

NEGATIVE E-REVIEWS AND PURCHASE INTENTION: EVIDENCE FROM SAUDI FAST-FOOD CONSUMERS

YASIR ABDUL KARIM BIN ZAID

Imam Mohammad ibn Saud Islamic University (IMSIU), College of Media and Communication, Riyadh, KSA.

IYAD A. AL-NSOUR*

Imam Mohammad ibn Saud Islamic University (IMSIU), College of Media and Communication, Riyadh, KSA. *Corresponding Author Email: laalnsour@imamu.edi.sa

Abstract

This study examines the impact of negative electronic reviews on Saudi consumers' purchase intentions, with a specific application to fast-food restaurants on Google Maps. The independent variable is conceptualized through three dimensions: review quality, review credibility, and review volume, each representing a distinct aspect of negative electronic reviews. A quantitative research approach was employed using a survey method. Data were collected through a structured questionnaire from a purposive sample of 387 consumers who had engaged with negative reviews on Google Maps. The data collection period extended from October 30, 2024, to February 8, 2025, focusing on customers of popular fast-food restaurants in Riyadh, Saudi Arabia. The findings reveal that review credibility has a significant effect on purchase intention, whereas the quality and volume of negative reviews exhibit limited or non-significant effects. Furthermore, the results indicate that negative electronic review factors collectively explain 26.6% of the variance in purchase intention. The study highlights the critical role of credibility as a key determinant in shaping consumer decision-making in digital environments. Based on these findings, the study recommends encouraging consumers to provide honest and detailed reviews, enhancing information clarity and accessibility, and utilizing visual content (e.g., images and videos) to improve communication and reduce misunderstandings on digital platforms.

Keywords: Electronic Reviews, Negative Reviews, Purchase Intention, Saudi Consumer, Fast Food Restaurants, Google Maps.

1. INTRODUCTION

Communication- and technology-driven marketing have become fundamental mechanisms for market penetration and effective engagement with target audiences (Cohen et al., 2024). This paradigm shift has fundamentally reconfigured the nature of firm–customer interactions, enabling unprecedented levels of market expansion and organizational growth (Sharma & Kumar, 2024). Consequently, firms have reoriented their strategic approaches across diverse markets to establish relationships with consumers that are not only efficient and rapid but also economically sustainable (Martinez & Thompson, 2024). In parallel, organizations increasingly prioritize expansion into large-scale markets, as smaller markets may constrain scalability, profitability, and long-term competitiveness (Green, 2023). Moreover, firms have intensified their communication infrastructures to maintain resilient connections with customers during periods of economic uncertainty and heightened labor market competition (Miller & Davidson, 2024).

The convergence of communication technologies and digital platforms—particularly social media—has significantly enhanced firms' capacity to reach broad audiences, elevate brand visibility, and improve financial performance (Chen & Wang, 2024). Social media, in particular, has evolved into a critical strategic asset, facilitating brand loyalty, strengthening corporate reputation, amplifying electronic word-of-mouth (eWOM), and enabling more precise customer targeting (Rowi et al., 2024). Additionally, interactive, technology-enabled advertising has emerged as a powerful tool for fostering two-way communication and cultivating long-term customer relationships (Suraña-Sánchez et al., 2024). Such advertising formats play a pivotal role in shaping consumers' purchase intentions and influencing their decision-making processes (Ngo et al., 2024).

Global investment in social media reached approximately \$270 billion in 2025, alongside a rapid increase in digital connectivity, with 5.24 billion internet users and 4.78 billion social media users worldwide (Synup, 2025). This digital acceleration has transformed corporate web interfaces into dynamic platforms that enable direct interaction and open dialogue with consumers (Rowi et al., 2024). These platforms offer advanced functionalities for evaluating brands and products, while simultaneously allowing users to express immediate feedback—whether positive or negative—along with their needs and expectations (Chen et al., 2023). As a result, consumers have gained greater control over brand narratives and expanded opportunities for peer-to-peer communication (Pangarkar et al., 2023). This transformation has effectively eliminated temporal and spatial barriers, facilitating seamless connectivity between firms and consumers (Suraña-Sánchez et al., 2024). Furthermore, such digital interactions have become central determinants of purchase intention and decision-making, while also enhancing customer satisfaction, trust, loyalty, and brand commitment (Al-Nsour, 2013; Capillary Technologies, 2024).

Within this context, electronic reviews (e-reviews) have emerged as a critical communication mechanism through which firms can systematically capture consumer opinions, behavioral trends, and evaluative judgments across digital platforms. These reviews may take multiple forms, including textual content, audio commentary, images, and visual representations (Benlahbib & Boumhidi, 2022). Fundamentally, e-reviews represent evaluative expressions grounded in actual user experiences (Qiu & Zhang, 2024), thereby reinforcing the importance of experiential knowledge sharing within digital ecosystems (Al-Nsour, 2020). They can be conceptualized as positive or negative statements generated by potential, current, or former customers and disseminated to a wide online audience (Power Reviews, 2023).

E-reviews constitute a rich and multifaceted source of consumer-generated information, offering substantial value to both individuals and organizations (Al-Nsour, 2023). From the consumer perspective, they provide authentic and relatively unbiased reflections of product and service experiences, serving as a critical input in shaping purchase intentions and decision-making processes (Rahman et al., 2024). From the organizational perspective, e-reviews reflect consumers' perceptions of their consumption experiences and, consequently, indicate a firm's effectiveness in managing and influencing these perceptions. Moreover, systematic analysis of e-reviews enables firms to identify key

determinants of customer satisfaction and recommendation behaviors (Yae-Ji & Kim, 2022). Accordingly, this study focuses on negative e-reviews generated by Saudi users on Google Maps. As one of the most prominent digital platforms, Google Maps facilitates user-generated content related to restaurant services, including image uploads, written reviews, and real-time evaluations. Its immediacy, accessibility, and widespread adoption make it a highly influential medium in shaping consumer perceptions and purchase intentions within the Saudi context, particularly in Riyadh.

2. PROBLEM STATEMENT

The rapid diffusion of digital technologies and social media platforms has fundamentally transformed the landscape of consumer–firm interactions, positioning electronic reviews as a central determinant of consumer behavior. Within this context, online reviews—particularly negative ones—have emerged as highly influential informational cues that shape consumer perceptions, attitudes, and purchase intentions. Grounded in signaling theory, negative reviews act as credible signals that reduce information asymmetry between consumers and firms, often exerting a disproportionately stronger impact than positive information due to negativity bias. Similarly, from the perspective of the Stimulus–Organism–Response (SOR) framework, negative electronic reviews represent external stimuli that influence consumers’ internal cognitive and emotional states, ultimately affecting their behavioral responses, including purchase intention.

In Saudi Arabia, the increasing penetration of digital platforms has intensified the role of user-generated content in shaping market dynamics. With approximately 35.3 million users—representing 95.3% of the population—actively engaging with online applications, digital platforms have evolved into powerful socio-commercial ecosystems where consumers actively share experiences through ratings, reviews, and visual content (Sprinklr, 2025; DataReportal, 2024). This widespread adoption has amplified the visibility and impact of negative consumption experiences, enabling them to spread rapidly and influence large audiences. Consequently, firms operating in highly competitive sectors, such as the restaurant industry, face increasing pressure to manage their online reputations and respond effectively to negative feedback. Moreover, Saudi Arabia’s rapidly expanding e-commerce sector—ranked 27th globally, with revenues reaching \$222.9 billion in 2024 and projected to grow to \$708.7 billion by 2033 (IMARC Group, 2024)—further underscores the importance of understanding the mechanisms through which digital interactions influence consumer decision-making. Platforms such as Google Maps, which enable real-time reviews, ratings, and visual content sharing, have become critical touchpoints in the consumer journey. Through features such as local directories and user-generated evaluations, these platforms significantly shape perceptions of service quality and trustworthiness.

Despite the theoretical and practical significance of negative reviews, a critical gap remains in the literature. While prior studies have extensively examined the influence of online reviews in global contexts, there is a persistent need to update empirical findings and test their applicability across different cultural and market environments. More

importantly, there is a notable scarcity of research within Arab and Saudi contexts, particularly concerning the impact of negative electronic reviews on consumer purchase intention in the restaurant sector. This gap limits the generalizability of existing theories and constrains the ability of practitioners to develop context-specific strategies. Accordingly, this study seeks to address this gap by examining the impact of negative electronic reviews on the purchase intention of Saudi consumers, with a specific focus on restaurant services presented on Google Maps. By integrating theoretical perspectives such as signaling theory and the SOR framework within the Saudi digital environment, this research aims to provide a more nuanced understanding of how negative reviews influences consumer decision-making in emerging markets.

3. RESEARCH OBJECTIVES:

The primary objective of this study is to examine the impact of negative electronic reviews on Saudi consumers' purchase intentions, with specific application to fast-food restaurant products presented on Google Maps. To achieve this objective, the study pursues the following specific objectives:

- a) To assess the level and prevalence of negative electronic reviews related to fast-food restaurant products on Google Maps.
- b) To evaluate the level of Saudi consumers', purchase intention toward fast-food restaurant products featured on Google Maps.
- c) To analyze the impact of negative electronic reviews on Saudi consumers' purchase intention toward fast-food restaurant products on Google Maps.

4. SIGNIFICANCE OF THE STUDY (RESEARCH CONTRIBUTIONS):

This study contributes to the existing body of knowledge by addressing a critical gap in the literature concerning the relationship between negative electronic reviews and online purchase intention within the Saudi context. Specifically, it extends current understanding by empirically examining how negative reviews related to fast-food restaurant products influences Saudi consumers' behavioral intentions. In doing so, the study enhances the contextual applicability of established theories—such as signaling theory and the Stimulus–Organism–Response (SOR) framework—within emerging digital markets. From a practical perspective, the study provides valuable insights for stakeholders in the fast-food restaurant sector in Saudi Arabia. It highlights the strategic importance of negative electronic reviews as a key determinant of consumer decision-making. By understanding how such reviews shape purchase intentions, managers and practitioners can develop more effective strategies to monitor, manage, and respond to online feedback. Furthermore, the findings offer actionable implications for improving product quality and service performance, as well as optimizing digital presence on platforms such as Google Maps. This, in turn, can enhance customer satisfaction, strengthen brand reputation, and support more informed managerial decision-making in a highly competitive digital environment.

5. LITERATURE REVIEW

5.1 Electronic Reviews

Electronic reviews (e-reviews) refer to online, user-generated information shared through digital platforms, which may take various forms depending on their accessibility, scope, and source (Le et al., 2024). These reviews constitute a critical component of electronic Reviews, serving as influential informational cues that shape consumer perceptions and decision-making processes. Importantly, e-reviews can fulfill dual functions—either reinforcing positive consumption decisions or warning against potential risks—depending on the nature of the product and the intent of the reviewer (Ahn & Lee, 2024). From a functional perspective, the persuasive power of electronic reviews varies across consumption contexts.

In the case of hedonic or promotional consumption (e.g., products associated with image enhancement such as photo-editing applications), evaluations tend to emphasize desirability and experiential value. Conversely, in preventive or utilitarian consumption contexts (e.g., antivirus software aimed at risk avoidance), negative reviews tend to exert stronger persuasive effects, as they highlight potential losses or failures (Anastasio et al., 2024). This asymmetry aligns with established theories such as negativity bias and signaling theory, where negative information is perceived as more diagnostic and credible.

Moreover, electronic reviews function as interactive communication tools that may be verbal (textual or spoken) or non-verbal (images, ratings), facilitating dynamic exchanges between information providers and recipients across digital platforms (Ahn & Lee, 2024). In this sense, e-reviews can be conceptualized as a process through which consumers evaluate and communicate their experiences—often including negative assessments—regarding products or services they have consumed. This process is supported by digital infrastructures and algorithmic systems that enable the creation, dissemination, and visibility of such content (Al-Nsour, 2022). At the consumer level, electronic reviews represent a rich and credible source of information, enhancing transparency, social interaction, and informed decision-making (Malkawi et al., 2025).

They also provide an outlet for emotional expression, allowing consumers to articulate dissatisfaction and share negative experiences, which in turn influence the purchase decisions of others (Qiu & Zhang, 2024). At the organizational level, e-reviews serve as a valuable feedback mechanism, enabling firms to better understand customer needs, identify service gaps, and respond to market expectations. By effectively leveraging such insights, companies can strengthen their competitive positioning and improve overall business performance (Bilal et al., 2021).

Empirical evidence further suggests that electronic reviews significantly contribute to key organizational outcomes, including increased sales, enhanced customer trust, and improved financial performance (Sun et al., 2021). Consequently, e-reviews have evolved into a strategic asset within digital marketing ecosystems, playing a pivotal role in shaping both consumer behavior and firm-level success.

5.2 Negative Electronic Reviews

Negative electronic reviews refer to evaluative statements generated by dissatisfied consumers who share their purchasing experiences with others, often highlighting product deficiencies and unmet expectations (Sansome et al., 2025; Alawneh et al., 2025). These reviews typically emerge when products or services fail to align with consumer expectations and may take multiple formats, including written text, images, or videos. In essence, they focus on identifying shortcomings encountered during product usage, such as poor quality, service failures, or unmet functional and experiential needs. From a conceptual standpoint, negative e-reviews constitute a form of electronic Reviews that reflects consumers' critical assessments of specific product attributes or service encounters (Naqrash et al., 2025). These evaluations may address various issues, including delivery delays, inadequate product quality, unsatisfactory customer service, or improper handling of customer complaints (Wang et al., 2021). As such, they serve as cautionary signals to other consumers, warning them against potential risks associated with products that do not meet expected standards (Mudambi & Schuff, 2024).

The expansion of the internet and social media has amplified the visibility, reach, and influence of negative reviews, transforming them into powerful drivers of public opinion and brand perception (Ahmad & Guzmán, 2021). Their impact is not uniform across contexts; rather, the tone and severity of negative reviews may vary across cultural and market environments, ranging from mild dissatisfaction to highly critical and reputationally damaging expressions (Chen et al., 2023). This variation underscores the importance of contextualizing negative reviews within specific socio-cultural settings. Negative reviews can be understood as digital expressions of dissatisfaction articulated through online platforms, often extending beyond brief criticisms to include detailed narratives of consumption experiences (Al-Nsour et al., 2021; 2022). These narratives provide rich, experience-based insights that enhance their credibility and persuasive power. Their widespread dissemination across e-commerce platforms, social media, and specialized forums further increases their potential to influence large audiences (Wang et al., 2021).

Importantly, negative electronic reviews perform a critical diagnostic function. They help uncover latent product or service deficiencies that may not be visible through traditional marketing communications (Naqrash et al., 2025). By offering detailed, experience-driven feedback, they provide prospective consumers with valuable information about potential risks and shortcomings (Min et al., 2023). When similar complaints are repeatedly observed across multiple reviews, they act as strong and credible signals of systemic issues, particularly in high-involvement or high-risk purchase contexts (Huang & Chen, 2023; Wang et al., 2024). Consequently, consumers tend to engage more deeply with negative reviews, carefully analyzing their content to minimize uncertainty and avoid unfavorable outcomes. This behavior aligns with information diagnosticity theory and negativity bias, which suggest that negative information is perceived as more informative, reliable, and influential in shaping decision-making processes (Ramanathan et al., 2024). Therefore, negative e-reviews play a pivotal role in guiding consumer judgments and shaping purchase intentions in digital environments.

5.3 Intensity and Impact of Negative Electronic Reviews

Negative online reviews—particularly those characterized by harsh or vitriolic language—represent a powerful expressive mechanism through which dissatisfied consumers articulate their disappointment following unfavorable consumption experiences (Sansome et al., 2025). Such reviews often emerge when the experienced performance of a product or service significantly deviates from prior expectations, leading to emotional responses such as frustration, anger, or perceived betrayal. In these cases, consumers tend to adopt a direct and confrontational tone, explicitly attributing responsibility to the firm or service provider (Moro & Esmerado, 2020).

This form of negative expression typically emphasizes specific product or service deficiencies and may include strong language reflecting dissatisfaction, calls for avoidance or boycott, and detailed accounts of recurring or unresolved issues. The intensity of such reviews is often amplified when consumers perceive that their complaints have been ignored or inadequately addressed, transforming the review into a form of symbolic retaliation or “consumer revenge” (Van Laer & De Ruyter, 2024; Alsahli et al., 2025). From a theoretical perspective, this behavior can be explained through expectation–disconfirmation theory, where negative disconfirmation—resulting from unmet expectations—triggers dissatisfaction and subsequent negative behavioral responses (Xie et al., 2023).

Importantly, negative reviews extend beyond individual expression to exert significant influence on broader consumer behavior. Empirical evidence indicates that such reviews not only damage a firm’s digital reputation but also have a direct and measurable impact on purchase decisions (Liu, 2023). Due to their emotional intensity and perceived diagnostic value, harsh reviews tend to spread rapidly and attract higher levels of attention and engagement compared to positive reviews (Tang et al., 2024). This aligns with negativity bias, which suggests that consumers assign greater weight to negative information when evaluating alternatives. Moreover, negative electronic reviews often contain detailed and experience-based information regarding critical attributes such as price, quality, and service performance (Zhang et al., 2023). This depth of information enhances their credibility and usefulness, positioning them as effective tools for risk reduction in consumer decision-making processes (Ramanathan et al., 2024). Repeated exposure to similar negative feedback further reinforces perceptions of risk and uncertainty, potentially eroding trust between consumers and brands (Mumuni, 2020).

From a managerial perspective, the handling of negative reviews has become a strategic necessity. Firms that fail to respond promptly and professionally risk long-term reputational damage and diminished customer trust (Rosario et al., 2023). In contrast, organizations that adopt proactive and transparent response strategies can mitigate negative impacts, restore customer confidence, and even strengthen relationships with their audiences (Chen & Lurie, 2023; Hajjli et al., 2024). Effective responses not only address immediate concerns but also signal accountability and commitment to service quality. Furthermore, negative reviews should not be viewed solely as a threat but also as a valuable source of insight. By systematically analyzing customer complaints, firms

can identify recurring issues, improve product and service quality, and enhance overall customer experience (Filiari & McLeay, 2023). In this sense, negative reviews contribute to organizational learning and continuous improvement. At a broader level, the impact of negative reviews extends across the entire digital ecosystem. A high volume of negative feedback can generate uncertainty, fear, and confusion among potential customers, thereby reducing a firm's ability to attract new consumers (Chen & Lurie, 2023; Albuquerque & Varga, 2024). Consequently, developing effective strategies to monitor, manage, and respond to negative reviews has become imperative for sustaining competitiveness in the digital marketplace.

In conclusion, negative electronic reviews represent a double-edged phenomenon. While they pose significant challenges to brand reputation and consumer trust, they also offer opportunities for improvement and engagement when managed effectively. Firms that respond constructively and promptly to negative feedback can not only mitigate adverse effects but also enhance customer satisfaction and build stronger, more resilient relationships with their consumers (Lee & Cranage, 2024; Al-Nsour et al., 2024).

5.4 The Effect of Negative E-Reviews on Digital Purchase Intention and Hypothesis Development:

Digital purchase intention refers to a consumer's willingness and planned likelihood to purchase a specific product within an online context at a given time or situation (Al-Qahtani & Al-Nsour, 2025). It reflects the degree of cognitive commitment or conviction a consumer holds toward acquiring a particular product (Prentice et al., 2023). As such, purchase intention represents a critical antecedent to actual buying behavior and constitutes a key stage in the consumer decision-making process (Hajli et al., 2023). From a theoretical perspective, purchase intention can be understood as a form of behavioral intention, consistent with frameworks such as the Theory of Planned Behavior (TPB), where intention serves as the most immediate predictor of actual behavior. However, the presence of intention does not necessarily guarantee purchase execution, as it may be influenced by situational constraints, perceived risks, or changes in preferences (Al-Adwan et al., 2024). In this sense, digital purchase intention represents a probabilistic assessment of whether a consumer will engage in an online transaction (Al-Nsour et al., 2023).

The formation of purchase intention is a dynamic and information-driven process. Consumers actively seek, evaluate, and interpret information—particularly from digital sources such as social media and electronic reviews—before forming purchase-related judgments (Cheung et al., 2023). Recommendations from other users, online reviews, and shared experiences play a central role in shaping these intentions, as they reduce uncertainty and enhance decision confidence (Hajli et al., 2023; Al-Nsour, 2024). This aligns with information adoption theory, which emphasizes the influence of externally generated information on consumer attitudes and intentions. Furthermore, digital purchase intention is closely associated with consumers' evaluative processes, including comparisons of alternatives, assessment of perceived value, and expectations of future outcomes (Lim et al., 2024). It also reflects consumers' anticipation of satisfaction and

their perceptions of potential benefits and risks associated with a purchase (Albuquerque & Varga, 2024). In this regard, purchase intention serves not only as a behavioral predictor but also as a cognitive framework through which consumers interpret marketing stimuli.

Importantly, social media platforms and digital communication channels have significantly enhanced the role of user-generated content in shaping purchase intentions. Electronic reviews and eWOM disseminated via platforms such as Facebook, Instagram, YouTube, and other applications provide rich, experience-based information that influences consumer preferences and brand perceptions (Al-Nsour, 2017; Ngo et al., 2024). These platforms facilitate continuous evaluation of products and services, enabling consumers to make more informed and comparative decisions (Mulyono et al., 2025). Notably, negative evaluations play a particularly influential role in shaping purchase intention. They enhance consumers' cognitive processing by drawing attention to potential risks and shortcomings, thereby influencing attitudes, perceptions, and final decisions (Dwivedi et al., 2024). As a result, purchase intention in digital environments is often shaped by a combination of impressions, perceived credibility, prior experiences, and persuasive informational cues derived from negative eWOM (Tarta & Pasaribu, 2024). Overall, digital purchase intention represents a complex, multidimensional construct influenced by cognitive, social, and informational factors. In highly connected digital ecosystems, it is increasingly shaped by electronic reviews and online interactions, highlighting the critical role of reviews in influencing consumer behavior and guiding decision-making processes.

5.4.1 The Quality of Negative E-Reviews:

The quality of negative electronic reviews refers to the extent to which user-generated evaluations shared عبر digital platforms—such as commercial websites and social media—are perceived as objective, detailed, accurate, and credible (Lee & Cranage, 2024). As a key dimension of electronic word-of-mouth (eWOM), review quality represents a critical determinant of the informational value and persuasive effectiveness of online content. From a theoretical standpoint, the quality of negative reviews is closely associated with information diagnosticity and argument quality within the Elaboration Likelihood Model (ELM). High-quality reviews provide clear, structured, and evidence-based information that enhances consumers' ability to process content through the central route, leading to more stable and influential attitudes. In contrast, low-quality reviews may lack depth or credibility, thereby reducing their persuasive impact. Empirically, review quality is considered a fundamental criterion for assessing the effectiveness of negative evaluations in shaping consumer perceptions and purchase decisions (Parikh et al., 2018). Reviews that include rich, contextualized information—such as precise descriptions of the consumption experience, temporal and spatial context, and specific product or service failures—offer greater cognitive value to consumers. This, in turn, enhances their perceived reliability and usefulness for decision-making (Albuquerque & Varga, 2024). Furthermore, high-quality negative reviews contribute significantly to the formation of consumers' mental images of products and services, influencing both attitudes and behavioral intentions (Liang & Turban, 2023).

Their structured and detailed nature increases their credibility, making them more likely to be relied upon when evaluating alternatives. Consequently, the quality of negative evaluations is grounded in a set of objective and formal criteria—such as clarity, completeness, relevance, and accuracy—that collectively determine their impact on consumer judgment (Parikh et al., 2018). Based on the above theoretical and empirical arguments, the following sub-hypothesis is proposed:

- ***H11: The Quality of Negative Electronic Reviews has a Statistically Significant Effect on the Purchase Intention of Saudi Consumers at the 5% Significance Level.***

5.4.2 The Credibility of Negative E-Reviews:

The credibility of negative electronic reviews is significantly enhanced when they are supported by evidence-based details. Consumers who report specific problems are expected to provide precise, verifiable information rather than relying on vague or generalized statements. Such details may include clear descriptions of the issue, its direct causes, and the contextual circumstances under which it occurred (Peña-García et al., 2024). The inclusion of this level of specificity increases the informational value of the review and strengthens its reliability, thereby enabling other consumers to make more informed and rational decisions (Majumder et al., 2022). Moreover, evidence-based reviews often incorporate visual or multimedia elements—such as photos or videos—that substantiate the reported issues. These forms of supporting evidence enhance the perceived realism and authenticity of the review, allowing potential consumers to better interpret the situation beyond subjective or emotional expressions (Abdel Wahab et al., 2022). This aligns with information credibility theory, where tangible evidence increases trust in the message and its source. Consequently, rational and well-substantiated evaluations are more likely to be perceived as trustworthy and persuasive (Chen et al., 2023). In addition to evidential support, objectivity and neutrality constitute essential dimensions of high-quality negative reviews. A credible review is not solely focused on highlighting deficiencies but rather reflects a balanced assessment that considers multiple aspects of the product or service (Bin Khunin & Al-Nsour, 2024). Such neutrality signals fairness and reduces the perception of bias, thereby enhancing the diagnostic value of the review. In contrast, reviews that are overly emotional or one-sided may be perceived as less reliable and potentially misleading (Peña-García et al., 2024). Transparency further reinforces the credibility of negative reviews. Transparent reviews provide clear, consistent, and honest accounts of the consumer experience, enabling readers to assess the validity of the claims being made (Zhang et al., 2023). The absence of transparency, on the other hand, may raise doubts regarding the authenticity and accuracy of the evaluation. Empirical evidence suggests that the clarity and completeness of the review content play a crucial role in shaping its perceived credibility and influence (Güler & Huseynov, 2021; Wang, 2022). Overall, the integration of detailed evidence, objectivity, and transparency enhances the credibility and persuasive power of negative electronic reviews. These attributes increase consumers' confidence in the information provided and strengthen the role of such reviews as reliable inputs in the decision-making process.

Based on the above theoretical and empirical arguments, the following sub-hypothesis is proposed:

- ***H012: Negative Electronic Reviews have a Statistically Significant Effect on Saudi Consumers' Purchase Intention at the 5% Significance Level.***

5.4.3 The Volume of Negative Electronic Reviews:

The volume of negative electronic reviews has emerged as a critical factor in shaping consumer behavior, particularly in the context of widespread digitalization and the proliferation of online evaluation platforms (Güler & Huseynov, 2021). With the increasing accessibility of user-generated content, consumers can easily review large quantities of feedback before making purchasing decisions, thereby amplifying the influence of negative reviews (Zhang et al., 2023). As a result, consumers increasingly rely on aggregated online evaluations to form comprehensive judgments about product quality and performance (Masri et al., 2025). From a theoretical perspective, the volume of negative reviews enhances information availability and strengthens social proof, making the information more salient and influential in shaping consumer perceptions. Unlike isolated reviews, a high volume of negative feedback signals consistency and reduces perceived uncertainty regarding product quality. Consequently, consumers interpret repeated negative evaluations as strong indicators of underlying product or service deficiencies (Kim et al., 2023). Importantly, the impact of negative reviews extends beyond individual expressions of dissatisfaction. The accumulation of negative feedback contributes to the formation of collective perceptions and plays a central role in shaping brand reputation (Hollenbeck & Proserpio, 2021). Empirical studies suggest that a higher volume of negative reviews leads to a decline in perceived brand reliability and consumer trust, ultimately influencing purchase decisions (Ahmad & Laroche, 2024; Kim et al., 2023). Furthermore, when negative reviews repeatedly highlight similar issues, they reinforce unfavorable brand associations and diminish a firm's ability to attract new customers (Masri et al., 2025). This cumulative effect increases the perceived risk associated with the product, making consumers more hesitant to engage in purchase behavior. Over time, the growing volume of negative feedback intensifies its impact, making it increasingly difficult for brands to recover their market position and restore consumer confidence (Kim & Hwang, 2023; Vermeer et al., 2024). In addition, the psychological impact of review volume should not be overlooked. Exposure to a large number of negative reviews can amplify negative emotions and cognitive biases, leading consumers to adopt more risk-averse decision-making strategies (Ammar & Al-Nsour, 2026). Even when personal experiences may differ, the dominance of negative information can discourage positive purchase intentions (Kim & Hwang, 2023). *Based on the above theoretical and empirical arguments, the following sub-hypothesis is proposed:*

- ***H13: The volume of negative electronic reviews has a statistically significant negative effect on Saudi consumers' purchase intention.***

After reviewing the previous literature related to the subject of the study, it was possible to develop a study model that links independent and dependent variables as follows:

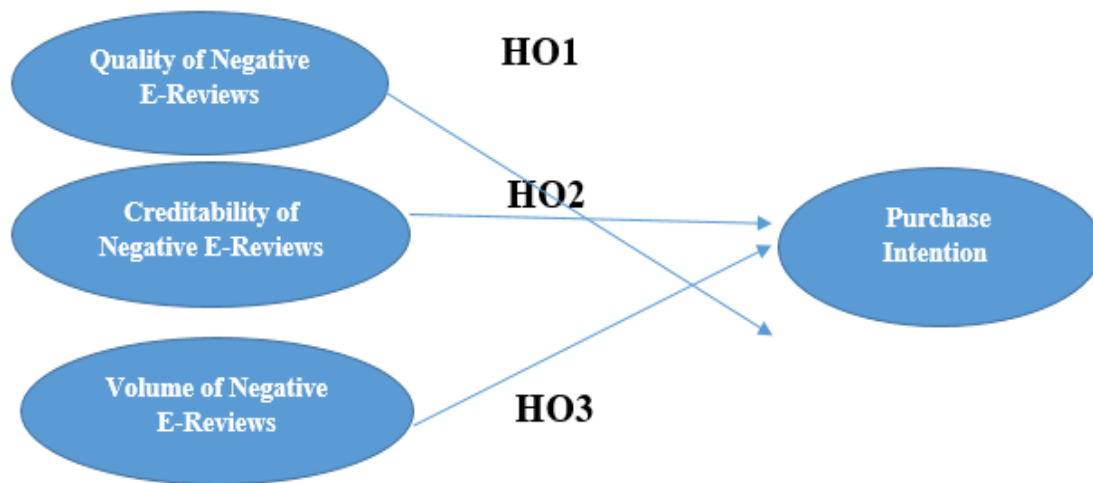


Figure (1): Research Model

Source: Xiao, Q. (2016). The Impact of Negative Online Review on Consumers' Purchase Intention: A Dual-Process Perspective. *International Journal of u-and e-Service, Science and Technology*, 9 (12), 139-152.

6. RESEARCH METHODOLOGY:

1) Research Design: This study adopts a quantitative research approach, which is considered most appropriate for achieving the study objectives. Quantitative research involves the systematic collection of data and its transformation into numerical form, enabling the application of statistical techniques to test relationships and draw valid conclusions (Creswell & Creswell, 2023). It is particularly suitable for examining causal relationships between variables using structured measurement and statistical modeling (Bryman, 2024). In this study, the quantitative approach is employed to examine the relationship between negative electronic reviews and Saudi consumers' purchase intention. To analyze these relationships, the study utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS software, which is appropriate for predictive analysis and complex model testing.

2) Type of Study: This research is classified as a descriptive, cross-sectional survey study, which is widely used in quantitative research to describe phenomena and examine relationships among variables (Tobi & Kampen, 2023). Descriptive research provides a systematic and accurate representation of the characteristics, trends, and correlations associated with a given research problem. In the present study, survey methodology is used to collect data from consumers of fast-food restaurants listed on Google Maps. This approach enables the researcher to capture consumer perceptions, experiences, and behavioral intentions related to negative electronic reviews, thereby generating insights with practical and managerial relevance.

3) Research Population: The target population of this study consists of customers of popular fast-food restaurants listed on Google Maps in Riyadh, Saudi Arabia. Based on predefined selection criteria, a total of 31 restaurants were identified as representing the study population. The selection criteria were as follows:

- The restaurant must be classified under the “fast food” category according to recognized directories (e.g., www.qaym.com/city/57).
- The restaurant must be a well-known international (foreign) fast-food brand.
- The restaurant must have available electronic reviews on Google Maps in 2025.
- The restaurant must be located within Riyadh city.

4) Research Sample: The study sample was drawn from consumers who had posted negative electronic reviews on Google Maps for the selected fast-food restaurants. A non-probability purposive sampling technique was employed, as it is appropriate for targeting individuals who possess relevant experience and specific knowledge related to the research phenomenon. The data collection process involved identifying consumers who had provided negative reviews and inviting them to participate in the study by completing a structured questionnaire. The questionnaire was carefully designed, reviewed by academic experts (judges) to ensure content validity, and then distributed electronically. The target sample size was 387 respondents, and data collection was conducted over the period from October 30, 2024, to February 8, 2025. Accordingly, the sample is classified as a non-probability, purposive sample of digital consumers.

5) Unit of Analysis: The unit of analysis in this study is the individual Saudi consumer who has experience with fast-food restaurants in Riyadh and has posted a negative electronic review on Google Maps during the study period (2024–2025). This unit is appropriate as the study focuses on individual perceptions, evaluations, and purchase intentions in response to negative reviews.

Table 1: Research Population

<i>Restaurant</i>	<i>Restaurant</i>	<i>Restaurant</i>	<i>Restaurant</i>
Green Cottage	KFC	Taco Hut	Albaik
Lebanese Corner	Chicken Texas	Fire House	Mama Noura
Baba Habas	Taxi	Alkhafeef	Vanellis
Domino's Pizza	Burger Box	BAAK	Hamburgini
Maestro Pizza	Alshekh_Burger	Johnny Rockets	Al Tazag
Pizza Hut	Hardees	Jan Burger	Herfy
Sbaroo Pizza	Darin Sea Food	McDonalds	Shawarmer
	Gennehrst	Tom Tom	Kudu

Source: www.qaym.com/city

6) Research Instrument and Data Sources: To collect primary data, this study employed a structured questionnaire designed specifically to align with the research objectives and conceptual framework. The questionnaire consisted of closed-ended items measured using a five-point Likert scale ranging from (1) “strongly disagree” to (5)

“strongly agree.” This scale was selected due to its widespread use in quantitative research and its ability to capture variations in respondents’ attitudes, perceptions, and behavioral intentions with a high degree of reliability. The questionnaire was developed based on previously validated scales from the literature, with necessary modifications to ensure relevance to the study context. It was also reviewed by academic experts to ensure content validity, clarity, and appropriateness before distribution. In addition to primary data, the study relied on a wide range of secondary data sources to support the theoretical foundation and contextual background. These sources included:

- Peer-reviewed articles published in international scientific journals
- Academic books and publications from local and international universities.
- Master’s and doctoral theses (both print and electronic).
- Reports and publications issued by government institutions and industry bodies related to fast-food restaurant classifications.
- Published statistical reports and market data of the sector.
- Relevant materials from commercial reports, newspapers, and specialized journals.

These diverse sources contributed to strengthening the theoretical framework, supporting hypothesis development, and ensuring the academic rigor of the study.

7. DESCRIPTIVE ANALYSIS OF STUDY VARIABLES:

1) Independent Variable: Negative Electronic Reviews: The independent variable—negative electronic reviews of fast-food restaurants via Google Maps—was measured using 17 items. The results indicate that 13 items were rated at a high level, while 4 items reflected moderate responses. The overall mean score for this variable was 3.747 (SD = 0.906), indicating a high level of perceived negative e-reviews. This finding was supported by 61.1% of respondents, suggesting that negative reviews are prominently perceived among users of Google Maps. To provide a more nuanced understanding, the main variable was decomposed into three sub-dimensions:

- **Quality of Negative Electronic Reviews:** The quality of negative e-reviews was measured using 6 items, all of which were rated at a high level by respondents. The overall mean score was 3.824 (SD = 0.948), indicating a high perceived level of review quality. This result was supported by 62.6% of respondents, suggesting that negative reviews are generally perceived as detailed, informative, and useful.
- **Credibility of the Source of Negative Reviews:** The credibility of the source of negative e-reviews was measured using 6 items, of which 2 were rated high and 4 moderate. The overall mean score was 3.284 (SD = 0.940), indicating a moderate level of perceived credibility. This finding was supported by 37.6% of respondents, reflecting some degree of uncertainty or variation in trust toward the sources of negative reviews.
- **Volume of Negative Electronic Reviews:** The volume of negative e-reviews was measured using 5 items, all of which were rated at a high level. The overall mean score

was 4.132 (SD = 0.828), indicating a high perceived volume of negative reviews. This result was strongly supported by 83.2% of respondents, highlighting the widespread presence and visibility of negative feedback on Google Maps.

2) Dependent Variable: Purchase Intention —Saudi consumers' purchase intention toward fast-food restaurants via Google Maps—was measured using 5 items. Among these, 1 item was rated at a high level, while 4 items reflected moderate responses. The overall mean score was 3.158 (SD = 1.109), indicating a moderate level of purchase intention. This finding was supported by 43% of respondents, suggesting that consumers exhibit cautious or balanced purchasing tendencies in light of available online information.

8. CONSTRUCT RELIABILITY AND VALIDITY:

8.1 Construct Reliability: Construct reliability assesses the internal consistency of measurement items and reflects the extent to which indicators of a latent construct are correlated and measure the same underlying concept (Triwidyati & Tentama, 2022). It represents the proportion of true variance relative to the total variance in the scale scores and serves as an indicator of the stability and consistency of the measurement model (Fornell & Larcker, 2019). In this study, Composite Reliability (CR) was employed to evaluate internal consistency. Compared to traditional Cronbach's alpha, CR provides a more accurate and comprehensive assessment, particularly in structural equation modeling contexts such as PLS-SEM. According to established guidelines, acceptable CR values should range between 0.70 and 0.95 (Hair et al., 2014). As shown in Table (2), all composite reliability values fall within the recommended threshold (0.70–0.95), indicating a satisfactory level of internal consistency across all constructs. Therefore, the measurement model demonstrates adequate reliability and is suitable for subsequent hypothesis testing.

8.2 Convergent Validity (Average Variance Extracted – AVE): Convergent validity refers to the extent to which a set of indicators representing a latent construct converge or share a high proportion of variance (Henseler et al., 2014). It is commonly assessed using the Average Variance Extracted (AVE), which measures the amount of variance captured by a construct relative to the variance due to measurement error (Dilekli & Tezci, 2019). The recommended threshold for AVE is 0.50 or higher, indicating that the construct explains at least 50% of the variance in its indicators. Values exceeding 0.70 are considered highly satisfactory, while values below 0.50 suggest insufficient convergent validity. The results presented in Table (2) show that all AVE values exceed the minimum threshold of 0.50, confirming that the constructs exhibit adequate convergent validity. This indicates that the measurement items sufficiently represent their respective latent variables and can be reliably used in further analysis.

8.3 Discriminant Validity: Discriminant validity assesses the extent to which a construct is empirically distinct from other constructs in the model (Tukowicz et al., 2017). It ensures that each latent variable captures a unique concept and is not overly correlated with other variables. This study evaluates discriminant validity using two approaches:

A) Indicator (Item) Reliability: Indicator reliability refers to the degree to which individual measurement items accurately represent their corresponding construct (Sam, 2013). A commonly accepted threshold is that factor loadings should exceed 0.70, indicating that the item shares substantial variance with its construct. The results reported in Table (2) indicate that all item loadings exceed the threshold of 0.70. This confirms that all indicators are statistically reliable, valid, and appropriate measures of their respective latent constructs (negative e-reviews and purchase intention).

Table 2: CR, Rho_A and AVE

Construct	Rho_A	AVE	CR	Item Validity	Items
Quality	0.807	0.501	0.816	0.743	QUA1
				0.806	QUA2
				0.415	QUA3
				0.296	QUA4
				0.802	QUA5
				0.769	QUA6
Credibility	0.743	0.534	0.807	0.738	CR1
				0.168	CR2
				0.744	CR3
				0.744	CR4
				0.687	CR5
				0.669	CR6
Volume	0.919	0.729	0.931	0.849	SIZE1
				0.891	SIZE2
				0.899	SIZE3
				0.837	SIZE4
				0.790	SIZE5
Buying Intention				0.768	BI1
				0.732	BI2
				0.814	BI3
				0.773	BI4
				0.755	BI5

B) Fornell–Larcker Criterion: The Fornell–Larcker criterion is widely employed to assess discriminant validity by comparing the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs in the model (Fornell & Larcker, 1981).

According to this criterion, a latent construct should explain a greater proportion of variance in its own indicators than it shares with other constructs, thereby demonstrating empirical distinctiveness (Hilkenmeier et al., 2020). The results presented in Table (3) indicate that the square root of the AVE for each construct exceeds its corresponding inter-construct correlations.

This finding confirms that each latent variable exhibits sufficient discriminant validity, as it shares more variance with its own measurement items than with other constructs in the model. Accordingly, the measurement model satisfies the Fornell–Larcker criterion, providing further support for its validity and robustness.

Table 3: Fornell Larcker Criterion

Items	BI	Cre	Qua	Size
BI	0.769			
Cre	0.455	0.659		
Qua	0.449	0.669	0.670	
Size	0.444	0.534	0.656	0.854

8.4 Multicollinearity Assessment (Variance Inflation Factor – VIF): The Variance Inflation Factor (VIF) is used to assess the presence of multicollinearity among independent variables in the structural model. Multicollinearity occurs when predictor variables are highly correlated, which can inflate standard errors, distort regression coefficients, and reduce the reliability and interpretability of the model estimates (Shrestha, 2020). VIF values are calculated for each independent variable to determine the extent to which it overlaps with other predictors in the model. In the context of PLS-SEM, VIF values start from 1 and have no theoretical upper bound. However, established statistical guidelines suggest that:

- VIF < 5 indicates that multicollinearity is not a serious concern
- VIF between 5 and 10 suggests moderate multicollinearity that may require attention
- VIF > 10 indicates severe multicollinearity, which may compromise the accuracy and stability of regression estimates (Shrestha, 2020)

The results presented in Table (4) show that all VIF values are below the threshold of 5, indicating that multicollinearity among the independent variables is not problematic. Therefore, the model satisfies the required assumptions for statistical analysis, and the estimated relationships can be considered reliable and robust.

Table 4: VIF

Construct	VIF
Qua	2.338
Cre	1.863
Size	1.809

9. STRUCTURAL MODEL ASSESSMENT (PATH ANALYSIS):

Path analysis, as an extension of multiple regression, is widely employed to examine causal relationships among latent variables within a theoretical model (Normawati & Kismiantinim, 2019). In the context of PLS-SEM, it enables the estimation of direct effects between constructs and provides key statistical indicators—such as path coefficients (β), t-values, and p-values—to assess the strength, direction, and significance of hypothesized relationships (Hair et al., 2022). The statistical decision rule indicates that a p-value less than 0.05 signifies a statistically significant relationship at the 5% significance level. Additionally, the sign of the standardized path coefficient (β) determines the direction of the relationship, where a negative sign (–) indicates an inverse relationship between variables. The results presented in Table (5) demonstrate that all path coefficients between the dimensions of negative electronic reviews (quality,

credibility, and volume) and purchase intention are statistically significant ($p < 0.05$). This confirms the presence of meaningful relationships between the independent constructs and the dependent variable. Furthermore, the direction of the coefficients indicates that negative electronic reviews exert a negative effect on Saudi consumers' purchase intention toward fast-food restaurants. Accordingly, all proposed sub-hypotheses are empirically supported.

Coefficient of Determination (R^2):

The coefficient of determination (R^2) measures the explanatory power of the model by indicating the proportion of variance in the dependent variable explained by the independent variables (Hair et al., 2020). Common guidelines classify R^2 values of 0.02 as weak, 0.13 as moderate, and 0.26 or higher as substantial. In this study, the R^2 value for purchase intention was found to be 0.272, indicating a moderate to substantial level of explanatory power. This suggests that the independent variable—negative electronic reviews and its three dimensions—explains approximately 27.2% of the variance in Saudi consumers' purchase intention toward fast-food restaurants. Consequently, approximately 72.8% of the variance remains unexplained, indicating the presence of additional factors not included in the current model that may influence purchase intention. While negative eWOM plays a significant role, other variables—such as brand image, price perception, service quality, or trust—may further enhance the model's explanatory capacity.

Model Fit (Goodness of Fit – GoF):

The Goodness of Fit (GoF) index provides an overall assessment of the model's predictive performance by evaluating both the measurement and structural components (Chin & Dibbern, 2010). It reflects how well the proposed model explains the observed data. According to established benchmarks (Odekerken-Schröder & Van Oppen, 2005):

- GoF < 0.10 indicates no fit
- GoF ≥ 0.10 indicates a small fit
- GoF ≥ 0.25 indicates moderate fit
- GoF ≥ 0.36 indicates large fit

The results in Table 5 indicate that the model achieves a moderate level of fit, suggesting that the proposed model demonstrates an acceptable level of predictive accuracy. However, the moderate GoF also implies that there is room for improvement in enhancing the model's overall performance.

Such improvements may involve: incorporating additional relevant variables, refining the relationships between constructs, and enhancing measurement precision. Overall, the GoF results confirm that the model possesses adequate but not optimal predictive capability, supporting its validity while highlighting opportunities for further refinement.

Table 5: Path Analysis Coefficients

Relationship	Sample Mean	Std. Error	T Test	P-Value	Decision	f ²	R ²	GOF
Qua -> BI	0.247	0.088	2.748	0.006	Supported Positive Relationship	0.012	0.266	0.317
Cre -> BI	0.147	0.067	2.094	0.036	Supported Positive Relationship	0.43		
Size-> BI	0.219	0.073	3.042	0.002	Supported Positive Relationship	0.038		

10. DISCUSSION OF FINDINGS:

Negative electronic reviews have attracted significant attention in e-commerce research, not only because they reflect unfavorable consumer experiences but also due to their disproportionately strong influence on consumer behavior compared to positive reviews. Prior studies consistently demonstrate that consumers tend to assign greater importance to negative reviews, perceiving them as more diagnostic and informative regarding potential risks and hidden product attributes (Qiu & Zhang, 2023). From a theoretical perspective, this aligns with negativity bias and the asymmetric effect, whereby negative information exerts a stronger cognitive and behavioral impact than positive information (Yaqci Koc & Sahin, 2023). Consequently, even a limited number of negative reviews can significantly deter potential customers, despite the presence of numerous positive evaluations. Furthermore, negative reviews are often perceived as more credible, as they are less likely to be associated with promotional intent and more likely to signal genuine product or service shortcomings (Mishra & Shukla, 2023). Importantly, recent research suggests that the impact of negative reviews is not unidimensional but rather operates through mediating mechanisms such as perceived risk, perceived product quality, and emotional responses (Anastasiei et al., 2025). These mechanisms collectively shape consumers' cognitive evaluations and ultimately influence their purchase intentions. Empirical evidence further confirms that negative reviews can directly reduce purchase intention and discourage repeat patronage, particularly in service-based industries such as restaurants (Abdullah et al., 2024). In line with this theoretical foundation, the present study examined the impact of negative electronic reviews on Saudi consumers' purchase intention in the context of fast-food restaurants on Google Maps. The independent variable was operationalized through three key dimensions: review quality, review credibility, and review volume. The findings reveal that the quality of negative reviews exerts a strong influence on purchase intention. The high mean values (ranging between 3.50 and 4.14) indicate that respondents perceive detailed and well-structured negative reviews as highly impactful. This result is consistent with prior studies, which highlight that detailed reviews enhance information diagnosticity and increase consumers' sensitivity to potential risks (Taecharunroj & Mathayomchan, 2024; Zhang et al., 2022). High-quality negative reviews provide richer contextual information, enabling consumers to form more accurate mental representations of the service experience. However, this finding should be interpreted with caution, as some studies suggest that the impact of review quality may be context-dependent. For instance, Zhang et al. (2023) found that

the negative effect of review quality can be mitigated when firms actively engage with customer feedback. Similarly, Kim et al. (2023) demonstrated that effective managerial responses—such as timely apologies or compensation strategies—can reduce the adverse impact of negative reviews on consumer behavior. These findings highlight the moderating role of service recovery and firm responsiveness in shaping the influence of negative reviews. Overall, the results of the current study reinforce the critical role of negative electronic reviews—particularly their quality—in shaping consumer purchase intentions. At the same time, they underscore the importance of contextual and managerial factors that may attenuate or amplify this effect. Finally, the findings indicate that negative electronic reviews do not entirely negate consumers' purchase intentions; rather, they lead to a moderate reduction in the likelihood of purchase, highlighting their significant yet non-deterministic influence on consumer decision-making (Wang et al., 2023; 2025). This suggests that digital purchase intention is a multidimensional construct, shaped by the interaction of several key factors, including the volume and quality of electronic reviews, perceived credibility, and consumers' individual characteristics such as technological competence and personal evaluation capabilities. Notably, the results reveal that the isolated effect of credibility remains comparatively moderate when contrasted with other more influential determinants, particularly review quality and volume.

From a demographic perspective, the sample exhibited a balanced gender distribution, with males representing 50.7% and females 49.3% of respondents. This near-equilibrium enhances the representativeness of the data and reduces the likelihood of gender-related bias in interpreting the study findings. In terms of age, the predominance of respondents aged over forty indicates a higher level of engagement among older consumers. This demographic characteristic may have influenced the results, as prior research suggests that older individuals tend to adopt more cautious, analytical, and risk-sensitive approaches when evaluating online reviews and making purchasing decisions (Wang et al., 2025).

Regarding educational attainment, the majority of participants held a bachelor's degree, reflecting a relatively high level of cognitive and analytical capability within the sample. This level of education likely enhances consumers' ability to critically process negative electronic information and interpret review content before forming purchase intentions (Ahn & Lee, 2024). Furthermore, the dominance of government employees within the sample suggests a segment characterized by income stability and job security. Such factors may influence consumption behavior, particularly in terms of financial planning, risk aversion, and purchasing consistency. Consequently, the income distribution revealed that a substantial proportion of respondents reported monthly earnings exceeding 15,000 SAR, indicating that the sample predominantly represents a middle- to upper-income segment. This group is generally more capable of making independent and well-considered purchasing decisions, which may further shape how negative electronic reviews are interpreted and integrated into the decision-making process.

Based on the study findings, several practical recommendations are proposed:

- Encourage customers in Saudi Arabia to provide honest and detailed reviews on Google Maps, given their significant influence on consumer decision-making.
- Ensure that restaurant managers offer clear, accessible, and user-friendly information about products and services through integrated digital platforms.
- Respond to negative reviews promptly and professionally to mitigate reputational damage and restore customer trust.
- Develop effective service recovery strategies that address customer complaints and transform negative experiences into positive outcomes.
- Utilize visual content (e.g., short videos or images) to clarify services and reduce misunderstandings that may lead to negative feedback.

11. THEORETICAL AND PRACTICAL IMPLICATIONS:

This study extends the literature on negative electronic reviews by providing evidence from the Saudi digital context, demonstrating that the volume and quality of negative reviews alone are insufficient to significantly influence purchase intention unless supported by high source credibility. This finding highlights credibility as a critical mediating factor in the relationship between eWOM and consumer behavior, while also reinforcing the Elaboration Likelihood Model (ELM). Specifically, even highly competent consumers tend to rely on central processing when the credibility of reviews is uncertain, emphasizing that decision-making is driven by the integration of quality, credibility, and individual capabilities, rather than information quantity alone. From a practical perspective, the results suggest that restaurants and digital platforms should prioritize credibility, transparency, and responsiveness when managing negative reviews. Simply increasing the number or improving the wording of reviews is insufficient without ensuring their trustworthiness. Firms should enhance the digital customer experience by providing clear, accurate, and accessible information, while also treating negative reviews as a strategic tool for service improvement and trust-building. Additionally, implementing review verification mechanisms (e.g., verified users) can further strengthen credibility and reduce the impact of misleading content.

12. LIMITATIONS AND FUTURE RESEARCH:

This study is subject to several limitations. First, it is confined to the restaurant sector in Saudi Arabia, which may limit the generalizability of the findings to other sectors such as retail, tourism, hospitality, or digital services. Second, the analysis is restricted to Google Maps reviews, while consumers may rely on other platforms (e.g., TripAdvisor, Instagram), potentially leading to different outcomes. Third, the study focuses exclusively on negative reviews, without considering the interaction between positive and negative eWOM, which may provide a more comprehensive understanding of consumer behavior. Finally, the use of purposive (non-probability) sampling may limit the representativeness

of the results. Accordingly, future research is encouraged to expand across different sectors and platforms, and to conduct comparative studies to identify context-specific effects of online reviews. Further studies may also adopt qualitative approaches to explore the underlying motivations behind consumers' responses to negative reviews. Additionally, incorporating mediating or moderating variables—such as brand loyalty, trust, and consumer characteristics—could provide deeper insights into the relationship between negative eWOM and purchase intention.

13. CONCLUSION:

The study findings indicate that negative electronic reviews are generally characterized by high quality, as they provide detailed and informative content that enhances their usefulness for consumers. Such reviews exert a stronger negative influence on Saudi consumers compared to superficial evaluations, as they are perceived as offering both tangible and intangible evidence regarding product or service performance. With the increasing reliance of Saudi consumers on Google Maps as a primary source for evaluating well-known restaurants, high-quality negative reviews—particularly those that are detailed and credible—demonstrate a multiplicative effect on purchase intention. This amplifies their persuasive power, especially when the content is negative. Furthermore, the findings reveal that a high volume of negative reviews significantly reduces purchase intention, particularly in trust-based service sectors such as restaurants, healthcare, tourism, and hospitality. This underscores the critical role of both review quality and volume in shaping consumer perceptions and behavioral intentions within digital environments.

Acknowledgment: The Corresponding Author is Iyad A. Al-Nsour * Imam Mohammad ibn Saud Islamic University (IMSIU), College of Media and Communication, Riyadh, KSA. . laalnsour@imamu.edu.sa

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