R-studio (all tweets since 2010) using the official Coursera handle.

Data Analysis

The data was cleansed by removing stop-words, re-tweets, punctuation, etc. Though there are various ways to perform multi-lingual text analysis, we have only focused on reviews posted in English and hence have removed reviews that were not written in English. Since we intend to perform sentiment and emotion analysis on the textual-data, reviews having over 100 words were considered (which is the minimum criteria for accurate scores) (Ref: IBM Watson). The final dataset for analysis contains 3229 reviews. Topic-modeling, sentiment analysis and emotion analysis was performed on this cleansed data to extract the scores based on user views. We have used topic-modeling since topic-modeling helps to extract important and new themes by analysing words from textual data (Aggarwal & Zhai, 2012, p. 107; Blei, 2012) without chances of potentially-biased scenarios (Jelveh, Kogut, & Naidu, 2015). LDA and Gibbs sampling technique was preferred because latent variables are represented in a probabilistic way by generating an estimated probability of a document being represented by a topic and the probability of a word being used for representing a topic (Blei et al., 2003). Topic-modeling results in a document-term matrix containing various topics and related terms. The topics were treated as observed variables of the path-model. The generated probabilities, sentiment scores and emotion scores were standardised to represent values like Likert scale (1= strongly disagree; 5= strongly agree). 'sentimentr' package in R was used for performing the sentiment and emotion analysis. Sentiment and emotion scores are used since analysing the sentiments/emotions provides a much deeper insight. The positive or negative polarity of sentiments gives the text valence score, while the emotion (anger, anticipation, disgust, fear, joy, sadness, surprise, trust) scores provide the affective-cognitive understanding of the textual content (Chatterjee, 2019).

The steps followed for extracting the important qualitative themes from the social-media data are discussed below:

Step 1: After the social-media data (tweets) is cleansed, "LDA tuning" is performed on the social-media feeds to find out the optimal number of topics that can be generated.

Step 2: Based on the optimal number of topics generated, topic modeling is performed to generate the topics and the probability scores.

Step 3: Based on discussion among the researchers based on the formula of Boyatzis (1998) (given below), the important topics relevant for the particular context are chosen and results are coded.

$$\frac{[2 * (no.of\ times\ both\ coders\ A\ and\ B\ saw\ it\ present)]}{[(no.of\ times\ coder\ A\ saw\ it\ present) + (no.of\ times\ coderB\ saw\ it\ present)]}$$

We have used this technique to explore important themes from textual data inspired from earlier research works where researchers have used NLP and text mining techniques to extract important information from the text and one popular technique to extract important themes by analysing the words in a text is through topic modeling (Aggarwal & Zhai, 2012, p. 107; Wei & Croft, 2006; Blei, 2012).

Based on the themes generated, the conceptual model is developed. For testing the model of interest, a quantitative based analysis is performed. But the uniqueness of this study is that we have used user-generated data to generate the dataset for quantitative analysis, thus providing a new avenue for performing research analysis. The steps followed for preparing the quantitative-based dataset are discussed below:

Step 1: After the user generated data (customer reviews in Coursera) is cleansed, "LDA tuning" is performed on the social-media feeds to find out the optimal number of topics that can be generated. It is to be noted that each review is treated as a separate document for performing topic modeling.

Step 2: Based on the optimal number of topics generated, topic modeling is performed to generate the topics and the probability scores.

Step 3: Based on the factors in the model of interest and the topics generated through topic modeling of the user generated content, a Naïve Bayes classification (the formula is given below) is performed to find out the presence of a topic in a particular document. If the topic is present, the probability score of the particular topic is populated. For the topic which is not present, the field is left blank.

$$p(C|T) = \frac{p(C)p(TM_1|C)p(TM_2|C) \ldots\ldots p(TM_n|C)}{p(T)}$$

Where, TM_1, TM_2, TM_3, .., TM_n are the topics and C={factor, not a factor}.

Step 4: The result of the above step is a matrix which is around 95.94% sparse. Based on the emotion and sentiment scores, the documents which are almost similar are then grouped together, to impute the missing values based on the cosine based similarity formula given below.

$$Cos\,(A,B) = \frac{A.B}{||A||\,||B||} = \frac{\sum_{i=1}^{n}(r_{ui} \cdot r_{vi})}{\sqrt{\sum_{i=1}^{n} r_{ui}^2}\sqrt{\sum_{i=1}^{n} r_{vi}^2}}$$

Where, r_{ui} is the term similarity score given by user u to term i.

Step 5: After all the probability scores are populated for all the factors, the scores are normalized on a scale of 1-5 using the sentiment and emotion scores. The resulting matrix is the dataset for the quantitative based analysis.

The dataset was then analysed using SEM technique. The reason behind using SEM is that SEM has the ability to give accurate calculations of probability distribution of data (Urbach & Ahlemann, 2010; Baabdullah, Alalwan, Rana, Kizgin, & Patil, 2019). We have used SMART PLS (v 3.2.8) for the SEM analysis. The topic-modeling and textual analysis was performed using R 3.4.0 platform.

Results

Results of the thematic based analysis of the social media feeds generated the themes “value addition”, “course content”, “clear examples”, “easy to understand”, ”easy to follow”, “topic cover”, “practical examples”, “interesting topic”, “course duration”, “reliability of course”, “assignments”, “course quality”, “recommend the course”, “videos to watch”, “course materials to read”, “good deals”, “value for money”, “facilitator skills”, “good slides”, “discussion forum”, “enjoyed the course”, “loved the course” and “review scores”. These are grouped into mainly nine themes, namely, offers and deals (“good deals”, “value for money”), emotional connect (“enjoyed the course”, “loved the course”), topic cover (“topic cover”, “practical examples”, “interesting topic”), course quality (“value addition”, “course content”, “clear examples”, “course quality”), facilitator quality (“easy to understand”, ”easy to follow”), platform innovativeness (“assignments”, “videos to watch”, “discussion forum”, “review scores”), course reliability (“reliability of course”), usage intention (“recommend the course”), and convenience (“course duration”, “course materials to read”).

Table 1 provides information regarding the various measurement items for our analysis. The measurement items are actually the themes generated after analysing the topics from the topic-modeling output. The recommended lower boundary for composite reliability (CR), chronbach alpha (CA), and average variance extracted (AVE) is 0.70 (Hair, Anderson, Tatham, & Black, 1998; Hair, Black, Babin, & Anderson, 2010). The model demonstrated satisfactory reliability (CA, CR, AVE >0.50 for all the constructs) (refer Table 1). In case of factor loadings (refer Table 1) we find that all the items have a good loading. Discriminant validity tests whether the constructs for measurement are unrelated (Chin, 2003) (refer Table 2). Discriminant validity in this study is measured using Fornell-Larcker Criteria and HTMT tests (Fornell & Larcker, 1981; Henseler, Ringle, & Sarstedt, 2014). The result shows satisfactory discriminant validity.

Table 1. Information regarding measurement items [factor loadings, variation inflation factor (VIF), average variance extracted (AVE), composite reliability (CR), Chronbach Alpha (CA).]

				Reliability measures		
Measures (References)	**Measurement Items**	**Factor Loadings**	**VIF**	**AVE**	**CR**	**CA**
Offers and Deals (Conditional Values)	OD1: Good deals.	0.90	1.23	0.71	0.83	0.60
	OD2: Value for money.	0.78	1.23			
Emotional Connect (Emotional Values)	EC1: Really liked the course.	0.91	1.96	0.69	0.87	0.78
	EC2: Enjoyed and loved the course.	0.87	1.74			
	EC3: Emotional score.	0.70	1.44			
Course Quality (Quality Values)	CQ1: Good course design	0.93	1.13	0.65	0.78	0.50
	CQ2: Course is easy/difficult to understand	0.66	1.13			
Facilitator Quality (Quality Values)	FQ1: Facilitator has good communication skills.	0.91	1.13	0.66	0.79	0.51
	FQ2: Facilitator is knowledgeable.	0.69	1.13			
Course Reliability (Quality Values)	CR1: Course topics are valid and reliable.	0.86	1.32	0.75	0.85	0.66
	CR2: Authentic and valid course certificates.	0.87	1.32			
Compatibility (Functional Values)	COM1: Manage product design to suit needs.	0.86	1.32	0.75	0.86	0.66
	COM2: Is compatible with all devices.	0.87	1.32			
Convenience (Functional Values)	CON1: Videos and lectures can be watched as per convenience.	0.89	1.35	0.75	0.86	0.68
	CON2: Easy to complete courses at own pace.	0.84	1.35			
Topic Cover (Epistemic Values)	TC1: Good topic and information cover.	0.98	1.59	0.75	0.85	0.76
	TC2: New techniques and real life examples are taught.	0.72	1.59			
Platform Innovativeness (Epistemic Values)	PI1: Forum for discussion	0.80	1.15	0.68	0.81	0.53
	PI2: Slides, Materials, Videos available on platform to access anytime.	0.85	1.15			
Usage Intention	UI1: Liked/loved the course	0.89	1.31	0.74	0.85	0.66
	UI2: Recommend the course to others.	0.83	1.31			

Note: results displayed upto two decimal places.

Table 2. Information regarding measurement items [discriminant validity measures using Fornell-Larcker and Heterotrait-Monotrait Ratio (HTMT) tests].

	COM	CON	CQ	CR	EC	FQ	UI	OD	PI	TC
COM	0.864*									
CON	0.026*, 0.044**	0.868*,								
CQ	0.035*, 0.063**	0.041*, 0.088**	0.805*,							
CR	0.059*, 0.090**	0.109*, 0.165**	0.060*, 0.126**	0.863*,						
EC	0.054*, 0.069**	0.094*, 0.125**	0.022*, 0.059**	0.000*, 0.039**	0.830*,					
FQ	0.082*, 0.141**	0.028*, 0.064**	0.044*, 0.104**	0.019*, 0.035**	0.060*, 0.078**	0.811*				
UI	0.098*, 0.149**	-0.027*, 0.058**	0.047*, 0.076**	0.037*, 0.054**	0.526*, 0.687**	0.141*, 0.237**	0.861*,			
OD	0.081*, 0.124**	-0.014*, 0.055**	0.058*, 0.100**	-0.019*, 0.089**	0.034*, 0.082**	0.127*, 0.229**	0.105*, 0.169**	0.843*,		
PI	0.040*, 0.067**	0.016*, 0.031**	0.072*, 0.139**	0.037*, 0.066**	0.051*, 0.069**	0.118*, 0.228**	0.123*, 0.210**	0.088*, 0.150**	0.825* ,	
TC	0.088*, 0.134**	0.072*, 0.096**	0.057*, 0.096**	-0.001*, 0.055**	0.069*, 0.102**	0.060*, 0.109**	0.011*, 0.011**	0.040*, 0.065**	0.064*, 0.091**	0.864*,

Note: COM: Compatibility; CON: Convenience; CQ: Course Quality; CR: Course Reliability; EC: Emotional Connect; FQ: Facilitator Quality; UI: Intention to use; OD: Offers and Deals; PI: Platform Innovativeness; TC: Topic Cover.

**Fornell-Larcker Criteria Values*

***HTMT Values*

Extant literature have stated different threshold values for the fit indices: Standardised Root Mean Square Residual (SRMR) value (<0.08), Chi-square ratio degrees of freedom (X^2/df) < 3.0 (Hair et al., 2010; Hair, Ringle, & Sarstedt, 2013). In this study, the measurement model demonstrated good-fit-indices: SRMR=0.059, X^2/df =2.786.

Figure 2 depicts the standardised regression path-coefficients for relationships in the model under study. All the paths except the path (Course Quality→ Intention-to-use e-Learning platforms) have significant influences (p-values<0.1). The hypotheses findings are shown in Table 3. We find that though 8 paths are significant, some beta-values are negative indicating a negative association. Thus, hypotheses H3, H6 and H9 are refuted. The path-coefficients (β-values) are used to measure the influence of factor 1 on factor 2. In this study, we notice that emotional connect (emotional values) has the highest influence on intention to use a particular e-learning platform (β=0.521). Course reliability (epistemic values) (β=0.038) have the lowest influence on usage-intentions.

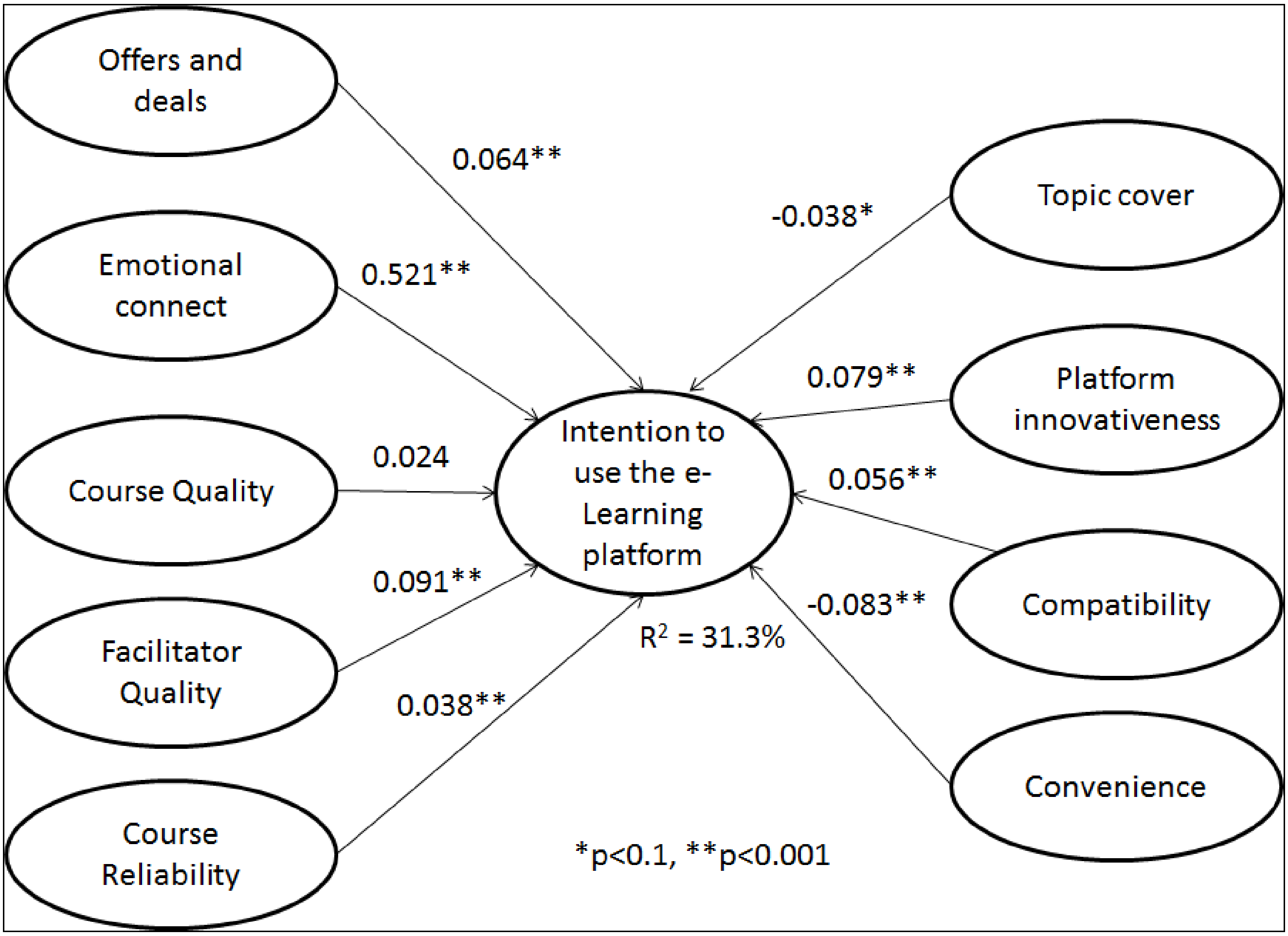

Figure 2. The path co-efficient of the various paths.

Table 3: Hypotheses results, Standard deviation (std. dev.), t-statistic, confidence intervals (C.I.), beta values, and results.

Hypothesis number: Paths	***Std. Dev.***	***t-statistics***	***C.I. 2.5%***	***C.I. 97.5%***	***β*-value, *p*-value**	**Conclusion**
H1: Offers and Deals→Intention-to-use e-Learning platforms.	0.016	3.968	0.034	0.094	0.064, $p<0.001$	Significant
H2: Emotional Connect→ Intention-to-use e-Learning platforms.	0.014	37.409	0.494	0.548	0.521, $p<0.001$	Significant
H3: Course Quality→ Intention-to-use e-Learning platforms.	0.015	1.584	-0.005	0.054	0.024, $p>0.1$	Refuted
H4: Facilitator Quality→ Intention-to-use e-Learning platforms.	0.015	5.954	0.063	0.121	0.091, $p<0.001$	Significant
H5: Course Reliability→ Intention-to-use e-Learning platforms.	0.016	2.369	0.011	0.069	0.038, $p<0.001$	Significant
H6: Topic Cover→ Intention-to-use e-Learning platforms.	0.021	1.839	-0.076	0.005	-0.038, $p<0.1$	Refuted
H7: Platform Innovativeness→ Intention-to-use e-Learning platforms.	0.015	5.287	0.046	0.105	0.079, p<0.001	Significant
H8: Compatibility→ Intention-to-use e-Learning platforms.	0.016	3.523	0.026	0.086	0.056, p<0.001	Significant
H9: Convenience→ Intention-to-use e-Learning platforms.	0.022	3.803	-0.117	-0.037	-0.083, p<0.001	Refuted

Discussion:

In this study, we have attempted to explore the various values that affect usage intention in case of e-Learning services using a unique mixed-method approach utilising only user-generated content. Additionally, we have utilised a novel NLP-SEM based approach for path-model analysis. For evaluating this approach, online-customer-reviews and Tweets about Coursera were utilised. This study has used a CVT perspective to evaluate the impact of various values on usage-intention. The hypotheses results are discussed below:

H1 examined the positive association between offers and discounts (conditional values) and intention to take up courses from an e-Learning platform. Similar to what earlier researchers (Qasim et. al., 2019; Suman et al., 2019) have found, findings reveal that conditional values and usage-intention are positively associated. The influence (β=0.064) of offers and discounts on usage-intention is good which might be due to the fact that an user when taking up an online course compares with other branded providers to find out which provider is offering better deals. If the course structures are almost similar, users tend to take up the course from the provider who offers better deals.

H2 explored the positive influence of emotional connect (emotional values) on intention to take up courses from an e-Learning platform. Findings reveal a strong significant positive association (β=0.548). This is similar to what earlier researchers have found in contexts like, consumption of organic food (Qasim et al., 2019), customer's purchase intention (Asshidin et al., 2016), etc. Possible reasons can be: First, users develop an emotional bonding with a particular provider when they feel that the courses offered by the provider are good and are value for money. Second possible reason can be the good presence of various quality courses in the platform that satisfies the customer needs which develops a feeling of loyalty among the customers.

H3, H4 and **H5** examined the positive relationship between quality values (course quality, facilitator quality and course reliability) with intention to take up courses from an e-Learning platform. Unlike what earlier researchers (Ali et al., 2018; Albelbisi & Yusop, 2019) have found, the study results show that course quality has no significant relationship with intention to take up courses from an e-Learning platform. However, what earlier researchers have found (Higginbotham & Myler, 2010; Berkel et al., 2018; Belanger & Carter, 2008; Seufert, 2012; Silic et al., 2018; Ray et al., 2019a), facilitator quality and course reliability have positive relationships with intention to take up courses from an e-Learning platform. Some possible reasons can be: First, earlier researchers have found that course quality (Li et al., 2011; Yang et al., 2017) and course flexibility (Liao et al., 2011) has a positive influence on usage-intention. However, due to the large number of popular e-Learning providers providing the same course, in this modern era, the users generally look for better deals (as evident from hypothesis H1) rather than course quality. However, the facilitator quality matters because the way the facilitator delivers the course will affect the learning process. Hence, we feel that the course design, the quality of contents taught in a course, the value addition of a particular course, the difficulty in understanding, the information quality, etc. play an important role in affecting customer's behavioural-intention. Second, in this present era of services marketing, most e-learning providers are trying to develop courses which will help in career growth. Hence the quality of the courses does not play a significant role. However, if the certificate provided by the e-Learning platform is not accepted by various job providers, it won't be useful for a user to take up courses from that particular provider. Hence, course reliability plays a significant role.

H6 and **H7** examined the positive association between epistemic values (topic cover and platform innovativeness) and intention to take up courses from an e-Learning platform. Results of this study reveal a negative relationship between topic cover and intention to use the e-Learning platform. This is unlike what earlier researchers (Lee et al., 2017; Choe & Kim, 2018) have found. The possible reason can be that the topics covered, the new techniques taught, etc. will be of not much value to users unless the facilitator taking the course can make it interesting. The other possible reason might be that users look for courses which cover important topics within a less amount of time. So if there are lots of topics available, users might feel that the facilitator may not be able to teach all the topics properly. Additionally they might also feel that it might be better to first learn a few topics within a particular time rather than taking up a course which covers a lot of topics and put pressure on them. This is also evident from hypothesis H4. We also see that in line with earlier researchers, (Wang & Huang, 2014; Zhang et al., 2017), we find a positive relationship (β=0.105) between platform innovativeness and behavioural intention. The possible reasons can that user look for e-Learning platforms which provides some technical facilities for enhancing the learning process like intelligent bots to handle user queries, forum for discussion, webinars to attend the lectures live and discuss with people from different places, etc.

H8 and **H9** explored the positive impact of functional values (compatibility and convenience) on intention to take up courses from an e-Learning platform. Similar to what earlier researchers have found in contexts like, using self-service technologies (Jia et al., 2012), etc., findings reveal a good influence (β=0.086) of compatibility on behavioural-intentions. Possible reasons can be: First, in case of e-Learning services, users need the platform to perform properly. Second users prefer platform which is very responsive. Thus, system quality and platform quality matter a lot. However, unlike what earlier researchers have noted in contexts like, use of video games (Bassiouni et al., 2019), and mobile payment services (Gao & Waechter, 2015), results of the study show that convenience has a negative influence on intention to use a e-Learning service. The possible reason might be that user might feel that if the courses can be taken anytime without a specific time period in mind, they will lose focus. Hence, convenience can play a negative role in affecting user decisions.

Theoretical Implications

This study has three main theoretical implications. First, this research has utilised the user-generated content to examine the conceptual path-model. Researchers in future can utilise this technique to utilise the abundant data available in various platforms for various research studies in various contexts. Since, collecting data for quantitative studies takes time, effort, and sometimes money, utilising the abundant data for analysing a conceptual model can become an alternative to quantitative research using path-models in future. Since topic modeling is used to find out the words/terms related to the user-generated content, this study can also be utilised as an alternative to qualitative research since the themes will provide the emic-perspectives of the customers who have used the service.

Second, this study provides an avenue for future researchers to utilize the user-generated content to explore not only the values or factors influencing user's intention but also barriers that affect user's decisions. Additionally, this study can be extended to generate a plethora of themes which can help in formulating better research models. Third, this study contributes to the e-Learning literature by exploring the various values from the customer's viewpoint as relevant from their posts. This is help researchers to gain a deeper insight from the online customer reviews. Finally, this study will help researchers working on topic modeling techniques. Here, Gibbs sampling in LDA is used and the probability scores are used to generate the data. This study provides a simple technique to utilise the probability scores. However, researchers can work on advanced techniques like hLDA in future.

Implications for Practice

This study will help managers for the following reasons. First, utilising the user-generated contents may be cost-effective since taking proper quantitative surveys of a large population may involve some investment. However, the user-generated content is easily available in company websites/social-media pages. This can be easily extracted and analysed. The availability of the user-generated content and the regular posts by users will help managers to get the instant views of customers unlike what happens in qualitative or quantitative-based studies. Second, this study provides an alternative way to qualitative and quantitative survey based path-models analysis. Using the NLP-based approach will help managers get easy and quick views of customers. Customers keep posting their views regularly and if a service has a wider presence, the company will be able to capture the perspectives of a wider population very easily. This will help them to analyse what aspects they lack and formulate their strategies as per the situation. If the service providers find out that the customers are favouring a certain factor, they may analyse and find out if that factor is an advantage or some issues that the customers are facing. If the factor turns out to be an issue, the service providers need to take required actions sooner than later. Hence, this study will be hugely beneficial for the service-providers. Third, the study results show that in case of e-

Learning services, though all the values (offers and deals, emotional connect, facilitator quality, course reliability, platform innovativeness, and compatibility) play an important role, emotional connect is the major predictors. This shows that managers need to focus more on the emotional aspect. Additionally, in the e-Learning sector, the website/app. functionality plays a huge role since it's the only medium though which the customer can learn and view the courses. If the platform is not functioning properly, it will result in dis-satisfied customers. Managers will also need to improve the facilitator quality. This shows that users choose an e-Learning service based on the offers and deals, course reliability, facilitators and emotional attachments. Companies to stay in the competition need to provide value-laden courses which will be beneficial for the users in future. Service-providers need to keep updating their course content regularly so that the courses provided will help the users in their career. Users usually take up courses which will be beneficial in their career growth. The service-providers need to keep a check on the facilitators and also the course pedagogy so that the quality of the service can be properly maintained. We also find that the users have mentioned "recommend courses" as an important factor. The loyal customers or the satisfied customer will refer others in their friends/peer circle to take up the courses from the service-providers they feel are good. This will also help the service-providers since they can easily promote their services through this loyal customer base without spending much in promotions.

Limitations and Future Directions

This study has a few limitations. First, this study will help only those service-providers who are providing services for quite some-time. Second, this study has used LDA based technique. However, there are other topic-modeling techniques like, hLDA, LSA, etc. Future researchers can work on finding out the best method by performing a comparison-based study. Third, the model did not demonstrate good discriminant validity measures which may be due to poor variation inflation factor scores. Future researchers can find some new ways to measure the validity and reliability of data generated from user-generated content. Additionally, future researchers can also work on combining the qualitative, quantitative and NLP-based approaches. In this study, only the online reviews and comments were considered. In future, researchers can also extract important information from the images/audio/videos posted by users regarding the service using neural network techniques, like convolution neural networks.

Conclusion:

In this modern era, the availability of abundant user-generated data in the form of online-customer-reviews/comments in social-media pages or company websites can not only help new customers choose a particular service but also help service-providers get an insight on the customer's perspectives. This study attempted to utilise a mixed-method approach using the user-generated content (online customer-reviews and tweets) for an e-Learning provider

(Coursera) to explore the values that affect user's decisions. The NLP-based approach has made use of topic-modeling techniques using LDA. While the findings of the thematic based analysis generated themes, like, "value addition", "easy to follow", "topic cover", "reliability of course", "course quality", "recommend the course", "videos to watch", "good deals", "value for money", "facilitator skills", "discussion forum", "review scores", etc. the quantitative based analysis of the customer reviews revealed that offers and deals, emotional connect, facilitator quality, course reliability, platform innovativeness, and compatibility are important predictors of user's intention to take up courses from e-Learning platforms.

Statement on Open Data, ethics and conflict of interest:

The data used from the Coursera 100k dataset is publicly available and is also cited properly in the text. The data taken from Twitter is also available for research purpose and the user ids are not shared anywhere. Also the authors have no conflict of interest to report.

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