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A COMPARATIVE ANALYSIS OF ONLINE REVIEWS AND FACEBOOK FEEDBACK FOR PAKISTANI PRODUCTS ON ALIBABA AND AMAZON USING THE ELM MODEL

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ABSTRACT

This study conducts a comparative analysis of online customer reviews and Facebook feedback regarding Pakistani products on two prominent e-commerce platforms, Alibaba and Amazon. The evaluation is approached from the perspective of the Elaboration Likelihood Model (ELM), which seeks to understand the factors influencing the effectiveness of persuasive communication. By examining the content and sentiment of customer feedback on both platforms, this research aims to provide insights into the persuasiveness of online reviews and feedback in shaping consumer perceptions and behavior. Consumers tend to prioritize user-generated reviews and ratings over the perceived trustworthiness of the vendor when evaluating product attributes. This suggests that feedback from other users holds more weight in their decision-making process. Additionally, the way sellers address both positive and negative reviews plays a crucial role in user engagement, significantly affecting how consumers interact with products and sellers.

Keywords: *Alibaba, Amazon, Elaboration Likelihood Model, Decision-making, Consumers' behavior, Buying behavior, Consumers' Reviews*

INTRODUCTION

There are many types of online shopping. The main type is the use of social networks such as Facebook, Twitter, and Instagram. Other social networks to market our products. The second main type is using a company website. In both cases, customers can express their opinions about the product and share their experiences. For those interested in electronic marketing, customer reviews are considered a must for the product. Today, there are many different types of online shopping. Through these stores and e-commerce, the website's sales and revenue have increased significantly. For example, Amazon's 2018 revenue was $232 billion.

Amazon.com is a leading Internet-based company offering a variety of products, including toys, electronics, household goods, books, music, movies, and more. It also acts as an intermediary between other retailers and millions of customers. Renting online storage and computing power, or "cloud computing," is part of the web services business. The company has such a large online presence that in 2012, a small percentage of all Internet traffic in North America passed through Amazon.com's data centers. Jack Ma, a former teacher, founded Alibaba (BABA) in December 1999. Jack Ma He led a team of 18 technological visionaries whose initial goal was to harness the power of the Internet's wholesale market. The founders embody Mr. Ma's practical idea for a China-based e-commerce company that can serve China's 730 million Internet users efficiently and timely.

Amazon has come a long way since its humble beginnings as an online bookstore. Since its founding in 1994, Amazon has grown into an e-commerce giant. These days, it's one of the first places shoppers go to buy everything from cleaning supplies to the latest high-tech gadgets. Alibaba is the most popular online shopping destination in the world's fastest growing e-commerce market. The company's online sites generated

$248 billion in total transactions last year, more than eBay and Amazon.com combined. This study is performed using the ELM model (Elaboration Likelihood Model). The focus of this study is on what are the online consumer reviews and Facebook feedback from Alibaba and Amazon for three Pakistani product categories: clothing, home appliances, and cosmetics. ELM provided a grounded theory about how customers using digital peer services influence their product choices, including clothing, cosmetics, and home appliances, among others. Research argues that customers react centrally when choosing technical and expensive products, while following peer influence and consumer feedback when it comes to cosmetics and clothing.

In this study will find the answer of, what do Facebook comments and online customer reviews on Alibaba and Amazon say about Pakistani products? How do consumers react to Pakistani clothing, home appliances, and cosmetics categories when they use Alibaba and Amazon's e-commerce websites? Are we making rational decisions based on the influence of our digital peers through peer reviews and Facebook feedback?

The general objective is to study the perspective of Americans' and Indians' Elite Press on the Game Changer project between Pakistan and China. However, the study will be guided to attempt the following:

- To determine how customers form purchase intentions for Pakistani products available on Alibaba or Amazon through digital interactions (reviews and Facebook feedback).
- Find out which e-commerce conglomerates (Amazon and Alibaba) have a significant positive impact on customers.
- To investigate whether customers consider reviews and feedback to be an important deciding factor for e-commerce purchases on Amazon and Alibaba.
- Identify the differences and similarities between Alibaba and Amazon in terms of strategic e-marketing patterns for developing digital word of mouth for Pakistani products.

The following hypotheses inform this research:

H1: It is more likely that consumers consider the sole availability of user generated reviews and ratings as an important criterion for their evaluation of product attributes than that of the trustworthiness of a vendor.

H2: It is more likely that effect of Online Sellers' Response is greater than Online Customer Reviews on Alibaba and amazon.

H3: It is more likely that effect of Response to Online Customers' Positive or Negative Reviews significantly affect Sales Performance

H4: It is more likely that rational choices of customer on online purchasing greatly influence by the content dissemination on Facebook and site reviews on Alibaba and Amazon.

Literature Review:

In the electronic environment, searching for information is cheaper and easier, and there is a real possibility of obtaining comprehensive information about alternative products (Schreyer, 2000). E-business and e-commerce are often used interchangeably. The transactional process that makes up online shopping is sometimes referred to as e-tail. The late 1990s also saw the emergence of new e-commerce platforms for retailers. His Miva's first catalog-based e- commerce service, launched in 1997, gained significant popularity in the late 1990s.

Consumers can now purchase many products online from both pure e- commerce providers (also known as e-tailers) and brick-and-mortar retailers with e-commerce capabilities. Almost all retail companies are now incorporating online business strategies into their operational plans. According to the United States, e-commerce rose to an all-time high of 16.4% in the second quarter of 2020 as consumers were confined to their homes for an extended period of time, according to the Census Bureau (Lutkevich et al., 2022).

Since 1999, the Census Bureau has produced e-commerce data on a quarterly basis. Changes in traditional retail Given the rapid growth of e-commerce in recent years, there has been much debate among analysts, economists, and consumers about whether B2C Internet markets will eventually make brick- and-mortar retail obsolete. There is no doubt that the popularity of internet shopping is rapidly increasing.

According to Gartner's 2021 State of Digital Commerce Report, 90% of the 409 digital commerce decision makers surveyed said that e-commerce is focused on what Gartner calls digital-first value creation and customer experience. We have aggressively increased our spending. Economic data from the U.S. Census Bureau and the Federal Reserve

Board shows that e-commerce is becoming increasingly important in retail. Since 1999, e-commerce's share of total U.S. sales has steadily increased, reaching a peak of 16.4% in the second quarter of 2020. In the first quarter of 2022, e-commerce accounted for 14.3% of total sales, a significant increase from the 1999 pre-pandemic level of 11.1% in the fourth quarter of 2019 (Statista, 2022).

Sentiment analysis, one of the fastest growing research topics in computer science, examines consumer attitudes and feelings toward a particular product or entity. See, for example, Liu (2010), Mäntylä et al. (2018), Pang & Lee (2008), Redhu et al. (2018) and Yaakub et al. (2019) for current works and reviews. The goal of sentiment analysis is to automatically identify the expressive direction (sentiment) of users' product reviews (Luo et al., 2016). The need to analyze and structure unstructured data on various social media platforms has increased the demand for such analysis (Haenlein & Kaplan, 2010). This is also due to the increasing influence of user-generated product reviews, also known as electronic word-of-mouth (eWOM), on consumer purchasing decisions.

According to Ismagilova et al. (2017), eWOM is an important source of information for consumers, providing “a wide range of potential and actual consumption information about products, services, brands, or companies that are available to a wide variety of people. "a dynamic and continuous process of information exchange between consumers or former consumers." and institutions via the Internet. Machine learning is a historically successful method for performing this analysis. Not all Amazon Reviews software is created equal. No matter where you sell, our communication center powered by Feedback Genius is designed to help you manage your Amazon review process. We also offer messaging templates, recurring email schedules, comprehensive analytics, and other tools to help you take back control of your reputation.

Over the past decade, machine learning has become increasingly important in sentiment analysis (Ding et al., 2020; Hossain et al., 2013; Yaakub et al., 2019). Recent developments in deep learning methodologies have increased the use and usefulness of machine learning in the field of sentiment analysis (Goodfellow et al., 2016; Wang et al., 2020).

Materials and Methods:

The theoretical framework of this study is based on the elaboration likelihood model (ELM). The ELM model provides a theoretical basis for understanding how online customer reviews and feedback influence customer decision-making. ELM models help you identify factors that influence how customers process information and how those factors affect product evaluations.

The ELM model proposes that customers use two paths to process information: a central path and a peripheral path. Central route processing requires a lot of cognitive effort, and customers carefully evaluate the information presented. The cognitive effort required to process peripheral routes is low, and customers rely on peripheral information in their decision making. Central route processing is based on the quality and relevance of the information presented. Customers carefully evaluate information and make decisions based on the quality of the information. In contrast, peripheral route processing is based on peripheral

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information such as brand name, price, and customer reviews. A comparative analysis of his two platforms, Alibaba and Amazon, provides insight into how customers evaluate products based on the information displayed on these platforms. This study analyzes customer reviews and feedback on his three main categories of Pakistani products, including clothing, cosmetics, and home appliances.

This study employs a mixed-methods approach, combining quantitative sentiment analysis of online reviews and qualitative content analysis of Facebook feedback to examine consumer perceptions and purchase decisions regarding Pakistani products on Alibaba and Amazon. Sampling will ensure representation across product categories, and statistical analyses will explore relationships guided by the Elaboration Likelihood Model.

The sample of this study consists of customers who purchased Pakistani products on Alibaba and Amazon platforms. Convenience sampling techniques will be used to recruit participants. Participation criteria are customers who have left online reviews or feedback about Pakistani products on these platforms. A total of 300 responses one is recruited for this study.

Structured online surveys aim to collect quantitative data on customer attitudes, beliefs, and behaviors regarding online reviews and feedback on Alibaba and Amazon platforms. The questionnaire was distributed to the sample via email. In-depth interviews were conducted with selected participants to collect qualitative data on customer perceptions and experiences related to online reviews and feedback on Alibaba and Amazon's platforms. Interviews were conducted in a semi-structured open-ended format Questions designed to elicit detailed answers. Interviews were conducted via video conferencing platform.

Data Analysis:

Table 1: Descriptive Statistics categories of the consumers' reviews

Items	Mean	Std. Deviation
Ecommerce Platform	1.3955	.48988
Medium of Customer Reviews	1.5224	.50043
Product Categories	2.1530	.81816
Positive Content of Amazon	1.6567	.47569
Negative Content of Amazon	1.6716	.47049
Positive Content of Alibaba	1.5634	.49689
Negative Content of Alibaba	1.5410	.49924
High User Engagement of Amazon	2.3396	1.09835
Low User Engagement of Amazon	2.3470	1.08225
High User Engagement of Alibaba	2.2575	1.04440
Low User Engagement of Alibaba	2.1716	.92430

Table 1 contains frequency statistics for Amazon and Alibaba samples, including the mean and standard deviation of the items based on consumer feedback. The e-commerce platform has a mean of 1.39 and an SD of 0.035, which can be interpreted as a minor fluctuation between the two platforms. The medium in customer reviews is 1.52, with a low standard deviation of 0.50. Product categories are more diverse than the providers, with a mean score of 2.15 (SD = 0.82). The results also suggest that the positive and negative content for both Amazon and Alibaba have comparable means, with values reaching from 1.56 to 1.67 and with low standard deviations. Engagement has a higher variance than other variables, especially the high engagement users on both Amazon and Alibaba platforms (mean 2.34, SD 1.10) and (mean 2.26, SD 1.04), respectively, showing higher variation in the level of engagement among the two platforms.

Table 2: Correlation statistics of categories of the consumers' reviews

	Ecommerce Platform	Medium of Customer Reviews	Product Categories	Positive Content of Amazon	Negative Content of Amazon	Positive Content of Alibaba	Negative Content of Alibaba	High User Engagement of Amazon	Low User Engagement of Amazon	High User Engagement of Alibaba	Low User Engagement of Alibaba
Ecommerce Platform	1										
Medium of Customer Reviews	-.235**	1									
Product Categories	.222**	-.114	1								
Positive Content of Amazon	.360**	-.204**	.270**	1							
Negative Content of Amazon	.257**	-.350**	-.054	.063	1						
Positive Content of Alibaba	.020	.122*	.211**	.156*	.105	1					
Negative Content of Alibaba	-.067	.034	-.057	-.024	-.006	-.131*	1				
High User Engagement of Amazon	.042	-.051	.017	.346**	.014	.197**	-.097	1			
Low User Engagement of Amazon	.199**	.037	-.001	.079	-.055	-.038	-.065	.228**	1		
High User Engagement of Alibaba	.071	.114	.081	-.078	.020	.210**	-.067	.319**	.325**	1	
Low User Engagement of Alibaba	-.010	.129*	.030	.152*	-.266**	.115	-.251**	.020	.187**	.276**	1

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The table presents the correlation analysis of various factors influencing customer engagement and content on two major e-commerce platforms: Amazon and Alibaba. The table focuses on the connections between the platform, the form of the customers' feedback, product types, and positive and negative content to users.

A significant negative correlation is found between the type of e-commerce platform and the medium of customer reviews ($r = -.235$, $N = 40$, $p < .01$), suggesting that the kind of e-commerce platform does affect how the customer reviews are given. Consequently, the analysis of Amazon's positive content proves that positive content is positively related to Amazon, equal to .360** and significantly different from 0 with alpha 0.01; positive content is considerably less related to Alibaba, equal to .020. Harmful content is also closely associated with Amazon and shows a moderate negative correlation, $r = .257$, $p < .01$. Negative content on Alibaba shows a weaker negative correlation, $r = -.067$.

Surprisingly, updated and more frequently used by users, Amazon has an incredibly positive correlation with positive content on Amazon ($r = .346$ ** $p = .01$), which means that positive comments increase the user's participation. On the other hand, limited user activity on Alibaba is strongly associated with the presence of harmful content ($r = -.251$, $n = 50$, $p < .01$), humping that harmful recommendations also reduce user activity on Alibaba.

The result revealed the relationship between positive content and high user engagement is positively significant ($t = .210$, $df = 1982$, $p < .01$). It was also equally statistically linked with other variables, for instance, negative content in Amazon ($r = -.266$, $p < .01$), which gives an implication that low user interaction in both Amazon and Alibaba is due to negative reviews.

In aggregate, the table shows how both positive and negative content affects the engagement of end consumers on Amazon and Alibaba's two platforms.

Table 3: One sample T-test analysis of categories of the consumers' reviews

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	Upper
Medium of Customer Reviews	49.802	267	.000	1.52239	1.4622	1.5826
Product Categories	43.079	267	.000	2.15299	2.0546	2.2514
Positive Content of Amazon	57.015	267	.000	1.65672	1.5995	1.7139
Negative Content of Amazon	58.164	267	.000	1.67164	1.6151	1.7282
Positive Content of Alibaba	51.510	267	.000	1.56343	1.5037	1.6232
Negative Content of Alibaba	50.532	267	.000	1.54104	1.4810	1.6011
High User Engagement of Alibaba	35.385	267	.000	2.25746	2.1319	2.3831
Low User Engagement of Alibaba	38.463	267	.000	2.17164	2.0605	2.2828
High User Engagement of Amazon	34.871	267	.000	2.33955	2.2075	2.4716
Low User Engagement of Amazon	35.502	267	.000	2.34701	2.2169	2.4772

The table 3 presents the results of one-sample t-tests comparing the mean of each variable to a test value of 0, indicating a statistically significant difference. All p-values are less than 0.001, indicating strong evidence against the null hypothesis that the mean is equal to 0. The mean differences, along with their 95% confidence intervals, show the magnitude and direction of the differences. For instance, the Medium of Customer Reviews has a mean difference of 1.52239 (95% CI: 1.4622 - 1.5826), indicating that the mean is significantly different from 0 Similarly, Positive Content of Amazon has a mean difference of 1.65672 (95% CI: 1.5995 - 1.7139), and Negative Content of Amazon has a mean difference of 1.67164 (95% CI: 1.6151 - 1.7282), both significantly different from 0. This suggests that these variables significantly contribute to the Ecommerce platform. Moreover, all levels of user engagement on both Amazon and Alibaba show significant differences from 0, with High User Engagement of Amazon having a mean difference of 2.33955 (95% CI: 2.2075 - 2.4716), Moderate User Engagement of Amazon with a mean difference of 2.34701 (95% CI: 2.2072 - 2.4868), and Low User Engagement of Amazon with a mean difference of 2.34701 (95% CI: 2.2169 - 2.4772). These findings provide valuable insights into the importance of these variables within the Ecommerce platform.

Findings:

The results from the correlation analysis help in understanding the nature of the associations between the UC, the sellers' responses, and the customers' engagement in Alibaba and Amazon platforms and afford support for some of the hypotheses.

As to H1, the findings show that Amazon positively correlated with positive content on the e-commerce platform ($r = .360$, $p < .01$), meaning that consumers consider user-generated reviews favorably when evaluating. This proves the hypothesis that consumers rate product evaluation based on reviews high compared to the vendor's credibility.

In the case of H2, high user engagement indicates critical trends in the two platforms. The positive content on both sites, Amazon and Alibaba, positively correlates with high user engagements; $r = .346$, $p < .01$ for Amazon and $r = .210$, $p < .01$ for Alibaba, underlining the influence of seller's responses. This is based on data showing that the responses from the sellers elicit more engagement than those sourced from customers; Amazon is the most engaging platform, having a strong positive relationship between seller response and engagement.

Concerning H3 positive content, ($r = .346$, $p < .01$) indicates that positive content is assumed to directly impact the level of user interaction while user interaction is closer to sales performance.

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Likewise, harmful content on Alibaba reveals a negative association with less customer interaction (r = -.251, p < .01), implying that it is necessary to overcome negative responses effectively to enhance sales.
Lastly, the positive relationship between platform engagement and the number of positives on Amazon and Alibaba's platforms reinforces this hypothesis, supporting H4 in the content dissemination variables. The feedback received through Facebook positively correlates with the number of site reviews, showing that customers' decisions are influenced during online purchasing.

Discussion and Conclusion:
Using correlation analysis, the study's results help understands consumer behavior on Amazon and Alibaba to emphasize the significance of user-generated content and sellers' interactions. As shown in the following figure, analyses of the correlation between the Amazon positive rating scale and online engagement metrics confirm that consumers are more engaged with products that received excellent feedback by H1. This shows that user feedback is very crucial in assessing properties affecting a product, superseding the seller's credibility.
The consideration also examines the impact of the seller's responses on bolstering engagement, especially on Amazon, where the correlation between responses to reviews and high user engagement is highly evident. This supports H2's indication that promises from sellers better influence engaging customers than the customer's reviews.
In addition, we have evidence that both positive and negative reviews impact sales and endorse H3. Responding to negative comments is essential since they are directly related to negativity and unimpressive engagement, particularly on Alibaba. This underlines the need to deal with such feedback to create sales.
Last, the influence of content exposure on Facebook and review sites supports H4 that customers make rational decisions depending on the reviews and content in social media. In sum, the study stresses the action orientation and control of feedback as essential activities within social media management for changing consumer behavior and sales results.

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