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Exploring healthcare/health-product ecommerce satisfaction: A text mining and machine learning application

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ABSTRACT

In the digital era, online channels have become an inevitable part of healthcare services making healthcare/health-product e-commerce an important area of study. However, the reflections of customer-satisfaction and their difference in various subgroups of this industry is still unexplored. Additionally, extant literature has majorly focused on consumer surveys for customer-satisfaction research ignoring the huge data available online. The current study fills these gaps. With 186,057 reviews on 619 e-commerce firms from 29 subcategories of healthcare/health-product industry posted in a review-website between 2008 and 2018, we used text-mining, machine-learning and econometric techniques to find which core and augmented service aspects and which emotions are more important in which service contexts in terms of reflecting and predicting customer satisfaction. Our study contributes towards the healthcare/health-product marketing and services literature in suggesting an automated and machine-learning-based methodology for insight generation. It also helps healthcare/health-product e-commerce managers in better e-commerce service design and delivery.

1. Introduction

Consumer perception is vital for any organization, regardless of them being product and/or service-based. Both positive and negative perceptions resulting in consumer feedback and reviews are crucial for organizations to weigh their consumer-base. Consumer reviews provide such information, which assist organization to churn up various matrices like customer satisfaction (CSAT) and net promoter score (NPS) (Ho-Dac, Carson, & Moore, 2013). With deep internet penetration even in the remotest locations, consumers today are hooked online, whereby they share information, views in various online platforms via consumer reviews (Park, Gu, Leung, & Konana, 2014). While on the one hand, some organizations have a place within their website to enable the consumer to share his/her views/information through standardized quantitative or rating based fields, others have textual reviews; at times, both exist in coherence (Siering, Deokar, & Janze, 2018).

'Textual reviews' wherein a consumer can pour his/her heart out either in frustration or happiness are certainly one of the bests in terms of 'informative content'. Through this medium, organizations get a detailed understanding of consumer sentiments and emotions. Further, organizations do also get key insights into 'consumer psychology' in terms of how a consumer initial perceived a product/service vis a vis how s/he evaluated it post acquisition (Ye, Zhang, & Law, 2009). In fact, this insight helps specifically multifaceted service industries, like healthcare organizations for instance to deep-dive further to find how such sentiments, emotions and evaluations thereof actually lead the consumer to provide ratings. Importantly, with many healthcare/health-product ecommerce organizations now being in the fray, almost all of them seem to be preferring an omni-channel approach, whereby 'that' understanding gains further relevance.

Extant literature has extensively talked about how consumer reviews affect both an existing customer and a new customers' decision-making and the overall perceptions of the organization and its brand (Sharp, 2011). Studies that have primarily focused on healthcare services, have gone on to elaborate the rationales for making an online review helpful, almost to the point of it being 'invaluable' (Sandars & Walsh, 2009). However, extant literature has not focused on how the textual reviews can be used to find the reflectors and predictors of customer satisfaction in healthcare/health-product ecommerce (Sandars & Walsh, 2009; Sharp, 2011). This understanding is important as such an idea will help the healthcare/health-product ecommerce managers to make better service design, improved customer relationship management and

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efficient handling of customer reviews. The current study fills this gap. The key research question is: (a) How the opinion of the consumers of various service attributes leads to their overall satisfaction on healthcare/health-product ecommerce? (b) Whether importance of such attributes vary depending on the ecommerce subcategory? (c) Whether the textual reviews can be used to answer the above questions? (d) Whether the emotions expressed in such reviews reflects customer satisfaction?

Herein, we look to analyze consumer reviews and ratings specifically for the heathcare/health-product industry; primarily, healthcare/health-product ecommerce. In this attempt, at first, we analyzed the text of multiple reviews to explore diverse core and augmented (C&A) service aspects based on which consumers tend to give their reviews (textually). Then we looked at exploring how these overall and attribute wise sentiments and emotions lead to CSAT. Further, we show how healthcare/health-product ecommerce contexts change the above mentioned relationships. For example, the consumer expectations for a pharmacy and drugs ecommerce and a beauty products ecommerce is expected to be different. We explore such aspects in the third step. We also check the predictive power of the above mentioned variables to predict consumer satisfaction.

The structuring of this paper from hereon is as follows: the next section covers the theoretical model, followed by the methodology and the results. Discussion along with both the theoretical and practical implications follow. We conclude by highlighting the limitations and mention the future scopes as well.

2. Background study

2.1. Ecommerce customer satisfaction and customer ratings

Customer rating (CR) has been a major variable for marketers when it comes to assessing the progress of their action (Anderson, Fornell, & Lehmann, 1994). CR is known to enhance customer purchases, be it a new purchase or a repeat, which naturally results in organizational profitability (Anderson et al., 1994; Söderlund, 1998). But, what drives CR is a question that has plagued researchers for decades (Anderson & Sullivan, 1993; Martensen, Gronholdt, & Kristensen, 2000; Mouwen, 2015). This is particularly seen in cases where consumer heterogeneity and multiple business models exist (Grewal, Chandrashekaran, & Citrin, 2010). In fact, it is this 'heterogeneity' that leads to differential importance from consumers to differing service attributes.

To explain CSAT in ecommerce, extant literature has explored various underlying constructs like value, trust and service quality (Oh, 1999; Szymanski & Hise, 2000; Taylor & Baker, 1994; Zeithaml, Parasuraman, & Malhotra, 2002), using survey-based methods for data collection (Pappas, Pateli, Giannakos, & Chrissikopoulos, 2014; Wang et al., 2019). Nevertheless, it is important to understand user-generated ratings using user-generated information, as they would be free of various biases. Studies using user-generated content has focused on how pre-purchase and post-purchase attribute wise ratings impact the CR or CSAT on ecommerce (Posselt & Gerstner, 2005). Some have also tries to check whether the impact of such variables change over time and over product category (Dholakia & Zhao, 2010; You, Bhatnagar, & Ghose, 2016). However, it may be noted that both qualitative and quantitative data need to be combined in order to reflect or predict CR, as textual reviews are often rich source of information and the correct manifestation of consumer opinions. Extant literature has not focused on this aspect while studying consumer satisfaction with ecommerce firms using user-generated content (Dholakia & Zhao, 2010; Posselt & Gerstner, 2005). Our study is crucial in the sense that it acts as a bridge between theory and practice. We propose a methodology, whereby we look to create insights from user ratings through textual reviews by using text mining along with econometric and machine learning methods.

2.2. Online reviews

Online reviews also are extremely informative for 'prospective consumers', who're possibly uninformed or even ill-informed. The reviews, especially the ones, which are consistent, affect the purchase decision-making process. Organizations, thereby at times, often tend to go out of their way in trying to ensure getting positive reviews and ratings, which in turn helps them leverage their brand worth and brand value.

Extant literature has covered many dimensions of online reviews vis a vis its relevance and importance, when it comes to consumer decision-making, which in turn affects organizations' bottom line (Chevalier & Mayzlin, 2006; Duan, Gu, & Whinston, 2008). Extant literature has also focused on pricing and promotional strategies for organizations, for whom it is like a multi –period game (Ajorlou, Jadbabaie, & Kakhbod, 2016). While in the first half of the game, the focus remains on generating favorable online reviews, and the second half looks to leverage on the positive impact of the first half, which goes on to affect their price, sales and profits (Ajorlou et al., 2016). Understanding the underlying consumer psychological mechanisms leading to favorable reviews, vis a vis how organizations motivate consumers to do the same is also another area that has been explored in the past (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Mowen, Park, & Zablah, 2007). What motivates the bandwagon behavior in terms of providing incongruous online reviews are also explored (Cheung & Lee, 2012). Some researchers have found how the various types of customers or various types of purchase contexts can lead to difference in preferences and drivers of customer satisfaction (Ahani et al., 2019; Xu, 2020).

We primarily focus here on both metric and textual aspect of online reviews encompassing thereby the consumer sentiments and emotions holistically (Chatterjee, 2019; Siering et al., 2018). Interestingly enough, extant literature in healthcare services has not combined qualitative and quantitative information while explaining consumer satisfaction (Ng & Luk, 2019). In fact, in that sense, our study contributes to the extant literature (Ng & Luk, 2019). Moreover, it is important to note herein that attribute-wise sentiment mining and emotion mining has remained very limited, especially in healthcare marketing literature.

2.3. Text mining

True that 'structured data' is more comprehensible and useful; nevertheless, 'unstructured data' can yield much more information provided it is analyzed by combining both qualitative and quantitative techniques. 'Text mining' is one of the ways in which quantitative insights may be generated even from unstructured textual data. 'Text analytics' on the other hand, transforms the data processed from text mining, and creates actionable insights thereof. Text mining is used in document classification, topic modelling, translation, language identification, fake news detection, semantic mining, and chatbot development. Herein, following Hotho, Nürnberger, and Paaß (2005), we attempt to delve into textual reviews by pre-processing the text data at first, followed by text mining to create analyzable data. Further, text analytics is used to generate actionable insights.

However, in order to apply text-mining methods, it is important to have the unstructured text data clean and thereby ready; text pre-processing precisely helps in this endeavor. Pre-processing includes three phases: stop words removal, stemming and important word identification (Vijayarani, Ilamathi, & Nithya, 2015). Stop words include unnecessary words such as pronouns, prepositions, etc. Essentially, words that do not 'value-add' to the research context. Removal of such words is a necessity thereof, whereby the size of the text data reduces, and it helps in faster processing of the text data. Moreover, it also helps in ensuring that important data aren't lost in the mix, which are critical for text analysis (Feldman & Sanger, 2007). Removing 'stop words' involves multiple methods, such as mutual information method, Zipf's law method, classic method, and term-based random sampling. Once the clean dataset is available, they are stemmed to develop connections within sentences in an attempt to reduce similar information content (Vijayarani et al., 2015). Stemming may be done either by word truncation or statistical and/or mixed methods. The sole objective both stemming and stop words removal is to find the most important word. A common word for instance within the whole corpus is less important; however, a word oft repeated within a 'particular' document is certainly very important. Interestingly, this logic is captured in term frequency-inverse document frequency (TF-IDF) scores, which is used as a proxy of importance score of the words (Feldman & Sanger, 2007; Vijayarani et al., 2015).

The 'bag-of-words' (BoW) and parts-of-speech (POS) methods have been used for text analytics based on Brill (1995) recommendations. Further, we used POS tagging to identify the parts of speech a word per se. Herein, it may be noted that this is a very common method for feature selection from text (Asghar, Khan, Ahmad, & Kundi, 2014). Generally, when consumers articulate their views, they're nouns, while the views in themselves are adjectives; for example: "The bar in this hotel is classy"; while 'bar; is the noun, 'classy' is the adjective. Post the POS tagging, we use the BOW method after considering the nouns which carry the highest TF-IDF measures, thereby most important (Salton & Buckley, 1988); further, we club them under various service aspects. Scores of these words are further used in other data mining techniques in order to generate additional insights (Chatterjee, 2019).

Sentiment mining for ecommerce aspects as referred to above is the most common text analytics method; it could be done at the document level, sentence level or feature level. The two most common ways of identifying 'sentiment' include the Lexicon-based approach and statistical learning based approach (Feldman, 2013); while the most common way of identifying a sentiment within a text from the Lexicon-based approach is summating the sentiment scores of all the words in the text. The 'statistical learning based approach' could also be an alternative, whereby pre-marked data are used in various cutting edge machine learning techniques.

Given the prominence and importance of online reviews today, sentiment mining has become crucial in providing essential information, especially through overall as well as feature-wise sentiment mining techniques (Siering et al., 2018). Unfortunately extant research in the context of healthcare hasn't explored this feature enough (Chatterjee, 2019; Popescu & Etzioni, 2007; Siering et al., 2018). Given that we've attempted to use the same, our study gains more salience in terms of its contribution to extant literature (Popescu & Etzioni, 2007).

3. Hypotheses development

Exploring the antecedents of CSAT has been an important research domain in extant literature, covering service quality, trust, perceived value etc. (Garbarino & Johnson, 1999; Oh, 1999). There have also been attempts to understand how individual service attributes can lead to CSAT, as they are more accessible and diagnostic in nature. Moreover, according to the accessibility-diagnosticity (AD) model, such accessible and diagnostic input variables do lead to consumer outcomes, whereby we can consider individual service attributes as primary drivers of CSAT ratings (Vaidyanathan, 2000). However, these variables have different levels of accessibility and diagnosticity, which are reliant on consumer knowledge and/or his/her lack of information thereof. According to AD model, the influence of the memory of an input A on the attitude formation is directly proportional to its accessibility and inversely proportional to its diagnosticity. Moreover, the same is inversely proportional to its accessibility and directly proportional to its diagnosticity of other inputs (Lynch, 2006). Extending the above, the evaluation of various service aspects would have varied impact on consumer's overall satisfaction depending on their own and other aspects accessibility and diagnosticity.

As per multiple pathway anchoring and adjustment (MPAA) model, both personal characteristics of consumers (inside-out) and multiple attributes of services (outside-in) go on to build the consumer's overall attitude towards a service (Cohen & Reed, 2006). Therefore, a combination of multiple internal and external forces lead to the final consumer outcomes in terms of his/her purchase-decision making process for example. Factors that may impact the attitude formation are direct/imagined experience with the object, analytical attitude formation method, analogical reasoning, value and social-identity driven attitude etc. (Cohen & Reed, 2006). All of these together suggests that consumer attitude formation results from a complex mix of various types of factors.

Textual reviews provided by consumers give a vivid description of their experiences with a service (Chatterjee, 2019). Their sentiments expressed in textual reviews therefore about C&A service aspects are a rich source of information about a consumer's attitudes. As discussed earlier, such information are both accessible and diagnosable via text mining techniques, which essentially make them as primary reflectors of CSAT, as suggested by AD model (Lynch, 2006; Vaidyanathan, 2000). Extant literature explored the differential impact of the type of service aspects on consumer outcomes, which are of two types, i.e. core aspects, which provide basic benefits, such as food in a restaurant; and augmented aspects, which provide additional benefits, such as live music in a restaurant (Chatterjee, 2019). In a health ecommerce setting, it is important to study how sentiments towards C&A service aspects lead to overall satisfaction.

For the sake of managing consumer reviews in open online channels, it is also important to predict how changes made in C&A service aspects can affect consumer ratings. Therefore, the predictive power of the C&A service aspects in overall satisfaction is also an important area of study.

Therefore, we posit:

H1. Sentiment towards C&A service attributes has positive relationship with CSAT in healthcare/health-product ecommerce industry.

As per the MPAA model, along with service attributes, a consumer's personal characteristics do effect his/her overall attitude towards a service (Cohen & Reed, 2006). Consumer characteristics typically tend to finds its way of expressions through consumer emotions, which in turn leads to consumer outcomes. As per MPAA model, consumption emotions act as a medium for both outside-in and inside-out expressions of the consumers, which thus influence overall satisfactions (Cohen & Reed, 2006). Understandably, while positive emotions lead to favorable judgements, negative emotions may lead to harsher evaluations.

Textual reviews are certainly rich in information when it comes to consumer emotions. Extant literature has focused on how consumer emotions can be extracted from textual reviews (Chatterjee, 2019). However, unlike sentiment scores, emotion scores are multidimensional (Westbrook & Oliver, 1991); for instance, while on the one hand, we have positive emotions such as joy, trust, surprise etc., our negative emotions comprise as sadness, disgust, anger etc. Importantly, such emotions do not necessarily fall within the same dimension; in other words, they not only vary in terms of valence and degree, but also in terms of meaning and source (Westbrook & Oliver, 1991). Extant literature has dealt in detail on this aspect, establishing that such emotions do reflect a consumer's attitude and behavior (Chatterjee, 2019; Laros & Steenkamp, 2005).

However, extant literature has suggested that negative emotions lead to more diagnosticity (Filieri, 2016), which essentially makes the input variable stronger, as per AD model. Further, Cavanaugh, MacInnis, and Weiss (2016) have categorized emotions based on valence and arousal; for instance, while sadness may be a negative emotion, it is low on the arousal factor, while anger on the other hand, despite being a negative emotion too, is high on arousal. Additionally, it is important to note that a high arousal emotion is highly accessible, as it overcomes other cognitive processing (Filieri, 2016; Salehan & Kim, 2016), resulting thereby in higher effects of high arousal emotions. All these together lead to a very interesting focal point for our study, i.e. whether arousal, degree or valence of an emotion leads to different consumer outcomes.

The relationship with consumption emotion and customer satisfaction has been explained by the pleasure-arousal (PA) model by Ladhari

(2007). It suggests that the pleasure and arousal component of consumption emotions leads to positive cognitive state which in turn results in satisfaction and positive WOM. Extending the above, we argue that the expression of consumption emotions can be found in the textual reviews. Therefore the consumption emotions expressed in the textual reviews can reflect the satisfaction of the consumers. As per the PA models, as pleasure effects satisfaction, positive emotions are expected to be positively related with satisfaction. High arousal emotions are also expected to be more related to satisfaction that low arousal emotions (Ladhari, 2007). Therefore we posit:

H2a. Overall sentiment in textual review has significant relationships with CSAT in healthcare/health-product ecommerce industry.

H2b. Emotions expressed in textual review have significant relationships with CSAT in healthcare/health-product ecommerce industry.

Extant literature has suggested that consumers provide differential importance to various service aspects depending on the context of service (Xu, 2020). For instance, consumers give differential importance of service features for restaurants of different business models, such as fine dining vs. fast food restaurants. In an adventure travel business context, the relative importance of C&A service aspects tend to vary based on gender, demographics, travel goals and level of adventure (Matzler, Füller, Renzl, Herting, & Späth, 2008). In fact, in the hotel industry, the attribute level information generated from textual reviews have different influence on customer satisfaction depending on the type of the hotel (Xu, 2020). It has been also found that factors that consumers talk about and the factors that lead to their customer satisfaction can be different set of variables (Xu, 2020). The health oriented ecommerce industry also consists of various types of ecommerce. Some are generic, while some others focus on certain product segments, such as personal care, drug and pharmacy, eye-care, skincare, home health care etc. Therefore, the relative importance of C&A services vis vis the consumer emotions in reflecting and predicting consumer outcomes is expected to be different under these different contexts. Specific knowledge of such feature importance would help managers to create marketing plans focused to their own industry, while helping them manage customer reviews better.

Therefore, we further posit:

H3. The relationship strengths of the overall sentiment, aspect wise sentiments and emotions expressed in the textual review vary depending on the type of healthcare/health-product ecommerce.

All of the above hypotheses are important, as following Xu (2020), what consumers state in their reviews and what actually drives their satisfaction can be very different. This is because the underlying mechanism of review writing and underlying mechanism of customer satisfaction can be very different (Xu, 2020). Though we rely on the truthfulness of the review and emotion expressed, mere trivial relationship between the sentiments, emotions and overall satisfaction may not be true. Therefore further probe is important. Our approach is different from Xu (2020) as we adopted text mining and machine learning techniques along with econometric techniques to explain and predict customer satisfaction.

4. Empirical study

4.1. Data and processing

We have collected data about healthcare/health-product ecommerce firms from a website called trustpilot.com, which collects customer reviews about all types of ecommerce. We collected 186,057 reviews under the 'Health and wellbeing' category, which included 29 subcategories including 619 posts from healthcare/health-product ecommerce firms, posted between 2008 and 2018. The dataset had CR, a proxy of CSAT, in 1 to 5 point scale (1 = highly dissatisfied, 5 = highly satisfied), along with the textual review (title and main content) on the ecommerce firms. Fig. 1 summarizes the data processing and analysis framework. At first, we removed number and stop-words, blank spaces and punctuations etc. to make the initial pre-processed corpus. Next, we used lexicons NRC Word-Emotion Association Lexicon (also called EmoLex), created by Mohammad and Turney (2013) and found to be suitable for consumer review based analysis (Chatterjee, 2019; Siering et al., 2018) to get the overall sentiments (negative, positive) and 8 basic emotions from the text as listed in Table 1. In fact, similar methodology is common in information systems, data science and marketing literature (Dang, Zhang, & Chen, 2010; Mostafa, 2013; Taboada, Brooke, Tofiloski, Voll, & Stede, 2011).

For sub-category-wise analysis, we have chosen top six subcategories based on the number of reviews available: fitness and nutrition (40,708), beauty and wellness (35,065), drugs and pharmacy (15,443), cosmetic (13,121), skincare (12,795) and eye treatment (10,269). We found that the attribute-specific sentiments expressed in the text for these six sub-categories only as the attributes are different for different sub-categories. Further, we followed the bag-of-words method suggested by Chatterjee (2019) for finding sentiments attribute-wise; at first we found the nouns which occurred at least in 5% of the reviews (using package developed by Nguyen, Nguyen, Pham, and Pham (2016)). Following this, 4 experts and 9 users of healthcare/health-product ecommerce helped us to divide the nouns in various service attributes. The final list of nouns in various service attributes have been given in a supplementary file. The attributes found included service, product, delivery, price, facility, equipment and time. Further, in order to find attribute-wise sentiments, we have broken the texts in sentences to see if at least one word did relate to an existing attribute, following which we looked for the sentiment of such sentences. For example, a review on beauty and wellness segment says: "Love the product I ordered (BRANDNAME) – so pigmented and long-wearing. it's hard to believe it's not conventionally made. Love the free shipping and the eco-conscious packaging!". Based on the bag of words, here the part which is relevant to the attribute called "product" is "Love the product I ordered and the eco-conscious packaging!", Sentiment of this portion is used as the sentiment of "product" for the given review. Table 1 gives the statistical summary of the data.

4.2. Explanatory models

We have used linear regression analysis for finding the explanatory power of the insights generated from the review text. This is done in line with extant literature (Chatterjee, 2019; Siering et al., 2018). However, we have also included ordered logistic models expecting non-linear relationships and as the dependent variable is categorical rating (Chatterjee & Mandal, 2020). We analyzed the data as a whole and subcategory wise. For overall analysis, we only used the sentiment and emotion scores from the whole text and the title sentiment. For the subcategory wise analysis, we considered attribute-wise sentiments along with the variables as described above.

The result of the overall analysis suggests that the sentiment of the title and the body best reflects consumer satisfaction. Among emotions, anger and fear have very strong negative effect on satisfaction, while joy has strong positive effects. Uncertain emotions such as anticipation and surprise, though are positive in valence, have negative relationship with overall satisfaction. The effect of other emotions, though statistically significant, are very small. The result supports H2a and H2b.

While we try to compare the sub-categories, the above-mentioned impact of overall sentiment of the title and the body along with the emotions holds true, thus further supporting H2a and H2b. Some emotions specifically associated with some sub-categories include disgust with drugs and pharmacy, eye-treatment and beaut-wellness; sadness with skincare and eye-treatment. In terms of the ecommerce attributes, product assortment, services available and delivery are found to be most important for most of the sub-categories. Time aspects are most

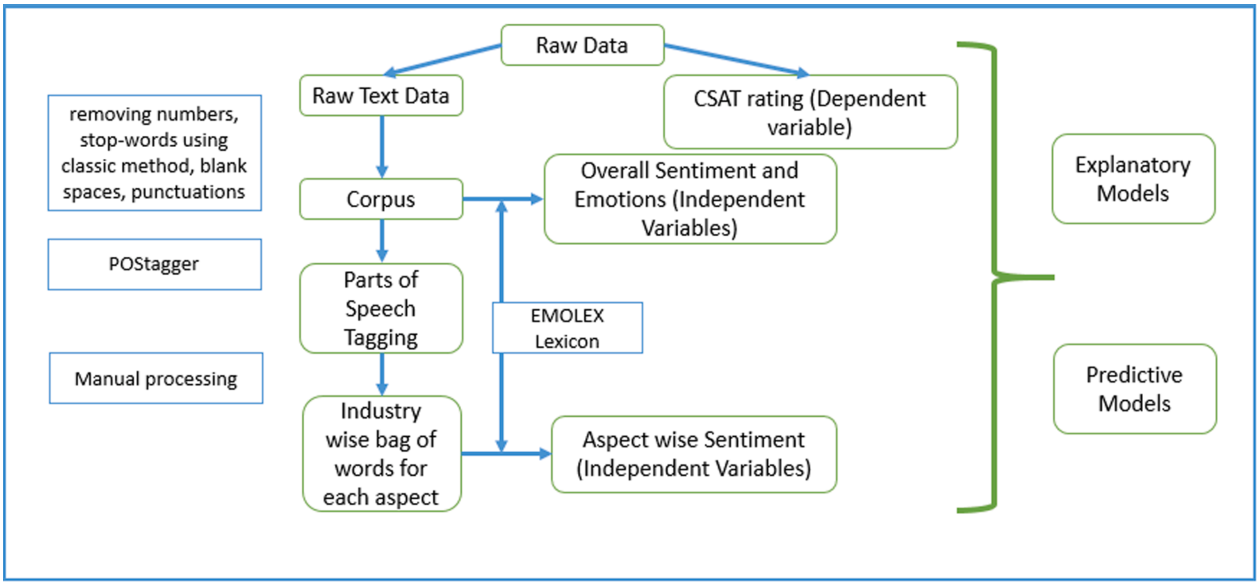

Fig 1. Flowchart for data handling and model building.

important for eye-treatment along with drugs and pharmacy. Price is important for cosmetics, beauty and wellness along with drugs and pharmacy; however as per the order-logistic regression it has not relationship with customer satisfaction for any category. Equipment and facility is important for fitness, drugs and skincare subcategories. The above results suggests that aspect wise sentiment can reflect customer satisfaction, thus supporting H1. However, the relative importance of overall sentiment, aspect wise sentiments and emotions expressed in the textual review vary depending on the type of healthcare/health-product ecommerce, which supports H3.

The models were free from multi-collinearity and heteroscedasticity issues. Table 2 summarizes the models.

4.3. Predictive models

We also used the predictive power of overall sentiment and emotions scores, and aspect-wise sentiment score in predicting overall satisfaction. We have used 100 fold validation method to check the outsample validity of the predictive models. For analysis we have used Linear Regression, XGboost, Random Forest and Decision tree (CART) as the methods. All these methods are commonly used for comparative analysis of the explaining power of machine learning models. As per Table 3, while XGboost and Random Forest show better predictive power in terms of lower root mean square error (RMSE), the linear regression model performs almost equally well. Thus, we can use linear regression model for predictive analysis too; the advantage being that the regression model is theoretically explainable.

4.4. Feature importance comparisons

For robustness check of the results obtained in the explanatory models, we further analyzed the predictive models to get the feature importance of various emotions and aspect wise sentiments for various subcategories. The supplementary file has detailed values of the feature importance scores, expressed in percentage terms where the total of the feature importance of all emotions and aspect wise sentiments is 100.

As per the results, joy, anger and disgust are most important emotions, while anger plays a very important role for cosmetics and disgust for eye-treatment. Unlike the regression results, in the predictive models, we find little feature importance of fear. Anticipation, sadness, trust and surprise are of less importance.

In terms of the service aspects, product, service and delivery are most important aspects as compared to the other four aspects. Service plays a very important role in case of fitness and nutrition, while product plays a very important role in beauty and wellness and cosmetics subcategories. In general, price plays a small role in the beauty and wellness category. Time is a crucial aspect for eye treatment. Figs. 2 and 3 gives the graphical representation of the above results.

5. Discussions

CSAT, which is an attitudinal aspect of consumer outcome, is of paramount importance when it comes to organizations looking to use a metric for assessing both consumer outcomes (Chang, 2015; Söderlund, 1998). Herein, based on user-generated information, we look to elaborate upon the antecedents of CSAT, specifically in healthcare/health-product ecommerce. We used textual qualitative reviews, and through text mining along with natural language processing techniques, we have attempted to derive insights from them. Sentiments and emotions expressed in a textual review for the overall service include our first salient finding. Moreover, we have also found the sentiments that have been expressed under specific service attributes, basing ourselves on keywords and bag of words. By and large, these insights form part of qualitative reviews, through which we have looked at explaining consumer outcomes. We also explored how the relationships as explained above, tend to vary over the multitude of business models.

Based on the regression results and the results obtained from feature importance scores, we can conclude that both the C&A service attributes do play a very important role when it comes to the 'types of ecommerce firms', especially in terms of reflecting and predicting CSAT. The above can be explained using MPAA model where consumer uses various pathways while building attitude (Cohen & Reed, 2006). This includes both personal characteristics of consumers (inside-out) and multiple attributes of services (outside-in). Therefore, a combination of multiple internal and external forces lead to the customer satisfaction, as supported in the results. The core attributes of ecommerce i.e., product assortment, services available and delivery, are most important. This is expected as per AD model, as the core attributes are more accessible and diagnostic (Vaidyanathan, 2000). The relative importance of product is higher for beauty and wellness as well as cosmetics, while the same for services is higher for fitness and nutrition. This is in expected lines, because the sub-category of beauty and cosmetics is heavily product centric, whereby it is the product performance and product quality that essentially lead to CSAT. On the other hand, service success in fitness

Table 1
Summary statistics of the variables in the models.

		Mean	Standard Deviation	Minimum	Maximum
All	Customer Rating	4.52	1.06	1	5
	Overall Sentiment Title	0.40	0.41	−1	1
	Overall sentiment Review	0.36	0.31	−1	1
	Anger	0.21	0.65	0	21
	Anticipation	1.05	1.52	0	44
	Disgust	0.17	0.58	0	17
	Fear	0.30	0.85	0	49
	Joy	0.98	1.32	0	38
	Sadness	0.33	0.89	0	26
	Surprise	0.41	0.81	0	21
	Trust	1.23	1.75	0	50
Fitness and Nutrition	Customer Rating	4.39	1.19	1	5
	Overall Sentiment Title	0.4	0.43	−1	1
	Overall sentiment Review	0.36	0.31	−1	1
	Anger	2.26	3.06	0	84
	Anticipation	0.74	1.67	0	56
	Disgust	0.29	0.79	0	18
	Fear	1.14	1.79	0	44
	Joy	0.24	0.73	0	17
	Sadness	0.36	0.96	0	22
	Surprise	1.06	1.53	0	38
	Trust	0.44	1.07	0	26
Beauty and Wellness	Customer Rating	4.53	1.04	1	5
	Overall Sentiment Title	0.4	0.41	−1	1
	Overall sentiment Review	0.36	0.3	−1	1
	Anger	2.28	2.66	0	53
	Anticipation	0.6	1.42	0	51
	Disgust	0.24	0.68	0	17
	Fear	1.08	1.52	0	31
	Joy	0.2	0.65	0	15
	Sadness	0.31	0.9	0	49
	Surprise	1.1	1.41	0	23
	Trust	0.34	0.93	0	26
Drugs and Pharmacy	Customer Rating	4.64	0.91	1	5
	Overall Sentiment Title	0.4	0.4	−1	1
	Overall sentiment Review	0.37	0.31	−1	1
	Anger	1.84	2.15	0	57
	Anticipation	0.46	1.23	0	26
	Disgust	0.17	0.57	0	12
	Fear	0.92	1.31	0	28
	Joy	0.11	0.45	0	9
	Sadness	0.24	0.78	0	27
	Surprise	0.74	1.05	0	29
	Trust	0.26	0.8	0	16
Cosmetics	Customer Rating	4.42	1.17	1	5
	Overall Sentiment Title	0.39	0.43	−1	1
	Overall sentiment Review	0.37	0.32	−1	1
	Anger	1.98	2.54	0	57
	Anticipation	0.51	1.35	0	30
	Disgust	0.21	0.68	0	14
	Fear	1.01	1.52	0	26
	Joy	0.16	0.58	0	16
	Sadness	0.22	0.67	0	17
	Surprise	0.94	1.27	0	26
	Trust	0.28	0.81	0	22
Skincare	Customer Rating	4.56	1.05	1	5
	Overall Sentiment Title	0.41	0.41	−1	1
	Overall sentiment Review	0.41	0.33	−1	1
	Anger	1.83	2.35	0	67
	Anticipation	0.41	1.2	0	29
	Disgust	0.16	0.58	0	14
	Fear	0.95	1.41	0	29
	Joy	0.13	0.49	0	10
	Sadness	0.17	0.59	0	16
	Surprise	0.87	1.19	0	21
	Trust	0.21	0.71	0	25
Eye treatment	Customer Rating	4.34	1.23	1	5
	Overall Sentiment Title	0.38	0.41	−1	1
	Overall sentiment Review	0.37	0.33	−1	1
	Anger	1.68	2.02	0	41
	Anticipation	0.42	1.08	0	24
	Disgust	0.14	0.5	0	8
	Fear	0.92	1.26	0	16
	Joy	0.12	0.44	0	6
	Sadness	0.17	0.55	0	10
	Surprise	0.72	0.95	0	10
	Trust	0.23	0.67	0	13

and nutrition often depend on consumers' motivations and discipline, which may be improved by services provided by ecommerce firms. Thus, service plays an important role in nutrition and fitness. Among the augmented aspects, time gets higher importance for eye-treatment along with drugs and pharmacy; for these two sub-categories, on-time delivery and on-time service is crucial. Price does have some importance for cosmetics, beauty and wellness along with drugs and pharmacy, as often such sub-categories are dependent on multiple and regular usage of products. Equipment and facility on the other hand, is important only for nutrition and fitness sub-category, as they often work in an omni-channel mode, where brick and mortar facilities and online ecommerce work conjointly. Thus, we conclude that the feature importance of consumer sentiments towards C&A service attributes vary depending on the type of healthcare/health-product ecommerce. This finding is in line with previous researchers who focus on the relative importance of core vs. augmented service aspects (Byrd, Canziani, Hsieh, Debbage, & Sonmez, 2016; Ravald & Grönroos, 1996).

We affirm the explanatory and predictive power of consumer emotions based on the results of the regression models and predictive models. A consumer's overall sentiment and title sentiment can reflect and predict his/her satisfaction the most. Further, it isn't surprising therefore that the most important emotions are higher arousal- anger, fear, disgust and joy. This can be explained by the PA model which suggests that the consumption emotions with higher arousal are more related to satisfaction (Ladhari, 2007). Specifically, disgust is more important in the sub-categories of drugs and pharmacy along with eye-treatment, while anger for cosmetics. This is in line with consumer identity literature related with cosmetics usage (Fabricant & Gould, 1993). Consumers of cosmetics ecommerce often have external locus on identity i.e., they look for social acknowledgement. Therefore the purchase context is psychologically distant, and any service failure in such a context, could lead to high arousal negative emotions such as anger (Davis, Gross, & Ochsner, 2011; Tatavarthy, Chatterjee, & Sharma, 2019). On the other hand, low arousal emotions such as anticipation,

Table 2
Explanatory Models.

Model	Regression							Ordered Logistic Regression						
Variables	Overall	Nutrition and Fitness	Beauty and Wellness	Drugs and Pharmacy	Skincare	Eye-treatment	Cosmetics	Overall	Nutrition and Fitness	Beauty and Wellness	Drugs and Pharmacy	Skincare	Eye-treatment	Cosmetics
AdjR2	0.2913	0.3451	0.2843	0.2234	0.3647	0.3351	0.4056							
AIC								252,654	62,557	47,562	18,218	15,746	15,499	19,227
(Intercept)	4.01***	3.76***	3.99***	4.25***	4.11***	3.68***	3.86***							
Overall Sentiment Title	0.63***	0.79***	0.62***	0.44***	0.5***	0.71***	0.67***	1.53***	1.62***	1.60***	1.32***	1.26***	1.57***	1.46***
Overall Sentiment Body	0.86***	0.95***	0.79***	0.58***	0.67***	1.03***	0.89***	2.83***	2.90***	2.75***	2.44***	2.33***	2.77***	2.67***
Anger	−0.28***	−0.29***	−0.29***	−0.2***	−0.25***	−0.14***	−0.33***	−0.41***	−0.43***	−0.46***	−0.23**	−0.40***	−0.23***	−0.49***
Anticipation	−0.06***	−0.07***	−0.07***	−0.06 ***	−0.08***	−0.05***	−0.04***	−0.16***	−0.13***	−0.18***	−0.22***	−0.24***	−0.13***	−0.14***
Disgust	−0.08***	−0.05***	0.03*	−0.19 ***	−0.1***	−0.27***	−0.11***	−0.03**	0.02 (NS)	−0.12***	−0.26**	−0.08 (NS)	−0.20*	−0.09 (NS)
Fear	−0.13***	−0.15***	−0.09***	−0.15 ***	0.04*	−0.02 (NS)	−0.04*	−0.25***	−0.25***	−0.19***	−0.28***	0.07 (NS)	−0.0 (NS)	0.05 (NS)
Joy	0.12***	0.12***	0.12***	0.1***	0.13***	0.14***	0.11***	0.26***	0.17***	0.31***	0.36***	0.32***	0.33***	0.23***
Sadness	−0.08***	−0.03***	−0.03***	−0.06 ***	−0.18***	−0.12***	−0.07***	−0.13***	−0.04*	−0.05(NS)	−0.11*	−0.27***	−0.14*	−0.11*
Surprise	−0.08***	−0.06***	−0.08***	−0.11 ***	−0.09***	−0.12***	−0.08***	−0.26***	−0.19***	−0.31***	−0.47***	−0.34***	−0.48***	−0.22**
Trust	−0.01 (NS)	0.03***	−0.01 (NS)	−0.01 (NS)	−0.01 (NS)	0.03*	−0.01 (NS)	−0.01 (NS)	−0.04**	−0.01 (NS)	−0.00 (NS)	0.03 (NS)	−0.02 (NS)	−0.00 (NS)
service		0.07***	0.11***	0.09***	0.16***	0.13**	0.14***		0.33***	0.02 (NS)	0.51*	0.62**	−0.01 (NS)	0.33*
product		0.02 (NS)	0.14***	0.12***	0.12***	0.11*	0.12***		0.00 (NS)	0.27**	0.20 (NS)	0.32*	−0.26 (NS)	0.17 (NS)
delivery		0.2***	0.15***	0.09*	0.31***	−0.01 (NS)	0.15***		0.17*	0.11 (NS)	−0.02 (NS)	0.74**	−0.11 (NS)	0.19 (NS)
price		−0.02 (NS)	0.11***	0.08*	0.11 (NS)	0.01 (NS)	0.18***		−0.27**	0.00 (NS)	0.08 (NS)	−0.43 (NS)	−0.17 (NS)	0.38 (NS)
time		0.04 (NS)		0.28***	−0.02 (NS)	1.03***			−0.27**		1.02***	−0.36 (NS)	3.37***	
facility			0.05 (NS)	−0.04 (NS)	−0.04 (NS)					1.37 (NS)	−0.55***	−0.51*		
equipment		0.25***							0.73**					
1|2								−2.37***	−1.92***	−2.32***	−2.76***	−2.43***	−1.94***	−2.18***
2|3								−1.72***	−1.37***	−1.69***	−2.19***	−1.98***	−1.26***	−1.55***
3|4								−1.05***	−0.69***	−0.98***	−1.51***	−1.37***	−0.53***	−0.85***
4|5								−0.08***	0.31***	0.01 (NS)	−0.48***	−0.33***	0.43***	0.09*

NS = Not significant, * means $p < 0.05$ and *** are $p < 0.0001$.

Table 3
RMSE scores of predictive models.

	Fitness & Nutrition	Beauty & wellness	Drugs & Pharmacy	Eye Treatment	Skincare	Cosmetic
Linear Regression	1.03	0.92	0.82	1.01	0.91	0.99
Xgboost	0.92	0.92	0.78	0.93	0.83	0.9
Random Forest	0.97	0.92	0.82	0.99	0.87	0.95
Decision tree	1.19	0.92	0.99	1.18	1.06	1.14

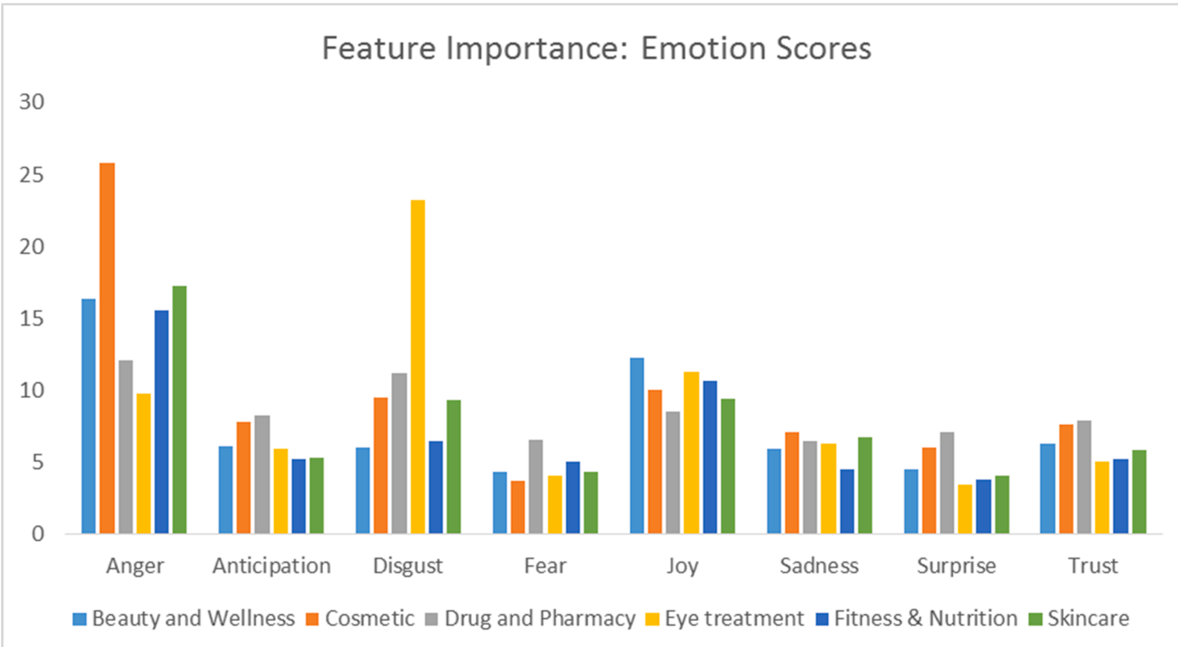

Fig 2. Average feature importance of emotions.

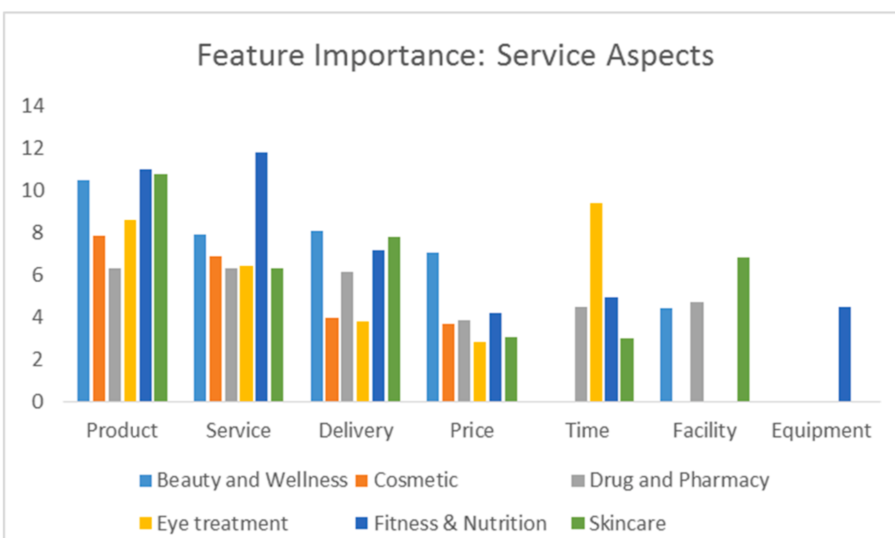

Fig 3. Average feature importance of service aspects.

sadness and trust are of less importance, as supported by PA model (Ladhari, 2007). Sadness does have some importance in the context of skincare category, possibly because skincare is often a psychologically close context, related to a consumer's identity (Lazar, 2011). Therefore, any service failure in skincare ecommerce may lead to low arousal negative emotions such as sadness (Davis et al., 2011). Based on the results, we conclude that consumer sentiments and emotions can and do reflect as well as predict CSAT in healthcare/health-product ecommerce industry. However, the feature importance of consumer emotions do tend to vary, depending on the type of healthcare/health-product ecommerce (del Bosque & San Martín, 2008).

5.1. Theoretical and methodological contribution

The paper has a number of theoretical and methodological contributions. Our first theoretical contribution is that the paper is a pioneering effort at exploring how the qualitative evaluations of the service aspects relate with CSAT, especially in the healthcare context (Siering et al., 2018). The importance of textual reviews has been extensively highlighted in extant literature thus far, (Brill, 1995; Hotho et al., 2005); however, what has remained unexplored is the method in combining both qualitative and quantitative data (Siering et al., 2018). Though the contribution in healthcare context is more applied in nature instead of core theoretical contribution, nuances in healthcare and health-product ecommerce context is very important. Healthcare being a multi-faceted service context, the theoretical underpinnings of customer satisfaction can result in very different reflectors and predictors, as found in our study. Thus the current contribution is important and unique in the healthcare context. On the other hand, the above is also a methodological contribution towards the literature which focus on ecommerce satisfaction study. Studies of ecommerce satisfaction was majorly survey-based with latent constructs like value, trust and service quality as the antecedents (Oh, 1999; Pappas et al., 2014; Szymanski & Hise, 2000; Taylor & Baker, 1994; Wang et al., 2019; Zeithaml et al., 2002). While some studies also included user generated content to study e-commerce satisfaction and tris to find the influence of pre and post-purchase attributes, they majorly relied on quantitative data obtained from review websites (Dholakia & Zhao, 2010; Posselt & Gerstner, 2005; You et al., 2016). This is the pioneering study which focus on ecommerce satisfaction using both quantitative and qualitative information from the user generated content, thus contributing to extant literature (Dholakia & Zhao, 2010; Posselt & Gerstner, 2005; You et al., 2016).

Our second important contribution lies in the fact that in extant literature dealing with textual reviews major importance have been given to overall or aspect-wise sentiments (Salehan & Kim, 2016; Siering et al., 2018; Ye et al., 2009); the usage of textual emotions scores has been limited thus far (Ahani et al., 2019; Wang et al., 2019). Through this study, we have found the emotions from textual reviews in order to explore how they relate to consumer outcomes (Salehan & Kim, 2016; Ye et al., 2009). While sentiments of various core and augmented attributes are expressed in the text, the emotions are often related to the results and experience of the usage of the ecommerce platform and the healthcare product/service. Thus by including the emotion elements in our study, we also explore how experiential outcomes is related to customer satisfaction. The relationship of experiential emotions and customer satisfaction is supported by PA model (Ladhari, 2007). Thus our study strengthens the above model.

Our third theoretical contribution is that we explored how the comparative importance of various service attribute-wise qualitative evaluations differ based on consumer outcomes in the healthcare service context (i.e. the subcategories of healthcare and wellbeing). Additionally, we also found that the importance of overall textual sentiment and textual emotions actually change while trying to reflect CSAT under the healthcare service context. True that past studies have dealt on how the service context impacts consumer evaluations (Ekinci & Riley, 2003; Matzler et al., 2008; Xu, 2020; Xu, Benbasat, & Cenfetelli, 2013), but when it comes to the healthcare/health-product ecommerce context, they're almost non-existent. The health oriented ecommerce industry also consists of various types of ecommerce, including generic ecommerce and more niche ecommerce. This varying context will lead to differential relative importance of C&A services vis a vis the consumer emotions in reflecting and predicting consumer. Specific knowledge of such feature importance would help managers to create marketing plans focused to their own industry, while helping them manage customer reviews better. Therefore, this is a pioneering study also in the context of healthcare CSAT literature.

We found that both core and augmented service attributes play crucial roles in reflecting and predicting CSAT in the healthcare/health-product ecommerce context. The above finding strengthens the MPAA model with additional evidences of validity of the model (Cohen & Reed, 2006). As per MPAA model, attitude formation happens based on inside-out and out-side in pathways and multiple internal (sentiment and emotions) and external variables (evaluations of service aspects) contribute towards satisfaction building. The current study ensures the same and contributes towards literature on usage of MPAA model in consumer behavior (Hasford & Farmer, 2016; Lynch, 2006).

5.2. Managerial implications

As regards managerial implications: the primary implication lies in its service design, which is often nontrivial decision for healthcare/health-product ecommerce firms, given that healthcare is often an amalgamation of multiple service aspects, whose importance may still be not known completely. We chose to focus both on C&A service aspects. The study that the former has higher importance than the latter. However, the relative importance of such aspects vary depending of healthcare/health-product ecommerce service contexts defined as the subcategories of the healthcare/health-product ecommerce industry. Therefore, the prioritization and resource allocation decisions during the service designing process should consider the above. When there's a resource allocation problem, ecommerce firms can use the regression models as objective functions and take investment decision for each service aspect which will improve CSAT.

Our study also gives a comparative analysis of the predictive models based on econometrics and machine learning and suggests that the econometric models work equally good in comparison to the most common machine learning models. Moreover, the information generated from the qualitative review can also be used to predict CSAT. Thus the study gives an automated system which can easily find the reflectors of CSAT in various service context giving suggestions where a healthcare/health-product ecommerce firm should focus. Ecommerce firms crunch huge set of data and automated predictive models suggesting potential service designs and handling consumer reviews via automated review management systems are important. This methodology of predictive machine learning models which is clubbed with text mining can extract relevant information from the text automatically and can find the relative importance of such information in predictive customer satisfaction, thus giving important marketing information to the managers in a dynamic ever-changing world.

Finally, the study suggested that both sentiment and emotions have explanatory power while reflecting CSAT. We further suggest such relative explanatory power varies depending on what type of healthcare/health-product ecommerce we are studying. During service failures, ecommerce contexts that are more close to self-identity (such as skincare) will result in low arousal emotions such as sadness while ecommerce contexts that are more close to social-identity (such as cosmetics) will result in high arousal emotions such as anger. This understanding is important for healthcare/health-product ecommerce service managers in service design, more specifically service recovery and customer relationship management strategy. For instance, based on the above understanding skincare ecommerce firms will focus on ensuring low arousal positive emotions (trust) via their recovery strategy while cosmetics ecommerce will try to induce high arousal positive emotions (joy). Therefore, the communication content and the recovery measures should also be designed accordingly.

5.3. Limitations and future scope

We have not studied the psychological mechanism that creates consumer attitude based on the sentiments and emotions felt by the consumer. Future research can bring in textual reviews in psychological experiments to give better clarity on this aspect. How such mechanism can lead to differential importance of different C&A attributes along with different sentiment and emotions in various healthcare/health-product ecommerce context should also be explored. Other variables, such as cultural and socio economic background of the consumers may also have an impact on the above mechanism. We could not study the same due to lack of data which can be studied by future researchers. The results can also be expanded in other healthcare/health-product ecommerce contexts, more so in Omni-channel contexts which is not done in the current study and can be explored in future. Possible bandwagon behavior in terms of providing incongruous online reviews can also be explored in the context of healthcare (Cheung & Lee, 2012). The bandwagon effect in the context of a healthcare product such as cosmetics may be high but such effect may not be present in eye-care, depending on how sensitive eye-care is to a customer in comparison to cosmetics. Future researchers can focus on the same. While using online reviews makes the data collection and information generation easier, one must keep in mind often the online reviews may not be a true representative of the customer sample. The demographic and psychographics of the consumers do drive their willingness to put reviews on online review channels (Manner, 2017). Therefore, while large dataset reduce the impact of bias, as is the case in our study, future researchers may try to overcome this limitation by including multiple review channels or combining both survey based and online review based findings.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2020.10.043.

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