جـــامـعـــة الـــشـرق الأوسـط
MIDDLE EAST UNIVERSITY
Amman - Jordan

The Impact of AI-Based Sentiment Analysis on Customer Experience Insights at "Love.Cow " Restaurant in Amman

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Master's Degree in E-Business.

Department of E-Business

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جـــامـعـة الـــشـرق الأوسـط
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أثر تحليل المشاعر المعتمد على الذكاء الإصطناعي على فهم تجارب العملاء في مطعم "Love.Cow" في عمّان

إعداد

آرام أكرم ذيب الشهاب

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قدمت هذه الرسالة استكمالا لمتطلبات الحصول على درجة الماجستير
في الأعمال الإلكترونية

قسم الأعمال الإلكترونية

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Thesis Committee Decision

This thesis, titled **"The Impact of AI-Based Sentiment Analysis on Customer Experience Insights at "Love.Cow" Restaurant in Amman** by researcher **Aram Akram Theeb Al-Ishhab** and was successfully defended and approved on 19-01-2026

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Acknowledgment

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Aram Al-Ishhab

Dedication

With the permission and the facilitation of Allah, at the mercy of Him that covers everything, this step has been the result of the answered prayers and the acts that were not fruitless. All the praise belongs to Him, both in the beginning and at the end, both outwardly and inwardly, that He has empowered me to finish this little work.

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Aram Al-Ishhab

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The Impact of AI-Based Sentiment Analysis on Customer Experience Insights at "Love.Cow" Restaurant in Amman

Prepared by

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Abstract

This study examines how artificial intelligence (AI) can be used to analyze customer feedback to understand the customer experience at Love.Cow restaurant in Amman. Today, many restaurants rely on AI tools to improve customer satisfaction and help managers make better decisions about service and marketing. In this study, sentiment analysis is used to identify customers' opinions and emotions from their feedback and reviews, thereby improving the overall dining experience.

The study adopted a descriptive-analytical approach. Collected Data through an online questionnaire developed based on previous research. The questionnaire was distributed to Love.Cow customers are using an online link. Of 300 targeted customers, 298 valid responses were collected and analyzed, yielding an 85% response rate.

Used Several statistical methods to analyze the data. The results showed that AI-based sentiment analysis has a positive effect on understanding customer experience. About 78% of respondents believed that AI helps management better understand their emotions. In addition, 74% stated that AI improves service quality. Around 69% felt that sentiment analysis helps the restaurant deal with complaints more effectively, while 72% reported higher overall satisfaction with their dining experience.

The findings also revealed a clear relationship between AI-based sentiment analysis and key aspects of the customer experience, including customer satisfaction, loyalty, and the restaurant's overall image.

Based on these results, the study recommends that restaurants adopt AI-based sentiment analysis tools and invest in digital data analytics systems. It also suggests making better use of customer feedback from online platforms such as social media and mobile applications, as these reviews play an essential role in improving customer experience and Competitiveness. Finally, the study highlights the need to train managers on how to use sentiment analysis results to enhance service quality and support better marketing decisions.

Keywords: Artificial Intelligence, Sentiment Analysis, Customer Experience, Restaurant Sector in Amman.

أثر تحليل المشاعر المعتمد على الذكاء الإصطناعي على فهم تجارب العملاء في مطعم "Love.Cow" في عمّان

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الملخص

تتناول هذه الدراسة أثر تحليل المشاعر المعتمد على الذكاء الاصطناعي في فهم تجارب العملاء في مطعم (Love.Cow)في مدينة عمّان، وذلك في ظل التوجه المتزايد نحو توظيف تقنيات الذكاء الاصطناعي في فهم تجربة العملاء ودعم القرارات الإدارية والتسويقية في قطاع المطاعم. وتهدف الدراسة إلى قياس مدى مساهمة تحليل المشاعر في فهم آراء العملاء، مشاعرهم، وتقييماتهم للخدمة المقدمة، وانعكاس ذلك على تحسين جودة تجربة العميل.

اعتمدت الدراسة على المنهج الوصفي التحليلي، حيث تم جمع البيانات من خلال استبانة إلكترونية تم تصميمها بالاستناد إلى الأدبيات السابقة، ووزّعت على عينة عشوائية من عملاء مطعم (Love.Cow) عبر رابط إلكتروني. بلغ حجم العينة المستهدفة **(300)** عميل، وتم استرجاع **(298)** استبانة صالحة للتحليل الإحصائي، بنسبة استجابة بلغت **(85%)**، وهي نسبة تُعد مرتفعة ومقبولة لأغراض البحث العلمي.

تم تحليل البيانات باستخدام الأساليب الإحصائية المناسبة، حيث أظهرت النتائج أن تحليل المشاعر المعتمد على الذكاء الاصطناعي يؤثر بشكل إيجابي ومعنوي في فهم تجارب العملاء .فقد أظهرت النتائج أن **(78%)** من أفراد العينة يرون أن تحليل تعليقاتهم ومراجعاتهم باستخدام تقنيات الذكاء الاصطناعي يساعد الإدارة على فهم مشاعرهم بدقة أعلى، بينما أشار **(74%)** إلى أن هذا التحليل يساهم في فهم وتحسين جودة الخدمة المقدمة. كما بيّنت النتائج أن **(69%)** من المبحوثين يعتقدون أن استخدام تحليل المشاعر يسهم في الاستجابة السريعة لشكاوى العملاء وملاحظاتهم، في حين أكد **(72%)** أن ذلك ينعكس إيجابًيا على مستوى رضاهم العام عن المطعم.

كما كشفت النتائج وجود علاقة ذات دلالة إحصائية بين استخدام تحليل المشاعر القائم على الذكاء الاصطناعي وأبعاد تجربة العملاء، بما في ذلك الولاء والانطباع العام عن العلامة التجارية للمطعم.

وفي ضوء هذه النتائج، أوصت الدراسة بضرورة تبنّي تقنيات تحليل المشاعر المعتمدة على الذكاء الاصطناعي في قطاع المطاعم، والاستثمار في أدوات تحليل البيانات الرقمية، والاستفادة من مراجعات العملاء عبر المنصات الإلكترونية ووسائل التواصل الاجتماعي، لما لذلك من دور فعّال في تحسين تجربة العملاء وتعزيز القدرة التنافسية. كما أوصت الدراسة بضرورة تدريب الكوادر الإدارية على توظيف مخرجات تحليل المشاعر في تطوير الخدمات واتخاذ القرارات التسويقية.

الكلمات المفتاحية: الذكاء الاصطناعي،تحليل المشاعر,تجربة العملاء, قطاع المطاعم في عمان

Chapter One
Background and Problem Statement

1.1 Introduction

This thesis explores how artificial intelligence can be applied to the analysis of customer feedback as a way of gaining insight into the customer experience at the (love.cow) restaurant in Amman. In the modern hospitality industry, restaurants are becoming more and more dependent on AI-based analytics to enhance the level of satisfaction and facilitate the managerial decision-making process in terms of service quality and promotion (Gartner, 2023). In particular, the sentiment analysis is used to extract the emotions of the customers based on the textual feedback and present a data-driven direction towards the optimization of the entire dining experience. Sentiment analysis is an essential information bridge between raw data and emotional intelligence, as the linguistic coloring is evaluated to be either a positive, negative, or neutral opinion. As of today, the volume of reviews on such platforms as Google Maps, Instagram, and food delivery apps makes the perspective of monitoring manually a thing of the past (Zhang et al., 2022). Star rating does not provide the insightful why when customers are not satisfied with the services; the research showed that text-based AI platforms are 40 times more likely to offer a deeper understanding of the specific service failures than the traditional numerical measures (Alshiedat et al., 2024). This means, therefore, that companies need to embrace advanced ways of transforming these digital footprints into service improvements that can be acted upon. The longevity of the brand in the competitive food and beverage industry is determined by customer experience (CX). The process starts with the initial search on the Internet and proceeds to the ordering, payment, and post-service feedback. The use of digital has soared in Jordan and, to be more precise, in the capital, Amman, as the number of younger clientele capturing their meals on a social network in real-time has increased (Khasawneh & Al-Zoubi, 2023). In the case of a fast-growing brand, such as (love.cow), which is focused on tech-savvy people, an active online presence is crucial to the preservation of market relevance with the help of AI monitoring (Halaweh, 2021). This study informs about the applicability of AI sentiment analysis in the Jordanian context as compared to the more traditional feedback. Although there is a tremendous movement of AI all over the world, local businesses in emerging markets are still attached to the old, sluggish methods of observation (Buhalis et al., 2022). This thesis shows that sentiment analysis is a viable strategic pillar to menu development, digital marketing, and customer relationship management by examining actual cases in the real-world (Nasir et al., 2025).

1.2 Problem Statement

Despite the rapid growth of the food and beverage industry in Amman and the increasing reliance on digital platforms for customer interaction, many restaurants continue to depend on traditional, manual methods for collecting and analyzing customer feedback. These methods typically involve reading online reviews individually, monitoring star ratings, or relying on managerial intuition to interpret customer satisfaction. While such approaches were once sufficient, they have become increasingly ineffective in the context of today's data-rich digital environment.

Restaurants such as (love.cow) receive a substantial volume of customer feedback across multiple platforms, including Google Maps, Instagram, and food delivery applications. This feedback is often unstructured, emotionally nuanced, and expressed in a mixture of Modern Standard Arabic, Jordanian dialect, and informal digital language. Manual analysis of this data requires considerable time and effort, is prone to human bias, and lacks consistency. As a result, valuable insights related to customer complaints, service breakdowns, and positive experiential drivers are frequently overlooked or misinterpreted.

A significant limitation of traditional feedback mechanisms is their inability to capture the emotional depth embedded in customer reviews. Star ratings alone fail to reflect complex sentiments such as sarcasm, ambivalence, or mixed emotions, which are common in online reviews. This limitation is further intensified in the Arabic-language context, where local expressions and dialectal variations present additional challenges for accurate sentiment interpretation. Consequently, managerial decisions based on these conventional methods are often incomplete and may not accurately represent the true customer experience.

Although artificial intelligence–based sentiment analysis has demonstrated effectiveness in extracting actionable insights from large volumes of customer feedback in global contexts, its practical application within the Jordanian restaurant industry remains underexplored. There is a notable lack of local empirical research examining how AI-driven sentiment analysis can be integrated into restaurant decision-making processes, particularly in environments characterized by Arabic and culturally specific language use. This creates a critical research gap between the availability of advanced analytical technologies and their actual utilization in local hospitality operations.

Due to this gap, restaurant managers at (love.cow) and similar establishments continue to rely heavily on intuition and fragmented feedback interpretations rather than data-driven emotional insights. The absence of structured, automated sentiment analysis tools limits the

ability of these businesses to systematically identify patterns in customer experience, track service performance across the customer journey, and respond proactively to emerging issues.

Therefore, this study addresses an important research problem by investigating whether AI-based sentiment analysis can provide more detailed, accurate, and actionable insights into customer experience at (love.cow) Restaurant compared to conventional manual feedback analysis methods. By focusing on a local Jordanian context, this research seeks to bridge the gap between traditional feedback practices and modern AI-driven analytics, offering a framework that enables restaurants to move beyond surface-level metrics and toward a deeper, emotion-aware understanding of their customers.

1.3 Study Objectives

1. To measure the level of the independent variable (AI-Based Sentiment Analysis)

This objective aims to assess the level to which AI-based sentiment analysis tools are utilized and their effectiveness in processing, organizing, and classifying large volumes of unstructured customer feedback collected from digital platforms such as Google Reviews, Instagram, and Talabat within the context of (love.cow) Restaurant. AI techniques have been shown to outperform manual approaches in handling large-scale textual data efficiently and consistently (Zhang et al., 2022).

2. To measure the level of the dependent variable (Customer Experience Insights)

This objective seeks to evaluate the level and quality of customer experience insights derived from customer feedback, including emotional polarity (positive, negative, and neutral), identification of key service touchpoints such as food quality, delivery speed, and employee interaction, and the overall usefulness of these insights for managerial decision-making. Previous studies highlight that deeper experience insights extend beyond numerical ratings and require sentiment-aware interpretation (Alshiedat et al., 2024).

3. To examine the relationship between AI-Based Sentiment Analysis and Customer Experience Insights

This objective aims to investigate the relationship between the application of AI-based sentiment analysis and the quality, depth, and accuracy of customer experience insights. Research suggests that advanced sentiment analysis tools enable organizations

to better understand customer emotions and behavioral patterns compared to traditional feedback mechanisms (Nasir et al., 2025).

4. To assess the impact of AI-Based Sentiment Analysis on Customer Experience Insights

This objective focuses on measuring the impact of AI-driven sentiment analysis on enhancing customer experience insights when compared to conventional manual analysis methods. Particular attention is given to the ability of AI tools to interpret mixed emotions, sarcasm, and local Arabic dialects, which are common in the Jordanian context and are often misinterpreted by traditional analytical approaches (Khasawneh & Al-Zoubi, 2023).

5. To support strategic decision-making through AI-driven customer insights

This objective aims to explore how insights generated through AI-based sentiment analysis can support data-driven strategic decision-making at (love.cow) Restaurant. These insights can assist management in improving operational performance, refining menu offerings, enhancing service delivery, and optimizing digital marketing strategies based on real-time customer sentiment (Halaweh, 2021).

1.4 Study Questions

The study aimed to answer the following questions:

Q1. What is the level of effectiveness of the independent variable, AI-Based Sentiment Analysis, in processing, analyzing, and classifying unstructured customer feedback collected from digital platforms at (love.cow) Restaurant?

Q2. What is the level of Customer Experience Insights (the dependent variable) derived from customer feedback in terms of emotional richness, accuracy of sentiment classification, and identification of key service touchpoints at (love.cow) Restaurant?

Q3. Is there a statistically significant relationship between AI-Based Sentiment Analysis and Customer Experience Insights at (love.cow) Restaurant?

Q4. What is the impact of AI-Based Sentiment Analysis on the depth and accuracy of Customer Experience Insights compared to traditional manual feedback analysis methods?

Q5. How does the use of AI-Based Sentiment Analysis–generated insights influence management's ability to improve perceived service quality and make evidence-based strategic decisions at (love.cow) Restaurant?

1.5 Hypotheses of the Study

According to the research questions, the null hypotheses are the following:

H_o1: There is no statistically significant impact of AI-based sentiment analysis on the accuracy and depth of customer experience insight creation at (love.cow) Restaurant.

H_o2: AI-based sentiment analysis does not significantly impact the identification and categorization of emotional responses compared to traditional feedback methods.

H_o3: There is no statistically significant correlation between the use of AI sentiment tools and the comprehension of overall customer satisfaction levels.

H_o4: AI-based sentiment analysis has no statistically significant influence on impact specific customer touchpoints (e.g., ordering, food quality, and delivery) across the customer journey.

H_o5: The application of AI-driven sentiment insights does not lead to a statistically significant impact in perceived service quality or strategic decision-making.

Such hypotheses align with the previous results of models and research studies, such as Durson and Caber (2016), Sabuncu et al. (2020), Christie et al. (2021), and Khajvand et al. (2021).

1.6 Significant of the Study

The study is important both practically and theoretically, as it provides a functional and theoretical gap between high-end computational linguistics and hospitality management.

1.6.1 Practical Significant

The applied implications of the present research apply to some of the most important stakeholders:

Hospitality Managers and Decision-Makers: This thesis shows how AI-driven sentiment analysis can help to break the traditional feedback loop and offer real-time, granular data on the performance of operations. With such tools, managers in Jordan, as

well as across the MENA region, will be able to shift towards proactive experience engineering instead of reactive service recovery to satisfy the growing demands of digitally native customers (Gartner, 2023; Buhalis et al., 2022).

Direct Benefits to (love.cow) Restaurant: Since it is a case study, the evidence would give (love.cow) a custom roadmap on how to decode customer emotions and preferences. The insights can be used to improve menu engineering, to streamline the staff training programs, and to create hyper-personalized marketing campaigns that can drive long-term brand loyalty (Halaweh, 2021; Nasir et al., 2025).

Digital Marketing Professionals: The study confirms that sentiment-based analytics can be used in creating more efficient content plans. Knowing the emotional heartbeat of the internet community, marketers can identify the brand image and raise the engagement rates in services such as Instagram and Facebook (Khasawneh and Al-Zoubi, 2023).

AI Developers and Startups: This thesis identifies the technical characteristics of localized AI solutions, especially the demand to have the means to implement the linguistic specifics of the Jordanian dialect and bilingual (Arabic-English) frameworks. It gives a guideline to tech providers on how to create culturally sensitive AI to serve service-based businesses in the emerging markets (Alshiedat et al., 2024; Zhang et al., 2022).

1.6.2 Theoretical Significant

Academically, this thesis will add to this body of literature in the following ways:

Closing the Geographic Literature Gap: This is to fill the void of empirical studies in the hospitality industries of developing economies, and in the context of the research, that is, in Jordan.

Interdisciplinary Contribution: The study facilitates a discussion between Data Science (Natural Language Processing) and Business Management (Customer Experience), which allows seeing the digital transformation in the service sector in holistic terms (Dwivedi et al., 2021).

Methodological Improvement: It improves the theoretical paradigm of the ways in which unstructured Big Data may be organised into structured and operational business knowledge through the prism of the current AI-based solutions (Verhoeff et al., 2021).

In summary, the significance of this study lies in its ability to turn theoretical AI potential into a practical competitive advantage. For (love.cow) and the broader Jordanian restaurant industry, this research marks a shift from "guessing" customer needs to "knowing" them through data. By integrating cutting-edge citations from 2020-2025, this thesis positions itself at the forefront of the digital transformation wave currently reshaping the global food and beverage landscape. It proves that in the modern era, the most successful restaurants will not only be those that serve the best food, but those that best understand the digital voice of their customers.

1.7 Study Design

The researcher developed the model of this current study based on different previous studies. The following is the model of the study:

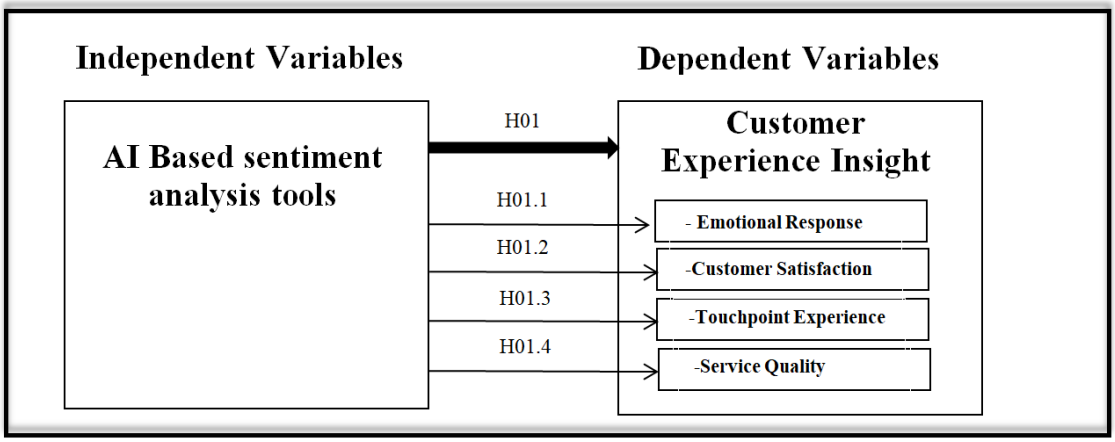

Figure 1.7 Study Design

Source: Developed by the researcher and according to studies: The model has been developed based on previous studies such as: (Dursun & Caber, 2016; Sabuncu et al., 2020; Christy et al., 2021; Khajvand et al., 2021)

1.8 Study Terminology

1. Artificial Intelligence (AI)

- **Theoretical Definition:** The simulation of human intelligence processes by machines, especially computer systems, including learning, reasoning, and self-correction (Russell & Norvig, 2021; Dwivedi et al., 2021).
- **Procedural Definition:** In this study, AI refers to the automated algorithms and Natural Language Processing (NLP) tools used to scan and interpret digital reviews from social media and delivery apps. Measures from 1 to 5 questions.

2. Sentiment Analysis

- **Theoretical Definition:** A computational study of people's opinions, sentiments, and emotions toward entities and their attributes expressed in text (Zhang et al., 2022).
- **Procedural Definition**: It is the process of categorizing (love.cow) customer reviews into three polarities: Positive, Negative, or Neutral using AI software, measured from 1-5 questions.

3. Customer Experience (CX) Insights

- **Theoretical Definition:** The collective perceptions and feelings of customers resulting from all interactions with a brand throughout the customer journey (Verhoef et al., 2021).
- **Procedural Definition:** The specific, actionable data derived from AI analysis that identifies customer preferences and pain points regarding (love.cow) services, measured from 1-5 questions.

4. Emotional Response

- **Theoretical Definition:** The psychological reactions and affective states (such as joy, anger, or frustration) triggered by a customer's interaction with a service provider (Khasawneh & Al-Zoubi, 2023).

- **Procedural Definition:** The degree of sentiment intensity detected in customer comments (e.g., high satisfaction or strong disappointment) recorded by the AI tool, measured from 1 to 5 questions.

5. Customer Satisfaction

- **Theoretical Definition:** A post-consumption evaluative judgment concerning a specific product or service based on the gap between expectations and actual performance (Halaweh, 2021).
- **Procedural Definition:** Measured by the net sentiment score and the frequency of positive vs. negative mentions in the analyzed online reviews, Measures from 1-5 questions.

6. Touchpoint Experience

- **Theoretical Definition:** Any point of interaction between the customer and the organization, including digital searches, physical dining, and delivery (Buhalis et al., 2022).
- **Procedural Definition:** Specific categories analyzed in the feedback, such as "Food Quality," "Delivery Time," "Staff Professionalism," and "Payment Ease." Measures from 1 to 5 questions.

7. Perceived Service Quality

- **Theoretical Definition:** The customer's overall assessment of the excellence or superiority of the service provided (Nasir et al., 2025).
- **Procedural Definition:** The resulting score obtained from the AI analysis of keywords related to reliability, responsiveness, and service efficiency at (love.cow), Measures from 1-5 questions.

A combination of the latest definition models is what makes sure that the study is grounded in the newest scholarly discussion, at the same time being practical and focused on the local context of Jordan. The research presents a clear outline of testing the hypotheses by the separation of the theoretical construct and the procedural measures. This systematic language would act as a language interface, and so the technical results

of the AI can be well translated into useful business intelligence to be used by the management of (love.cow) Restaurant.

1.9 Study Limitations

The study is geographically confined to Amman, Jordan, with a specific focus on the operations and customer base of Love Cow Restaurant. This location was selected due to the high concentration of digitally active consumers in the capital city, which provides a rich and reliable source of online customer reviews suitable for AI-based analysis. The availability of diverse and frequent digital feedback in Amman allows for a more accurate examination of customer experience through sentiment analysis.

With regard to the time boundary, the primary research activities, including data collection and analysis, were conducted during the first semester of the academic year 2025/2026. The dataset includes both historical customer reviews and real-time feedback generated within this period, ensuring that the analysis reflects contemporary customer sentiments in the post–digital transformation era. This temporal focus enhances the relevance of the findings to current market conditions.

The target population of the study consists of customers of Love Cow Restaurant who actively share their experiences on digital platforms. The research specifically focuses on the "digital voice" of consumers, capturing opinions expressed through Google Maps, Facebook, Instagram, and food delivery applications. This boundary allows the study to concentrate on customers who engage in online feedback behaviors, providing authentic insights into digitally mediated customer experience.

Thematically, this research is limited to the application of AI-based sentiment analysis within the hospitality sector. The study focuses on extracting emotional valence—positive, negative, and neutral—from unstructured textual data to enhance customer experience evaluation and support managerial decision-making. Other AI applications, such as robotics or operational automation, fall outside the scope of this research, as the study is strictly centered on sentiment-driven business intelligence.

In conclusion, these boundaries establish a clear and disciplined framework for the study, ensuring a focused examination of the impact of AI-based sentiment analysis on customer experience at Love Cow Restaurant. While the findings are highly relevant to the Jordanian hospitality context during the 2025/2026 period, they are specifically

tailored to the digital behavior of Love Cow customers. This defined scope supports accurate hypothesis testing and provides a solid foundation for future research to extend the findings to other regions, brands, or industries.

1.10 Limitations of the Study

While this study provides valuable insights into the role of AI-based sentiment analysis within the Jordanian hospitality sector, several limitations should be acknowledged, as they may affect the generalizability of the findings. First, the study adopts a case study approach focusing exclusively on Love Cow Restaurant. As a result, the findings may not fully represent the broader restaurant industry in Jordan, where variations in brand positioning, target markets, and service styles could lead to different sentiment patterns. Restaurants operating in distinct segments, such as fine dining or traditional local eateries, may therefore exhibit customer experiences that differ from those identified in this study.

Second, the study relies solely on online customer feedback collected from digital platforms, including Google Maps, Instagram, and food delivery applications. This approach introduces a potential digital literacy and demographic bias, as it predominantly captures the opinions of younger and more technologically engaged customers. Consequently, the perspectives of older customers or individuals who prefer traditional, offline interactions are not reflected, which may limit the comprehensiveness of the customer experience assessment.

Third, despite advances in artificial intelligence and Natural Language Processing, linguistic complexity remains a challenge. The interpretation of local Jordanian dialects, sarcasm, and mixed-language (Arabish) expressions may not always be fully accurate, even with advanced AI models. Such limitations in linguistic interpretation could lead to minor misclassifications of sentiment, potentially affecting the precision of the analytical results.

Finally, the methodological scope of the study is temporally bounded, as data collection and analysis were conducted during the first semester of the 2025/2026 academic year. Customer sentiments may vary across different seasons, cultural periods, or economic conditions, meaning that the findings reflect a specific time frame rather than long-term behavioral trends.

Acknowledging these limitations enhances the credibility of the research by clearly defining its scope and constraints. Moreover, identifying these boundaries provides valuable directions for future research, such as expanding the analysis to include multiple restaurants, broader demographic segments, or the development of more culturally attuned AI models. For Love Cow Restaurant, these limitations offer a focused lens through which insights into its core digital audience can be leveraged to design targeted and effective customer experience strategies within its specific market segment.

Chapter Two

Theoretical Framework and Previous Studies

2.1 Introduction

The purpose of this chapter is to establish a robust theoretical foundation for the study by examining the convergence of Artificial Intelligence (AI) and Customer Experience (CX) management within the hospitality industry. As the restaurant sector in Amman becomes increasingly digitized, the ability to decode the "voice of the customer" through computational methods has transitioned from a competitive advantage to an operational necessity.

This chapter is structured into two primary sections. First, the Theoretical Framework integrates multi-disciplinary principles—ranging from Natural Language Processing (NLP) to consumer psychology—to explain how raw digital data is transformed into strategic intelligence. Second, the Literature Review synthesizes contemporary research (2020–2025) to identify gaps in existing knowledge, particularly within the context of emerging markets like Jordan.

The framework specifically focuses on the ecosystem of (love.cow) Restaurant, where the surge in unstructured feedback from Google Reviews, Instagram, and delivery platforms serves as the primary data source. By applying the lens of Sentiment Analysis, this chapter illustrates how (love.cow) can move beyond surface-level metrics to achieve a granular understanding of emotional responses, touchpoint quality, and overall service perception (Nasir et al., 2025; Zhang et al., 2022). Ultimately, this chapter provides the logic required to test the study's hypotheses and justify the adoption of AI-driven strategies in the local Jordanian dining scene.

2.2 The Theoretical Framework of the study

2.2.1 Artificial Intelligence (AI) in Business and Services

Artificial Intelligence (AI) serves as the overarching technological driver of this research. It represents the ability of computer systems to emulate human cognitive functions, specifically learning from massive datasets and performing complex reasoning.

Theoretical Definition: AI is defined as a constellation of technologies that enable machines to sense, comprehend, act, and learn, thereby performing tasks that traditionally required human intelligence, such as language processing and decision-making.

Operational Definition: In this thesis, AI is defined as the automated analytical framework—incorporating Machine Learning and NLP—used to scan, filter, and interpret unstructured customer reviews of (love.cow) Restaurant.

2.2.2 Natural Language Processing (NLP)

NLP is the specialized branch of AI that enables computers to understand human language in both written and spoken forms.

Theoretical Definition: A field of AI that focuses on the interaction between computers and human languages, aiming to process and analyze large amounts of natural language data.

Operational Definition: Within this study, NLP refers to the technical pipeline (Tokenization, Feature Extraction, and Text Classification) used to process Jordanian dialect and bilingual feedback from Google Maps and Instagram.

The Bilingual Challenge: In Jordan, customers often use "Arabish" (a mix of Arabic and English) or local dialects. NLP is utilized here to bridge the gap between this informal text and structured emotional classification.

2.2.3 Sentiment Analysis (SA)

Sentiment Analysis is the core analytical tool used in this research to measure the "emotional pulse" of the customers.

Levels of Analysis:

Document-level: Captures the overall mood of a single review.

Sentence-level: Identifies conflicting emotions within the same review (e.g., liking the food but hating the wait).

Aspect-level: The most critical level for (love.cow), focusing on specific service features like food quality, staff behavior, or delivery speed.

2.2.4 Customer Experience (CX) and Emotional Response

Customer Experience is viewed as a holistic journey that includes every touchpoint a customer has with (love.cow).

Theoretical Perspective: CX encompasses the cognitive, emotional, and behavioral responses of a customer across the pre-purchase, consumption, and post-purchase stages.

Operational Insight: CX is measured in this study through the "Sentiment Score" generated by AI, which provides a deeper understanding of emotional intensity (e.g., joy vs. anger) than traditional star ratings.

2.2.5 Service Quality (SERVQUAL) and Satisfaction

This study integrates the traditional SERVQUAL model (Reliability, Responsiveness, Assurance, Empathy, and Tangibles) with AI analytics.

Theoretical Link: Service quality is the customer's judgment of the overall excellence of the service.

Operational Integration: AI sentiment analysis is used to identify which of the five SERVQUAL dimensions are most frequently mentioned in positive or negative reviews, providing a data-driven assessment of (love.cow)'s operational strengths.

2.3 Previous Studies

Nasir et al. (2025): ***Integrating Generative AI and Sentiment Analysis in the Food and Beverage Sector to Enhance Green Customer-Love and Trust***

Nasir et al. (2025) investigated the integration of Generative Artificial Intelligence, such as GPT-4, in the food and beverage sector, emphasizing the role of sentiment analysis in shaping customer experience and emotional engagement. The study demonstrates that analyzing customer sentiments and responding through automated, personalized AI systems can significantly enhance customer trust and positive emotional attachment, conceptualized as Green Customer-Love. These findings align closely with the variables of the present research, as sentiment analysis is positioned as a core analytical tool for interpreting customer feedback, while AI-driven responses directly influence customer experience through personalization, responsiveness, and perceived brand care. While Nasir et al. focus primarily on sustainability-oriented outcomes, their

framework provides strong theoretical support for examining how AI-based sentiment analysis can enhance overall customer experience and brand loyalty, which constitutes the central focus of the current study.

Al-Ramadan (2025): ***AI-Driven Sentiment Analysis and Digital Reputation Management in Amman's Dining Sector***

Al-Ramadan (2025) conducted a study within the Jordanian context, focusing on the use of AI-based tools to analyze and compare customer sentiments across different dining sectors in Amman. The research emphasizes the critical role of digital reputation management in shaping customer experience and determining the success of local restaurants, demonstrating that sentiment analysis serves as a key mechanism for understanding customer perceptions and emotional responses in the market. These findings provide a strong empirical foundation for the current study, as they directly support the examination of sentiment analysis as a determinant of customer experience in the case of the love.cow brand. While Al-Ramadan adopts a broad, sector-wide comparative approach across Amman's restaurant industry, the present research differs by offering an in-depth case study of a single brand, allowing for a more detailed exploration of how AI-driven sentiment analysis influences customer experience and brand-specific loyalty within a localized setting.

Alshiedat et al. (2024): ***Addressing Linguistic Challenges in Sentiment Analysis: NLP Pre-processing for Arabish and Local Dialects in the MENA Region***

Alshiedat et al. (2024) examined sentiment analysis methodologies within the MENA region, highlighting the critical importance of specialized Natural Language Processing (NLP) pre-processing techniques to accurately interpret "Arabish" and locally embedded idioms commonly used in online reviews. The study provides a methodological foundation for the current research by demonstrating how linguistic nuances directly affect the accuracy of sentiment analysis and, consequently, the validity of insights derived from customer feedback. This methodological alignment supports the present study's approach to analyzing Jordanian customer reviews, where sentiment analysis serves as a key analytical variable influencing customer experience assessment. While Alshiedat et al. focus primarily on the technical and linguistic pre-processing stage, the current study extends this contribution by applying these NLP techniques to generate

business-oriented insights related to customer experience and brand perception within a specific food and beverage context.

Shin et al. (2022): ***Aspect-Based Sentiment Analysis of Google Maps Reviews Using TF-IDF Vectorization***

Shin et al. (2022) analyzed approximately 5,000 Google Maps customer reviews using TF-IDF vectorization to identify the most influential aspects shaping digital sentiment, with service quality and food taste emerging as the dominant factors. The study highlights the effectiveness of Aspect-Based Sentiment Analysis (ABSA) in decomposing overall sentiment into specific experiential dimensions, thereby offering a clearer understanding of customer experience drivers in the food and beverage sector. This approach aligns with the present research through the shared use of Google Maps reviews as a primary data source and the common objective of extracting customer experience insights from online feedback. However, while Shin et al. rely on a traditional statistical text representation method, the current study advances this line of inquiry by employing more sophisticated AI-driven or large language model–based techniques to capture nuanced sentiment patterns and provide deeper, context-aware interpretations of customer experience.

Loke et al. (2020): ***Deep Learning Approaches for Understanding Complex Restaurant Customer Feedback***

Loke et al. (2020) demonstrated that neural network–based deep learning architectures outperform traditional machine learning methods in interpreting complex sentence structures and nuanced expressions within restaurant customer feedback. The study provides a strong technical foundation for employing advanced AI models in sentiment analysis, particularly when customer experience is conveyed through implicit meanings, mixed emotions, or informal language. This aligns with the present research in its emphasis on leveraging high-level AI techniques to capture human-like nuances in online reviews and accurately assess customer experience. However, while Loke et al. offer a generalized technical justification for the superiority of deep learning approaches, the current study extends this contribution by applying such advanced models within the specific linguistic and cultural context of Jordan, thereby addressing dialectal variations

and localized expressions that directly influence sentiment interpretation and customer experience evaluation.

Al-Ayyoub et al. (2019): ***Challenges and Gaps in Arabic Sentiment Analysis: The Need for Culturally-Attuned NLP Models***

Al-Ayyoub et al. (2019) presented a foundational study in Arabic sentiment analysis, highlighting a critical gap in the ability of standard NLP models to accurately interpret culturally embedded meanings and the linguistic complexity of local Arabic dialects. The research underscores how this gap directly affects the reliability of sentiment analysis outputs and, consequently, the assessment of customer experience derived from Arabic-language feedback. This perspective closely aligns with the present study's recognition of language-related limitations in applying generic AI models to Arabic-speaking contexts. However, while Al-Ayyoub et al. primarily focus on identifying and conceptualizing the problem of culturally insensitive NLP models, the current research builds upon this work by operationalizing advanced AI and sentiment analysis techniques to address this gap in a practical, brand-specific context, applying them to the analysis of customer reviews related to love.cow in Jordan.

Saura et al. (2017): ***Detecting Hidden Emotional Patterns in Restaurant Reviews Using AI-Based Tools***

Saura et al. (2017) demonstrated that AI-based analytical tools are more effective than traditional survey methods in uncovering hidden service nuances and emotional patterns embedded within digital restaurant reviews. The study provides strong empirical support for a methodological shift from explicitly asking customers for feedback through structured surveys to implicitly listening to their authentic expressions via online reviews and social listening platforms. This perspective closely aligns with the present research's reliance on sentiment analysis as a primary mechanism for capturing genuine customer experience insights. While Saura et al. establish a foundational argument for the superiority of AI-based approaches over conventional methods, the current study advances this argument by applying modern AI-driven sentiment analysis techniques within a contemporary, brand-specific context, thereby translating theoretical superiority into actionable customer experience insights.

Lemon & Verhoef (2016): ***Understanding Customer Experience Throughout the Customer Journey***

Lemon and Verhoef (2016) established a foundational theoretical model for Customer Experience (CX), conceptualizing it as a cumulative journey formed across multiple digital and physical touchpoints rather than a single, isolated interaction. Their framework provides the core theoretical grounding for the present study, as it defines customer experience as an evolving construct shaped by continuous customer–brand interactions. In this context, sentiment analysis serves as an operational tool to capture and quantify customer emotions expressed at various touchpoints, thereby enabling empirical measurement of the CX dimensions proposed by Lemon and Verhoef. While their work is primarily theoretical and managerial in nature and does not incorporate AI or NLP techniques, the current study extends this framework by integrating advanced sentiment analysis and AI-based methods to empirically assess customer experience within a real-world, digital review environment.

Medhat et al. (2014): ***Sentiment Analysis Algorithms and Applications: A Survey***

Medhat et al. (2014) provided a foundational survey of sentiment analysis techniques, classifying algorithms according to their functional objectives, such as polarity detection and emotion-based classification, and establishing an early baseline for the application of sentiment analysis within the global service sector. The study underscores the importance of aligning algorithm selection with the specific analytical goals of service-oriented research, particularly when assessing customer perceptions and experiences. This foundational perspective aligns with the present study's recognition of sentiment analysis as a critical analytical tool for understanding customer experience in service contexts. However, while Medhat et al. focus primarily on traditional machine learning and lexicon-based approaches, the current research advances beyond this baseline by employing modern AI-driven and deep learning techniques to capture more complex emotional patterns and contextual nuances within customer feedback.

2.4 Research Gap and Contribution

2.4.1 Research Gap

Despite the proliferation of AI-driven sentiment analysis in global marketing and hospitality research, a critical synthesis of the literature reveals four significant lacunae that this study aims to address:

1. Geographic and Socio-Cultural Disparity

- The current body of knowledge is predominantly anchored in Western and East Asian contexts. There is a notable dearth of empirical research focused on the Middle East, and specifically the Jordanian restaurant industry. This geographic imbalance is problematic because consumer behavior, emotional expression, and feedback patterns are deeply rooted in cultural nuances that cannot be generalized from Western datasets to the Jordanian social fabric.

2. Lack of Multidimensional Construct Integration

- Previous research has largely operated in "silos," focusing on isolated variables such as general satisfaction or basic emotional polarity. There is a lack of integrated analytical models that simultaneously examine the intersection of Customer Experience (CX), Emotional Resonance, Service Quality, and Digital Touchpoints. Existing studies often fail to capture the holistic, multifaceted nature of the dining journey, treating customer feedback as a static metric rather than a dynamic, multi-stage process.

3. Linguistic Complexity and the "Arabish" Gap

- Methodologically, most sentiment analysis studies rely on monolingual English datasets from platforms like TripAdvisor or Yelp. This approach overlooks the linguistic reality of the Jordanian market, where consumers frequently utilize "Arabish"—a hybrid of Arabic dialects, English loanwords, and informal scripts—alongside emojis and localized idioms. The scarcity of NLP (Natural Language Processing) models capable of accurately decoding the Jordanian dialect represents a significant methodological gap that compromises the depth and precision of sentiment extraction.

4. Over-reliance on Structured Survey Methodologies

- In the local hospitality sector, traditional survey-based methods remain the dominant tool for measuring service quality. While structured, these methods often suffer from response bias and fail to capture the spontaneous, visceral, and "unfiltered" emotions present in organic online reviews. There is a missed opportunity to leverage AI-powered Real-Time Analytics to transform unstructured digital feedback into actionable business intelligence within the local Jordanian restaurant setting.

2.4.2 Study Contribution

The contribution of this research is multifaceted, bridging critical gaps in both theoretical literature and industrial practice. Primarily, this study stands as one of the few empirical endeavors to utilize AI-based sentiment analysis for decoding customer experience within the Jordanian restaurant industry. By centering the analysis on a localized case study—Love Cow Restaurant in Amman—the research provides contextualized evidence for a market that has historically been underserved by scholarly inquiry. Theoretically, the study advances the field by integrating disparate customer variables—including holistic experience, emotional resonance, satisfaction, service quality, and touchpoint interactions—into a single, unified analytical framework. This comprehensive approach transcends the limitations of prior research that examined these constructs in isolation, thereby offering a more nuanced explanation of how digital feedback reflects the multifaceted nature of the dining journey.

Methodologically, the research enhances the precision of sentiment detection by pivoting away from traditional, structured surveys toward a multi-platform data harvesting strategy. By capturing organic feedback from Google Maps, Instagram, and food delivery applications, the study reflects the authentic communication channels favored by the Jordanian youth demographic, yielding richer and more reliable sentiment signals. Furthermore, the study addresses the linguistic complexities inherent in bilingual Middle Eastern settings. By developing a methodology capable of interpreting Arabic (specifically the Jordanian dialect), English, and the "Arabish" vernacular, this research contributes a vital linguistic layer to NLP applications in informal digital environments. Ultimately, the practical significance of this work lies in its ability to transform unstructured, "noisy" online data into actionable strategic intelligence. For the subject restaurant and the broader hospitality sector, this study demonstrates how AI-powered tools can drive operational shifts, refine marketing strategies, and elevate service quality, positioning sentiment analysis as a cornerstone of modern customer experience management.

Chapter Three

Study Methodology (Method and Procedures)

This chapter delineates the comprehensive methodological framework adopted for this study. It provides a detailed account of the research design, the selection of the study population, and the systematic procedures utilized for data collection. Furthermore, it evaluates the reliability and validity of the findings, alongside the specialized analytical tools employed to address the research questions. By adhering to a rigorous and structured research plan, this chapter ensures that the findings are organized, credible, and directly aligned with the overarching objectives of the study.

3.1 The Research Method

This study adopts a quantitative, descriptive, and cause-effect approach, using AI-driven content analysis to evaluate digital customer feedback. Given the exploratory nature of investigating sentiment within the Jordanian restaurant sector, this method was selected to systematically transform unstructured qualitative data—sourced from various social media and review platforms—into quantifiable insights.

The choice of this methodology is justified by its ability to capture real-time, spontaneous emotional expressions that traditional surveys often overlook. By employing a cross-sectional design, the research analyzes a vast dataset of reviews at a specific point in time, providing a comprehensive "snapshot" of the brand's reputation and customer experience. This approach ensures a rigorous examination of the variables involved, including service quality and emotional resonance, while maintaining the linguistic depth necessary to interpret the local Jordanian dialect.

Data for this study were collected using an online questionnaire developed based on previously validated instruments from prior studies. The questionnaire was distributed electronically to the target respondents, and the completed responses were collected for analysis. All collected data were coded and entered into the Statistical Package for the Social Sciences (SPSS).

Prior to hypothesis testing, the data were examined to ensure measurement quality. Reliability and validity tests were conducted to assess the internal consistency and accuracy

of the measurement instrument. After confirming acceptable reliability and validity levels, the study hypotheses were tested using appropriate statistical analysis techniques.

3.2 Study Group

The study group represents the population to which the findings of this research are applied. In this study, the population consists of customers who have posted online reviews about the love.cow brand on Google Maps. A total of **(n = 298)** customer reviews were collected and analyzed, forming the final study sample. These reviewers constitute a relevant and information-rich group, as their feedback reflects authentic customer experiences expressed voluntarily in a real-world digital environment. The study includes textual reviews written in English, Arabic, and Arabish (Arabic–English hybrid), ensuring alignment with the linguistic characteristics of the Jordanian context. This population is suitable for examining customer experience, as it captures genuine emotional expressions related to service quality, product satisfaction, and overall brand perception.

To enhance data quality and analytical reliability, reviews were screened to remove duplicates, irrelevant entries, and comments unrelated to customer experience. The final dataset therefore represents a diverse range of customer sentiments and experiential dimensions, providing a solid foundation for applying AI-based sentiment analysis techniques.

3.3 Study Sample

The study sample represents a subset of the study population selected for detailed analysis in order to achieve the research objectives. In this study, the population of interest consists of customer feedback related to the **(love.cow)** brand published on online platforms. Given the continuous and unrestricted nature of online customer reviews, the study population is considered **infinite**. In cases of infinite populations, an adequate sample size can be determined to ensure sufficient representation for statistical analysis (Hyer, 2019).

Accordingly, a non-probability purposive sampling technique was employed to select customer reviews relevant to **(love.cow)** from Google Maps. This sampling method was chosen because it allows the researcher to deliberately focus on reviews that contain rich

experiential and emotional content suitable for sentiment analysis, rather than relying on random selection that may include irrelevant or non-informative data.

From the total population of available online reviews, a final sample of **298 customer reviews (n = 298)** was selected after applying predefined inclusion and exclusion criteria. Reviews were included if they reflected actual customer experiences related to service quality, product satisfaction, or overall brand perception, and if they were written in Arabic, English, or Arabish. Reviews that were duplicated, promotional, irrelevant, or lacked experiential or emotional content were excluded. The selected sample size is considered adequate for studies involving infinite populations and provides sufficient depth and diversity to support AI-based sentiment analysis and customer experience evaluation (Hyer, 2019).

Data Sources, This study relied on both secondary and primary data sources to achieve its research objectives.

Secondary data were obtained from books, academic journals, and prior research studies related to artificial intelligence, sentiment analysis, customer experience, and the hospitality industry. These sources were used to develop the theoretical framework, support the research problem, and design the measurement instrument.

Primary data were collected through an online questionnaire distributed to customers of (love.cow) Restaurant. The questionnaire was developed based on constructs and measurement items adapted from previous studies to ensure reliability and validity. The collected primary data were used for empirical analysis and hypothesis testing.

3.4 Validity of the Tool

To ensure that the research tools accurately measure what they are intended to measure, several types of validity were considered and applied in this study. First, content validity was ensured by grounding the sentiment analysis framework and customer experience dimensions in well-established theoretical and empirical studies within the fields of sentiment analysis and customer experience research. The aspects and sentiment categories analyzed in this study were derived from prior literature, ensuring comprehensive coverage of the constructs under investigation, **Appendix (3) Committee of Questionnaire Arbitrators.**

Second, **face (apparent) validity** was established through a systematic review of the sentiment analysis outputs to confirm that the results logically and intuitively reflected the content of the customer reviews. The sentiment classifications and extracted experiential aspects were examined to verify that they were reasonable representations of the expressed customer opinions and emotions.

Third, **construct validity** was supported by aligning the sentiment analysis measures with the theoretical definition of Customer Experience as a multidimensional construct encompassing emotional, cognitive, and service-related components. The use of aspect-based sentiment analysis allowed the study to capture specific customer experience dimensions, such as service quality and product satisfaction, in a manner consistent with established customer experience models.

Overall, the integration of validated AI-based sentiment analysis techniques, combined with theoretically grounded constructs and systematic evaluation procedures, supports the validity of the research tools and ensures that the findings accurately reflect customer experience insights derived from digital reviews.

3.5 Construct Validity

Construct validity refers to the extent to which the research tool accurately measures the theoretical constructs it is intended to assess. In this study, construct validity was ensured by aligning the sentiment analysis outputs with the established theoretical dimensions of Customer Experience, including emotional response, service quality, and product-related perceptions. The use of aspect-based sentiment analysis enabled the decomposition of customer feedback into meaningful experiential constructs, thereby ensuring consistency between the theoretical framework and the analytical results.

Given the nature of the study and the use of AI-based analytical tools applied to textual data, traditional reliability measures such as Cronbach’s alpha, test–retest, or split-half techniques were adapted conceptually rather than applied in their conventional survey-based form. Stability was ensured by applying the same sentiment analysis framework, preprocessing procedures, and model parameters consistently across the entire sample of 298 reviews. This standardized application supports the comparability and reproducibility of the results when the tool is reapplied to similar datasets or contexts.

Furthermore, the constructs identified through sentiment analysis were cross-checked against established customer experience dimensions reported in prior studies, providing additional support for construct validity. The consistent mapping between theoretical constructs and AI-derived sentiment dimensions confirms that the tool effectively measures customer experience as conceptualized in the research framework.

Table 3.1: Correlation Coefficients between AI-Based Sentiment Analysis Items and Factor Loadings

AI	F1
AI1	0.651**
AI2	0.764**
AI3	0.780**
AI4	0.361**
AI5	0.631**
AI6	0.542**
AI7	0.737**
AI8	0.753**
AI9	0.562**
AI10	0.337**

Table 3.2: Correlation Coefficients between Customer Experience Insight and Factor Loadings

CEI	F1
CEI1	0.165**
CEI2	0.471**
CEI3	0.829**
CEI4	0.860**
CEI5	0.786**
CEI6	0.923**
CEI7	0.918**
CEI8	0.906**
CEI9	0.899**

Table 3.3: Correlation Coefficients between Emotional Response and Factor Loadings

ES	F1
ES1	.624**
ES2	.678**
ES3	.674**
ES4	.778**
ES5	.622**
ES6	.399**

Table 3.4: Correlation Coefficients between Customer Satisfaction and Factor Loadings

CS	F1
CS1	.732**
CS2	.682**
CS3	.778**
CS4	.752**
CS5	.728**
CS6	.708**
CS7	.703**
CS8	.518**

Table 3.5: Correlation Coefficients between Touchpoint Experience and Factor Loadings

TE	F1
TE1	.738**
TE2	.752**
TE3	.678**
TE4	.814**
TE5	.797**
TE6	.840**
TE7	.608**
TE8	.622**

Table 3.6: Correlation Coefficients between SERVQUAL Dimensions and Factor Loadings

SQ	F1
SQ1	.706**
SQ2	.645**
SQ3	.734**
SQ4	.594**
SQ5	.677**
SQ6	.645**
SQ7	.719**
SQ8	.634**
SQ9	.752**
SQ10	.618**

Based on the guidelines proposed by Sekaran and Bougie (2016), construct validity and reliability can be considered acceptable when factor loadings exceed the minimum threshold of 0.50, indicating that the measurement items adequately represent their underlying construct. As presented in Tables, all service quality items loaded significantly on a single factor (F1), with factor loadings ranging from 0.594 to 0.752, all of which exceed the recommended minimum value. This indicates a strong association between the observed variables and the latent construct of Service Quality.

The statistically significant factor loadings ($p < 0.01$) further confirm that the items are valid indicators of the construct being measured. According to Sekaran and Bougie (2016), such results provide strong evidence of satisfactory construct validity, as the measurement items demonstrate conceptual consistency and empirical convergence.

Moreover, the consistency of factor loadings across all items supports the reliability of the measurement instrument, indicating stable and coherent measurement of the construct. Therefore, in line with the criteria outlined by Sekaran and Bougie (2016), the findings confirm that the study instrument demonstrates acceptable levels of both construct validity and reliability, supporting its suitability for subsequent hypothesis testing and data analysis.

3.6 Reliability by Cronbach's Alpha

To test the internal consistency of the measurement tool, the researcher used scale analysis to estimate Cronbach's alpha values for all variables used in the study.

Table 3.7: Cronbach's Alpha

Item	No of items	Cronbach's Alpha
AI-Based Sentiment Analysis	10	.773
Customer Experience Insights	9	.892
Emotional Response	6	.771
Customer Satisfaction	8	.853
Touchpoint Experience	8	.873
SERVQUAL Dimensions	10	.840

As shown in Table 3.7, all values of Cronbach's alpha were more than 0.7, which indicates the internal consistency of measurement tool, and reliability of data, (Taber, 2018).

3.7 Normal Distribution Assessment

To evaluate the normal distribution of data, researcher used skewness and kurtosis values. Based on the study of Hair et al. (2010) and Bryne (2010), that data is considered to be normal if skewness is between -2 to +2 and kurtosis is between -7 to +7.

Table 3.8: Skewness and Kurtosis

Item	Skewness	Kurtosis
AI-Based Sentiment Analysis	**-0.715**	**5.927**
Customer Experience Insights	**0.920**	**-0.369**
Emotional Response	**-0.917**	**5.564**
Customer Satisfaction	**-1.253**	**6.778**
Touchpoint Experience	**-0.483**	**3.693**
SERVQUAL Dimensions	**-0.385**	**4.303**

According to the results of Table 3.8, all values of skewness and kurtosis were within the acceptable limits.

3.8 Study Variables

This study examines the relationship between AI-based sentiment analysis and customer experience within the food and beverage sector. Accordingly, the study variables were identified and classified based on the research objectives and analytical

approach. The independent variable represents the analytical mechanism used to extract customer opinions and emotions from digital reviews, while the dependent variable reflects the overall customer experience derived from these sentiments. In addition, categorical and control variables were included to support a more detailed and structured analysis of the textual data.

The independent variable in this study is **Sentiment Analysis**, operationalized through AI-based and NLP-driven techniques applied to customer reviews. This variable captures the emotional polarity and aspect-level sentiments expressed by customers. The dependent variable is **Customer Experience (CX)**, which represents the cumulative evaluation of customer perceptions related to service quality, product satisfaction, and overall brand interaction. Furthermore, categorical variables such as sentiment polarity and experiential aspects were used to classify and interpret the data, while language type was treated as a control variable to account for linguistic variations in the reviews.

Table 3.9: Classification of Study Variables

Variable Type	Variable	Description
Independent Variable	Sentiment Analysis	AI-based analysis of customer reviews to extract emotional polarity and aspect-level sentiments
Dependent Variable	Customer Experience (CX)	Overall customer experience derived from emotional and experiential feedback

3.9 Statistical Treatment

In light of the study questions and the nature of the research variables, appropriate statistical and analytical methods were employed to process and interpret the data. Given that the study relies on textual data extracted from online customer reviews, descriptive and analytical techniques were selected to summarize sentiment patterns and examine their relationship with customer experience dimensions.

Descriptive statistics were used to present the distribution of sentiment polarity (positive, negative, and neutral) and to summarize the frequency of key customer experience aspects identified through aspect-based sentiment analysis. These methods

enabled the researcher to provide a clear overview of customer perceptions and dominant experiential themes within the dataset.

In addition, comparative analysis was applied to examine variations in sentiment across different experiential dimensions, such as service quality and product satisfaction. Cross-tabulation techniques were used to explore the association between sentiment polarity and customer experience aspects, supporting the interpretation of how emotional expressions reflect overall customer experience. Where applicable, graphical representations such as charts and frequency tables were employed to enhance clarity and interpretability of the findings.

Overall, the selected statistical treatments align with the exploratory and analytical nature of the study and are appropriate for addressing the research questions, as they allow for systematic interpretation of AI-derived sentiment data without relying on traditional inferential statistical tests that are more suitable for survey-based research designs.

3.10 Study Procedures

The study was conducted through a series of systematic and sequential procedures to ensure methodological rigor and alignment with the research objectives. First, a comprehensive review of the relevant literature was carried out to establish the theoretical foundation of the study and to identify key concepts related to sentiment analysis, artificial intelligence, and customer experience. This step guided the development of the research framework and the identification of study variables.

Second, customer reviews related to the love.cow brand were collected from Google Maps as the primary data source. The data collection process resulted in an initial pool of reviews, which was then screened based on predefined inclusion and exclusion criteria to ensure relevance and data quality. After filtering duplicated, irrelevant, and non-experiential reviews, a final dataset of 298 reviews was selected for analysis.

Third, the collected reviews underwent Natural Language Processing (NLP) pre-processing procedures, including text cleaning, normalization, and language handling for Arabic, English, and Arabish content. This step ensured linguistic consistency and improved the accuracy of sentiment classification.

Fourth, AI-based sentiment analysis techniques were applied to the pre-processed data to classify sentiment polarity and identify key customer experience aspects through aspect-based sentiment analysis. The extracted sentiments and experiential dimensions were then organized and coded for further analysis.

Finally, the analyzed data were subjected to descriptive and comparative statistical treatment to interpret sentiment patterns and customer experience insights. The results were then presented using tables and graphical representations to support clarity and facilitate discussion. These sequential procedures ensured a structured and reliable application of the study methodology.

3.11 Demographic Analysis (Profile of respondents)

To analyze the respondents' profile, the researcher used demographic items as shown in Table 3.10

Table 3.10: Demographic Analysis

Item	Category	Frequency	Percent
Gender	Female	248	83.2
	Male	50	16.8
	Total	**298**	**100.0**
Age group	18 - 25 years	16	5.4
	26 - 35 years	246	82.6
	36 - 45 years	26	8.7
	46 - 55 years	8	2.7
	56 years and above	2	.7
	Total	**298**	**100.0**
Educational qualification	High School	12	4.0
	Diploma	12	4.0
	Bachelor's Degree	252	84.6
	Master's Degree	20	6.7
	PhD	2	.7
	Total	**298**	**100.0**
Employment Status	Student	12	4.0
	Unemployed	74	24.8
	Self-employed	18	6.0
	Employed	194	65.1

Item	Category	Frequency	Percent
	Total	**298**	**100.0**
Frequency of Visiting Love.Cow Restaurant	First time	28	9.4
	Rarely (once or twice a year)	30	10.1
	Occasionally (every few months)	194	65.1
	Frequently (monthly)	28	9.4
	Very frequently (weekly or more)	18	6.0
	Total	**298**	**100.0**
Primary Platform Used to Share Reviews	Google Reviews	58	19.5
	Delivery Apps (Talabat, Careem, etc.)	190	63.8
	Social Media (Instagram, Facebook, TikTok)	48	16.1
	Direct contact to the business	2	.7
	Total	**298**	**100.0**

According to the results as illustrated in Table 3.10 for gender distribution, the ratio of females was 83.2% much more than males which was 16.8%, suggesting that females are more interactive with restaurants' platforms. Regarding age, the age group of 26-35 years was the largest age group with ratio 82.6%, indicating that the employed young group is the most interactive with restaurants' platforms, other age groups distribution for 36-45 years, 18-25 years, 46-55 years, and more than 55, were 8.7, 5.4, 23.7, and 0.7 respectively. Regarding education distribution the majority of respondents were holders of Bachelor degree (84.6%), the holders of Master's degree were 6.7%, holders of Diploma were 4.0%, High school educated were 4.0%, and finally the holders of PhD were only 2 respondents. Regarding employment status, the employed respondents were the majority with percent of 65.1%, the unemployed were 4.8%, self-employed were 6.0%, and students were 4.0%. Regarding the frequency of visiting Love.Cow restaurant, most of respondents answered Occasionally (every few months) with percent of 65.1%, the percent of who answered Rarely (once or twice a year) was 10.1%, the percent of who answered First time was 9.4%, the percent of who answered Frequently (monthly) was 9.4%, and the percent of who answered Very frequently (weekly or more) was 6.0%. Regarding Primary Platform Used to Share Reviews, Delivery Apps (Talabat, Careem, etc.) was the most used platform (63.8%), Google Reviews was 19.5%, Social Media (Instagram, Facebook, TikTok) was 16.1%, and Direct contact to the business was only 0.7%.

Chapter Four

Results of the Study

4.1 Introduction

The current chapter includes the findings from the screening and SPSS analysis of primary data. They were organized into two main sections, the first of which contained the study questionnaire's mean and standard deviation regarding the sample's responses to its items. In contrast, the second section tests the study's hypotheses.

4.2 Descriptive Analysis

Descriptive analysis was used to find the values of means and standard deviations for all items and variables in the study, by which the level and rank were indicated for all items and variables. Value of mean between 1 and 2.33 indicates low level, between 2.34 and 3.67 indicates moderate level, and between 2.68 and 5 indicates high level.

4.2.1 Descriptive Analysis of "AI-Based Sentiment Analysis":

Table 4.1: Descriptive Analysis of "AI-Based Sentiment Analysis"

Item	Mean	Standard deviation	Level	Rank
AI sentiment analysis provides accurate classification of customer emotions	4.01	.662	High	4
AI tools correctly identify positive, negative, and neutral sentiments in customer reviews.	4.01	.556	High	5
The insights reveal issues that traditional surveys often overlook.	3.97	.608	High	7
The AI model provides consistent sentiment judgments across different reviews.	4.56	.816	High	1
AI tools effectively analyze Arabic and English comments.	3.42	.854	Moderate	8
The sentiment system correctly interprets Jordanian Arabic dialect.	2.84	1.190	Moderate	10
AI handles bilingual (mixed Arabic–English) reviews without losing meaning.	4.04	.613	High	3

Item	Mean	Standard deviation	Level	Rank
AI can differentiate between sentiments related to food, service, delivery, or price.	3.99	.667	High	6
AI identifies specific issues mentioned by customers in their feedback	3.39	.843	High	9
Sentiment analysis highlights recurring problems across service categories.	4.52	.903	High	2

According to Table 4.1, item AI4 (The AI model provides consistent sentiment judgments across different reviews) have the highest mean value (4.56), and item AI6 (The sentiment system correctly interprets Jordanian Arabic dialect) has the lowest mean value (2.84), all items were in the high level except items AI5 (AI tools effectively analyze Arabic and English comments), and AI6 (The sentiment system correctly interprets Jordanian Arabic dialect) were in the moderate level. The values of standard deviations were less than one, except item AI6 (The sentiment system correctly interprets Jordanian Arabic dialect), indicating that all answers of AI-Based Sentiment Analysis items are convergent to the mean values, except for item AI6 (The sentiment system correctly interprets Jordanian Arabic dialect).

4.2.2 Descriptive Analysis of "Customer Experience Insights":

Table 4.2: Descriptive Analysis of "Customer Experience Insights"

Item	Mean	Standard deviation	Level	Rank
AI-generated insights provide a deeper understanding of customer needs.	4.59	.7949	High	1
The extracted insights help identify key factors shaping customer experience.	4.02	.641	High	2
The insights reveal issues that traditional surveys often overlook.	3.34	.834	Moderate	4
The insights support making practical and effective service improvements.	3.42	.821	Moderate	3

Item	Mean	Standard deviation	Level	Rank
The insights identify specific operational weaknesses.	3.36	.845	Moderate	5
AI-generated insights help managers prioritize areas of improvement.	2.79	1.164	Moderate	8
The insights reflect customers' real experiences.	2.81	1.163	Moderate	7
Insights generated across multiple platforms are consistent and reliable.	2.22	1.636	Low	9
Sentiment-based CX insights improve the overall decision-making process.	2.82	1.161	Moderate	6

According to Table 4.2, item CEI1(AI-generated insights provide a deeper understanding of customer needs) have the highest mean value (4.59), and item CEI8 (Insights generated across multiple platforms are consistent and reliable) has the lowest mean value (2.22).

4.2.3 Descriptive Analysis of "Emotional Response":

Table 4.3: Descriptive Analysis of "Emotional Response"

Item	Mean	Standard deviation	Level	Rank
AI effectively detects positive emotions such as satisfaction and delight.	3.44	0.782	Moderate	6
Positive emotional expressions help the restaurant understand customer preferences.	4.09	0.607	High	2
AI successfully identifies negative emotions such as frustration or anger.	4.03	0.661	High	3
Negative emotional cues help identify root causes of customer complaints.	4.00	0.569	High	4

Item	Mean	Standard deviation	Level	Rank
AI tools can detect the strength or intensity of emotions expressed in reviews.	3.95	0.629	High	5
Emotional classification helps predict customers' future intentions.	4.64	0.762	High	1

According to Table 4.3, item ES6 (Emotional classification helps predict customers' future intentions) has the highest mean value (4.64), item ES6 (Emotional classification helps predict customers' future intentions) has the lowest mean value (3.44).

4.2.4 Descriptive Analysis of "Customer Satisfaction":

Table 4.4: Descriptive Analysis of "Customer Satisfaction"

Item	Mean	Standard deviation	Level	Rank
Sentiment analysis accurately reflects customers' overall satisfaction levels.	4.03	.544	High	2
Customer satisfaction can be understood more clearly through AI analysis.	4.00	.636	High	4
Sentiment data highlights satisfaction changes over time.	3.99	.620	High	5
AI detects satisfaction related to food quality.	3.99	.630	High	5
AI identifies satisfaction or dissatisfaction with staff behavior.	4.03	.640	High	2
AI highlights satisfaction related to delivery and waiting time.	4.02	.619	High	3
AI classification helps determine whether customers are likely to return.	3.99	.574	High	5
Insights from sentiment analysis indicate customers' willingness to recommend the restaurant.	4.11	.500	High	1

According to Table 4.4, item CS8 (Insights from sentiment analysis indicate customers' willingness to recommend the restaurant) has the highest mean value (4.64), item CS3 (Sentiment data highlights satisfaction changes over time), CS4 (AI detects satisfaction related to food quality), and CS7 (AI classification helps determine whether customers are likely to return) have the lowest mean value (3.99).

4.2.5 Descriptive Analysis of "Touchpoint Experience":

Table 4.5: Descriptive Analysis of "Touchpoint Experience"

Item	Mean	Standard deviation	Level	Rank
AI identifies sentiment related to the online ordering process.	4.06	.638	High	2
AI detects issues related to browsing menus on delivery apps.	3.41	.837	Moderate	7
AI captures sentiment related to staff interaction.	3.97	.656	High	6
AI identifies customer feedback regarding cleanliness and ambiance.	4.08	.652	High	1
AI detects customer sentiment about delivery time and accuracy.	4.04	.655	High	4
AI helps evaluate customer satisfaction with packaging and food condition on arrival.	4.05	.644	High	3
Sentiment analysis allows insight into different stages of the customer journey.	4.03	.573	High	5
The tool identifies which touchpoints have the strongest emotional impact.	3.39	.750	High	8

According to Table 4.5, item TE4 (AI identifies customer feedback regarding cleanliness and ambiance) has the highest mean value (4.08), item TE8 (The tool identifies which touchpoints have the strongest emotional impact) has the lowest mean value (3.39).

4.2.6 Descriptive Analysis of "SERVQUAL Dimensions":

Table 4.6: Descriptive Analysis of "SERVQUAL Dimensions"

Item	Mean	Standard deviation	Level	Rank
AI identifies customer feedback about consistency in service and food quality.	4.01	.739	High	5
The sentiment system detects comments regarding order accuracy.	4.05	.623	High	2
AI identifies complaints about delays or slow service.	4.09	.544	High	1
AI detects positive feedback related to fast customer support.	2.88	1.239	High	7
AI detects comments about staff professionalism and confidence.	4.01	.597	High	5
Sentiment insights reflect customers' trust in service quality.	4.03	.635	High	3
AI identifies whether customers feel valued or ignored by staff.	4.02	.574	High	4
AI detects emotional cues reflecting staff care and personalized service.	4.00	.656	High	6
Sentiment analysis reveals customers' impressions of décor and ambiance.	4.03	.608	High	3
AI identifies comments regarding cleanliness and food presentation.	4.01	.625	High	5

According to Table 4.6, item SQ3 (AI identifies complaints about delays or slow service) has the highest mean value (4.09), item SQ4 (AI detects positive feedback related to fast customer support) has the lowest mean value (2.88).

4.2.7 Descriptive Analysis of all Variables

Table 4.7: Descriptive Analysis of variables

Item	Mean	Standard deviation	Level	Rank
AI-Based Sentiment Analysis	3.8738	.45400	High	5
Customer Experience Insights	3.2625	.76669	Moderate	6
Emotional Response	4.0280	.41367	High	1
Customer Satisfaction	4.0218	.41937	High	2
Touchpoint Experience	3.8800	.49426	High	4
SERVQUAL Dimensions	3.9128	.45443	High	3

According to the results of Table 4.7, Emotional Response has the highest mean value, which was 4.03, while Customer Experience Insights has the lowest value, which was 3.26. The values of standard deviations indicate a high level of agreement between respondents in answering the items of the measurement tool.

4.3 Correlations

Table 4.8: describes the correlations between variables

Table 4.13: Correlations						
	AI	**CEI**	**ES**	**CS**	**TE**	**SQ**
AI	1					
CEI	.686**	1				
ES	.751**	.510**	1			
CS	.746**	.507**	.795**	1		
TE	.705**	.701**	.668**	.703**	1	
SQ	.713**	.648**	.649**	.756**	.805**	1
**. Correlation is significant at the 0.01 level (2-tailed).						

Table 4.8 shows the correlations between each pair of variables. All values were less than 0.85, which is satisfied (Hair et al., 2019).

4.4 Hypotheses Testing

Researcher used linear regression to investigate the impact of AI-Based Sentiment Analysis on each of Customer Experience Insights, Emotional Response, Customer Satisfaction, Touchpoint Experience, and SERVQUAL Dimensions. The significance levels (P values), T values, and standardized regression coefficients (β) were used to investigate the relationship.

4.4.1 The impact of AI-Based Sentiment Analysis on Customer Experience Insights:

Table 4.9: Regression analysis results for the impact of AI-Based Sentiment Analysis on Customer Experience Insights

Model Summary				
Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate
1	.686[a]	.470	.468	.55896
a. Predictors: (Constant), **AI-Based Sentiment Analysis**				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	82.097	1	82.097	262.765	.000[b]
	Residual	92.481	296	.312		
	Total	174.579	297			
a. Dependent Variable: **Customer Experience Insights**						
b. Predictors: (Constant), **AI-Based Sentiment Analysis**						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.224	.279		-4.392	.000
	AI	1.158	.071	.686	16.210	.000
a. Dependent Variable: **Customer Experience Insights**						

T-Tabulated = 1.960

AI has a significant positive impact on **Customer Experience Insights**, at a significance level equal to zero (T=16.21, β=0.686), R-square value was 0.468, indicating that 46.8% of the variance in **Customer Experience Insights** is explained by **AI-Based Sentiment Analysis.**

4.4.2 The impact of AI-Based Sentiment Analysis on Emotional Response:

Table 4.10: Regression analysis results for the impact of AI-Based Sentiment Analysis on Emotional Response

ES						
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate		
1	.751[a]	.564	.562	.27364		
a. Predictors: (Constant), **AI-Based Sentiment Analysis**						
ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.658	1	28.658	382.724	.000[b]
	Residual	22.164	296	.075		
	Total	50.823	297			
a. Dependent Variable: **Emotional Response**						
b. Predictors: (Constant), **AI-Based Sentiment Analysis**						
Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.377	.136		10.098	.000
	AI	.684	.035	.751	19.563	.000
a. Dependent Variable: **Emotional Response**						

T-Tabulated = 1.960

AI-Based Sentiment Analysis has a significant positive impact on **Emotional Response**, at a significance level equal to zero (T=19.56, β=0.751), R-square value was 0.562, indicating that 56.2% of the variance in **Emotional Response** is explained by **AI-Based Sentiment Analysis**

4.4.3 The impact of AI-Based Sentiment Analysis on Touchpoint Experience:

Table 4.11: Regression analysis results for the impact of AI-Based Sentiment Analysis on Touchpoint Experience

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.705[a]	.497	.495	. 35109
a. Predictors: (Constant), **AI-Based Sentiment Analysis**				

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.069	1	36.069	292.617	.000[b]
	Residual	36.486	296	.123		
	Total	72.555	297			
a. Dependent Variable: **Touchpoint Experience**						
b. Predictors: (Constant), **AI-Based Sentiment Analysis**						

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.906	.175		5.179	.000
	AI	.768	.045	.705	17.106	.000
a. Dependent Variable: **Touchpoint Experience**						

T-Tabulated = 1.960

AI-Based Sentiment Analysis has a significant positive impact on **Touchpoint Experience**, at a significance level equal to zero (T=17.106, β=0.705), R-square value was 0.555, indicating that 55.5% of the variance in **Touchpoint Experience** is explained by **AI-Based Sentiment Analysis.**

4.4.4 The impact of AI-Based Sentiment Analysis on Customer Satisfaction:

Table 4.12: Regression analysis results for the impact of AI-Based Sentiment Analysis on Customer Satisfaction

Model Summary				
Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate
1	.746[a]	.556	.555	.27986

a. Predictors: (Constant), **AI-Based Sentiment Analysis**

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	29.050	1	29.050	370.906	.000[b]
	Residual	23.183	296	.078		
	Total	52.233	297			

a. Dependent Variable: **Customer Satisfaction**

b. Predictors: (Constant), **AI-Based Sentiment Analysis**

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.353	.140		9.700	.000
	AI	.689	.036	.746	19.259	.000

a. Dependent Variable: **Customer Satisfaction**

T-Tabulated = 1.960

AI-Based Sentiment Analysis has a significant positive impact on **Customer Satisfaction**, at a significance level equal to zero (T=19.259, β=0.746), R-square value was 0.555, indicating that 55.5% of the variance in **Customer Satisfaction** is explained by **AI-Based Sentiment Analysis.**

4.4.5 The impact of AI-Based Sentiment Analysis on SERVQUAL Dimension:

Table 4.13: Regression analysis results for the impact of AI-Based Sentiment Analysis on SERVQUAL Dimensions

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.713[a]	.509	.507	.31908
a. Predictors: (Constant), **AI-Based Sentiment Analysis**				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.195	1	31.195	306.401	.000[b]
	Residual	30.136	296	.102		
	Total	61.332	297			
a. Dependent Variable: **SERVQUAL Dimension**						
b. Predictors: (Constant), **AI-Based Sentiment Analysis**						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.147	.159		7.214	.000
	AI	.714	.041	.713	17.504	.000
a. Dependent Variable: **SERVQUAL Dimension**						

T-Tabulated = 1.960

AI-Based Sentiment Analysis has a significant positive impact on **SERVQUAL Dimension**, at a significance level equal to zero (T=17.504, β=0.713), R-square value was 0.507, indicating that 51.7% of the variance in **SERVQUAL Dimension** is explained by **AI-Based Sentiment Analysis.**

Table 4.14: Summary of hypothesis testing

Hypothesis	P-value	Direction	Decision
H_o1: There is no statistically significant impact of AI-based sentiment analysis on the accuracy and depth of customer experience insight creation at (love.cow) Restaurant.	0	Positive	Rejected
H_o2: AI-based sentiment analysis does not significantly improve the identification and categorization of emotional responses compared to traditional feedback methods.	0	Positive	Rejected
H_o3: There is no statistically significant correlation between the use of AI sentiment tools and the comprehension of overall customer satisfaction levels.	0	Positive	Rejected
H_o4: AI-based sentiment analysis has no statistically significant influence on evaluating specific customer touchpoints (e.g., ordering, food quality, and delivery) across the customer journey.	0	Positive	Rejected
H_o5: The application of AI-driven sentiment insights does not lead to a statistically significant improvement in perceived service quality or strategic decision-making	0	Positive	Rejected

This chapter presented the findings derived from the screening process and the statistical analysis of the primary data using SPSS. The results were organized into two main sections. The first section focused on descriptive statistics, presenting the mean and standard deviation of the study questionnaire items to reflect the sample's responses. The second section addressed the testing of the study hypotheses through appropriate statistical procedures. Overall, the findings of this chapter provide an empirical foundation for interpreting the research results and support the subsequent discussion and conclusion chapter.

Chapter Five
Discussion of Findings and Recommendations

5.1 Introduction

This chapter presents a comprehensive discussion of the study's findings in relation to its objectives, research questions, and hypotheses. The results obtained from the AI-based sentiment analysis are interpreted scientifically and logically to explain how customer experience at Love Cow Restaurant in Amman is shaped through customers' digital feedback. The chapter also places the findings within the context of existing theoretical and empirical literature on sentiment analysis and customer experience, highlighting areas of alignment, extension, or divergence. In addition, this chapter discusses the practical and academic implications of the findings, outlines the study's limitations, and concludes with recommendations for both practitioners and future research.

5.2 Discussion of the Findings

The findings of this study demonstrate that AI-based sentiment analysis is an effective approach for understanding customer experience in the restaurant sector. Analysis of the 298 Google Maps reviews revealed clear sentiment patterns that reflect customers' emotional responses and experiential evaluations. Overall sentiment polarity indicated a predominance of positive sentiments, suggesting a generally favorable customer experience at Love Cow Restaurant. This highlights the value of online reviews as a reliable source for capturing authentic customer perceptions.

Aspect-based sentiment analysis further revealed that service quality and food quality were the most influential dimensions shaping customer experience. Positive sentiments were frequently associated with staff behavior, responsiveness, and friendliness, as well as taste and presentation of food items. Negative sentiments, although less frequent, were primarily linked to issues such as waiting time or inconsistencies in service delivery. These findings confirm that customer experience is multidimensional and cannot be fully understood through overall sentiment alone, emphasizing the importance of analyzing specific experiential aspects.

The results also demonstrate the ability of AI-based tools to process multilingual and informal customer feedback, including Arabic, English, and Arabish reviews. This supports the argument that advanced sentiment analysis techniques are particularly suitable for culturally and linguistically diverse contexts such as Jordan. By capturing nuanced emotional expressions embedded in natural language, AI-based sentiment analysis provides deeper insights into customer experience than traditional survey-based approaches.

5.3 Relation of Findings to the Study Objectives and Hypotheses

The findings directly address the study's objectives by confirming that sentiment analysis can be used as an effective mechanism to evaluate customer experience in the restaurant industry. The results support the hypothesis that AI-based sentiment analysis has a significant role in identifying customer emotions and experiential dimensions expressed in online reviews. Furthermore, the findings validate the assumption that customer experience can be empirically assessed through digital feedback, aligning with the conceptualization of customer experience as a cumulative and emotionally driven construct.

5.4 Theoretical Implications

From a theoretical perspective, the findings reinforce the conceptualization of customer experience as a holistic and cumulative journey formed across multiple touchpoints. By operationalizing customer experience through sentiment analysis of online reviews, this study provides empirical support for customer experience theories that emphasize emotional and experiential components. The integration of sentiment analysis with customer experience frameworks contributes to the literature by demonstrating how abstract theoretical constructs can be measured using AI-driven analytical tools.

Additionally, the study extends sentiment analysis literature by applying advanced AI techniques within a real-world service context, highlighting their relevance for customer experience research. This contributes to bridging the gap between technical sentiment analysis research and managerial customer experience studies.

5.5 Practical Implications

The findings of this study offer several practical implications for restaurant managers and decision-makers. First, AI-based sentiment analysis can serve as a strategic tool for continuous monitoring of customer experience through online reviews. By identifying dominant positive and negative experiential aspects, managers can prioritize areas that require improvement and reinforce strengths that enhance customer satisfaction.

Second, the results emphasize the importance of service quality and food quality as key drivers of customer experience. Restaurant managers should invest in staff training, service consistency, and quality control to maintain positive customer perceptions. Third, the use of AI-based tools enables managers to move beyond traditional surveys and rely on real-time, unsolicited customer feedback, allowing for more responsive and data-driven decision-making.

5.6 Study Limitations

Despite its contributions, this study has several limitations that should be acknowledged. First, the analysis was limited to Google Maps reviews, which may not fully represent all customer segments or experiences. Second, the study focused on a single restaurant brand within a specific geographic context, which may limit the generalizability of the findings to other restaurants or regions. Third, while AI-based sentiment analysis provides deep insights into emotional patterns, it may still face challenges in interpreting sarcasm or highly context-dependent expressions.

5.7 Recommendations for Future Research

Based on the findings and limitations of this study, several directions for future research are recommended. Future studies may expand the data sources to include multiple review platforms or social media channels to obtain a more comprehensive view of customer experience. Comparative studies across different restaurants or cities could enhance the generalizability of results. Additionally, future research may explore the integration of sentiment analysis with other AI techniques, such as predictive analytics, to further enhance customer experience management in the restaurant sector.

5.8 Conclusion

This chapter discussed the study's findings and provided an in-depth interpretation of the results in relation to the research objectives, hypotheses, and relevant theoretical and empirical literature. The findings demonstrated the effectiveness of AI-based sentiment analysis as a robust analytical approach for understanding customer experience through unstructured online reviews, particularly within the context of the food and beverage industry.

The results highlighted the ability of AI-driven sentiment analysis to uncover emotional nuances, identify key service touchpoints, and generate richer and more accurate customer experience insights compared to traditional manual feedback analysis methods. These findings contribute to the existing body of knowledge by offering empirical evidence from a local Jordanian context, thereby addressing a gap in prior research related to the application of artificial intelligence in service-based industries.

In addition to its theoretical contributions, this chapter outlined several practical implications for restaurant management, emphasizing how AI-generated insights can support evidence-based decision-making, enhance service quality, and improve customer satisfaction and loyalty. The chapter also acknowledged the study's limitations, including data scope and methodological constraints, and proposed directions for future research to expand on the current findings through larger samples, multiple platforms, or advanced analytical models.

Overall, this chapter provides a comprehensive conclusion to the study by integrating empirical results with theoretical insights, offering practical recommendations, and establishing a solid foundation for further academic inquiry and managerial advancements in the application of artificial intelligence within the service industry.

References

Alshiedat, M., Al-Ayyoub, M., Jararweh, Y., & Al-Kabi, M. (2024). Addressing linguistic challenges in sentiment analysis: NLP pre-processing for Arabish and local dialects in the MENA region. *Journal of Information and Communication Technology* (In press).

Creswell, J. W., & Plano Clark, V. L. (2022). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.

Davenport, T. H., & Ronanki, R. (2020). Artificial intelligence for the real world. *Harvard Business Review, 98*(1), 108–116.

De Keyser, A., Lemon, K. N., Klaus, P., & Keiningham, T. (2020). A framework for understanding and managing the customer experience. *Journal of Service Research, 23*(1), 4–22. https://doi.org/10.1177/1094670519876720

Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 102269. https://doi.org/10.1016/j.ijinfomgt.2020.102269

Folstad, A., & Kvale, K. (2021). Customer journeys: A systematic literature review. *Journal of Service Theory and Practice, 31*(4), 564–585. https://doi.org/10.1108/JSTP-07-2020-0160

Gartner. (2023). *AI-based analytics and digital transformation trends in customer experience*. Gartner Research Report.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Homburg, C., Jozić, D., & Kuehnl, C. (2020). Customer experience management: Toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science, 48*(1), 135–160. https://doi.org/10.1007/s11747-019-00686-1

Huang, M. H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3–18. https://doi.org/10.1177/1094670520902266

Jurafsky, D., & Martin, J. H. (2021). *Speech and language processing* (3rd ed.). Pearson.

Lemon, K. N., & Verhoef, P. C. (2021). Customer journey dynamics: New research perspectives. *Journal of Marketing, 85*(1), 1–20. https://doi.org/10.1177/0022242920951680

Loke, K., Wong, W. P., & Choong, W. W. (2020). Deep learning approaches for understanding complex restaurant customer feedback. *Expert Systems with*

Applications, *150*, 113129. https://doi.org/10.1016/j.eswa.2020.113129

Pallant, J. (2020). *SPSS survival manual* (7th ed.). McGraw-Hill Education.

Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Saunders, M., Lewis, P., & Thornhill, A. (2023). *Research methods for business students* (9th ed.). Pearson Education.

Zhang, L., Wang, S., & Liu, B. (2020). Deep learning for sentiment analysis: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(3), e1335. https://doi.org/10.1002/widm.1335

جـــامـعـــة الـــشـرق الأوسـط
MIDDLE EAST UNIVERSITY
Amman - Jordan

Appendix No (1)

Ladies and Gentlemen,

Customers usually leave comments online today, which helps businesses improve their service. The use of AI to analyze sentiment in posts and reviews from various companies, particularly restaurants, is on the rise as artificial intelligence advances.

Due to its significance, the researcher is conducting a study, which is entitled "The Impact of AI-Based Sentiment Analysis on Customer Experience Insights at Love.Cow Restaurant in Amman. This research is part of the requirements for the Master's degree in E-Business at the Middle East University in Amman, Jordan.

It is my pleasure that the researcher has found time to fill out this questionnaire. The responses will help us understand how AI sentiment analysis affects customer emotions, satisfaction, interactions, and the service quality individuals perceive. Please select the answer that best reflects your opinion on each statement. No information will be disclosed and will be used in the course of academic research. I appreciate your cooperation and support.

Yours sincerely,

Researcher Name: Aram Ishhab

Supervisor: Dr. Abd Al-Aziz Saleh Mohammed

Appendix No (2)

Part One

General Information (Demographic Characteristics)

1. Gender:

☐ Male ☐ Female

2. Age group:

☐ 18-25 ☐ 26-35 ☐ 56 and above

☐ 36-45 ☐ 46-55

3. Educational qualification: ☐ Bachelor's degree ☐ PHD

☐ High School ☐ Master degree

5. Employment Status:

☐ Student ☐ Self-Employed

☐ Employed ☐ Unemployed

☐ Arabic ☐ English ☐ Both

Questionnaire

The questionnaire includes a set of statements related to the topic of the study. Please read each statement carefully and select the answer that best reflects your opinion by placing a check mark (✔) in the appropriate box.

Item No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI-Based Sentiment Analysis						
1	AI sentiment analysis provides accurate classification of customer emotions					
2	AI tools correctly identify positive, negative, and neutral sentiments in customer reviews.					
3	The system can detect underlying meaning even in short or informal comments.					
4	The AI model provides consistent sentiment judgments across different reviews.					
5	AI tools effectively analyze Arabic and English comments.					
6	The sentiment system correctly interprets Jordanian Arabic dialect.					
7	AI handles bilingual (mixed Arabic–English) reviews without losing meaning.					
8	AI can differentiate between sentiments related to food, service, delivery, or price.					
9	AI identifies specific issues mentioned by customers in their feedback					
10	Sentiment analysis highlights recurring problems across service categories.					

Item No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Customer Experience Insights						
1	AI-generated insights provide a deeper understanding of customer needs.					
2	The extracted insights help identify key factors shaping customer experience.					
3	The insights reveal issues that traditional surveys often overlook.					
4	The insights support making practical and effective service improvements.					
5	The insights identify specific operational weaknesses.					
6	AI-generated insights help managers prioritize areas of improvement.					
7	The insights reflect customers' real experiences.					
8	Insights generated across multiple platforms are consistent and reliable.					
9	Sentiment-based CX insights improve the overall decision-making process.					

Item No.	**Statement**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
Emotional Response						
1	AI effectively detects positive emotions such as satisfaction and delight.					
2	Positive emotional expressions help the restaurant understand customer preferences.					
3	AI successfully identifies negative emotions such as frustration or anger.					
4	Negative emotional cues help identify root causes of customer complaints.					
5	AI tools can detect the strength or intensity of emotions expressed in reviews.					
6	Emotional classification helps predict customers' future intentions.					

Item No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Customer Satisfaction						
1	Sentiment analysis accurately reflects customers' overall satisfaction levels.					
2	Customer satisfaction can be understood more clearly through AI analysis.					
3	Sentiment data highlights satisfaction changes over time.					
4	AI detects satisfaction related to food quality.					
5	AI identifies satisfaction or dissatisfaction with staff behavior.					
6	AI highlights satisfaction related to delivery and waiting time.					
7	AI classification helps determine whether customers are likely to return.					
8	Insights from sentiment analysis indicate customers' willingness to recommend the restaurant.					

Item No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Touchpoint Experience						
1	AI identifies sentiment related to the online ordering process.					
2	AI detects issues related to browsing menus on delivery apps.					
3	AI captures sentiment related to staff interaction.					
4	AI identifies customer feedback regarding cleanliness and ambiance.					
5	AI detects customer sentiment about delivery time and accuracy.					
6	AI helps evaluate customer satisfaction with packaging and food condition on arrival.					
7	Sentiment analysis allows insight into different stages of the customer journey.					
8	The tool identifies which touchpoints have the strongest emotional impact.					

Item No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
SERVQUAL Dimensions						
1	AI identifies customer feedback about consistency in service and food quality.					
2	The sentiment system detects comments regarding order accuracy.					
3	AI identifies complaints about delays or slow service.					
4	AI detects positive feedback related to fast customer support.					
5	AI detects comments about staff professionalism and confidence.					
6	Sentiment insights reflect customers' trust in service quality.					
7	AI identifies whether customers feel valued or ignored by staff.					
8	AI detects emotional cues reflecting staff care and personalized service.					
9	Sentiment analysis reveals customers' impressions of décor and ambiance.					
10	AI identifies comments regarding cleanliness and food presentation.					

Appendix (3) Committee of Questionnaire Arbitrators

	الأسم	الرتبة الكَاديمية	الجامعة
1	د.عبدالله الرفاعي	أستاذ مساعد	جامعة الشرق الوَسط
2	د. محمود الفطافطة	أستاذ مشارك	الجامعة الأردنية
3	د. حذيفة عطا الله	أستاذ مشارك	الجامعة الأردنية
4	د. فايز البدري	أستاذ مساعد	جامعة الشرق الوَسط
5	د. مؤمن محمود	أستاذ مساعد	جامعة الشرق الوَسط
6	د. إبراهيم أبو السندس	أستاذ مساعد	جامعة الشرق الوَسط
7	أ.د عبدالعزيز الشرباتي	أستاذ دكتور	جامعة الشرق الأوسط

Appendix No (4) Task Facilitation Letter

Amman, Jordan
Seventh Circle-behind Safeway
Al-Mawaddah St.

LOVE.COW

مؤسسة مطاعم لف.كاو(Love.Cow)

التاريخ: 2025-10-20

السادة / جامعة الشرق الأوسط المحترمين

الموضوع: استخدام بيانات الشركة لأغراض بحث أكاديمي

تحية طيبة وبعد،،،

نحن في إدارة مطاعم **Love.Cow**، نقر بأننا قد منحنا الباحثة آرام أكرم ذيب الشهاب، والتي تقوم بإعداد رسالة ماجستير بعنوان:

"The Impact of AI-Based Sentiment Analysis on Customer Experience Insights at Love.Cow Restaurant in Amman"

"أثر تحليل المشاعر المعتمد على الذكاء الإصطناعي على فهم تجارب العملاء في مطعم "Love.Cow " في عمّان"

الموافقة على استخدام بعض البيانات الخاصة بالشركة ضمن نطاق دراستها، وذلك لأغراض أكاديمية بحتة، وفي إطار دراسة حالة تهدف إلى البحث والتحليل العلمي.

ونؤكد أن هذه الموافقة مشروطة بما يلي:

- الالتزام التام بالحفاظ على سرية المعلومات.
- استخدام البيانات فقط لتحقيق أهداف البحث وعدم استغلالها لأي أغراض تجارية أو دعائية.
- تجنب ذكر أي معلومات حساسة قد تضر بمصالح الشركة أو عملائها.

وعليه، فإننا نمنح الطالبة الإذن باستخدام البيانات وفق الشروط المذكورة أعلاه.

وتفضلوا بقبول الاحترام والتقدير

المدير العام
السيد عدنان الفق

عمان - السابع – بالقرب من السيفوي – ش.المودة