

What prevents full satisfaction? An aspect-based sentiment analysis of three-point TripAdvisor reviews from Michelin-Starred restaurants in France, Spain and Italy

Kusursuz (tam) memnuniyeti engelleyen nedir? Fransa, İspanya ve İtalya'daki Michelin Yıldızlı restoranlara ait üç puanlı TripAdvisor yorumlarının boyut/özellik tabanlı duygu analizi

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Abstract

What prevents a guest from awarding full satisfaction (defined as 4 or 5 stars) to Michelin-starred fine-dining restaurants? In this regard, the study examined this midpoint — where the gap between expectations and perceived performance is most pronounced — by analyzing 3-out-of-5-star TripAdvisor reviews that reflect neither complete satisfaction nor overt disappointment. Drawing on Expectation-Disconfirmation Theory, a keyword-based Aspect/Feature-Based Sentiment Analysis (ABSA) approach was applied to a dataset comprising 2,330 English-language reviews collected from 189 two- and three-Michelin-starred restaurants in France, Spain, and Italy. Reviews were examined across nine experiential dimensions developed specifically for this study (food quality, service and staff, ambiance and atmosphere, perceived value, wine and beverages, reservation and waiting, location and accessibility, dietary flexibility, and hygiene and cleanliness), and sentiment polarity was calculated at the dimension level using TextBlob. These findings offer an alternative perspective to the prevailing assumption that culinary performance (such as food quality) is the primary source of dissatisfaction in fine-dining experiences. Food quality recorded the lowest negative sentiment ratio (9.4%), while hygiene and cleanliness (28.4%), perceived value (26.2%), and reservation and waiting (17.9%) emerged as the primary sources of incomplete satisfaction in 3-out-of-5-star reviews. Furthermore, perceived value-driven dissatisfaction intensifies with increasing prestige (i.e., star level). The findings also reveal a marked deterioration in guests' overall sentiment in the post-pandemic period, with negative review rates rising from below 5% prior to 2020 to 14.2% in 2025. The findings demonstrate that what prevents flawless satisfaction in Michelin-starred fine-dining restaurants is often concealed not in culinary performance but in other dimensions of the experience.

Keywords: Fine-dining experience, customer satisfaction, aspect-based sentiment analysis (ABSA), Michelin starred restaurants, Expectation-Disconfirmation Theory

Öz

Bir konunun Michelin yıldızlı bir fine-dining restorana tam memnuniyeti simgeleyen 4 veya 5 puan vermesini engelleyen nedir? Bu doğrultuda çalışma ne tam memnuniyeti ne de açık hayal kırıklığını yansıtan 5 üzerinden 3 puanlı TripAdvisor yorumlarını analiz ederek beklenti ile algılanan performans arasındaki boşluğun en belirgin olduğu bu orta noktayı mercek altına almıştır. Beklenti-Onaylanmama Teorisi'nden yola çıkan çalışma, Fransa, İspanya ve İtalya'daki iki ve üç Michelin yıldızlı 189 restorandan toplanan 2.330 İngilizce yorumdan oluşan bir veri seti üzerine, anahtar kelime temelli bir Boyut/Özellik Tabanlı Duygu Analizi (ABSA) yaklaşımı uygulanmıştır. Bu kapsamda yorumlar bu çalışma için oluşturulan dokuz deneyimsel boyut (yemek kalitesi, servis ve personel, ambiyans ve atmosfer, algılanan değer, şarap ve içecekler, rezervasyon ve bekleme, konum ve erişilebilirlik, diyet esnekliği ile hijyen ve temizlik) üzerinden incelenmiş ve duygu polaritesi TextBlob kullanılarak boyutlar düzeyinde hesaplanmıştır. Bulgular, fine-dining yemek deneyiminde memnuniyetsizliğin temel nedeninin mutfak performansı (yiyecek kalitesi gibi) olduğu yönündeki hakim varsayıma farklı bir pencere açmaktadır. Yemek kalitesi en düşük olumsuzluk oranını (%9,4) kaydederken, hijyen ve temizlik (%28,4), algılanan değer (%26,2) ile rezervasyon ve bekleme (%17,9) 3 puanlı yorumlardaki tam olmayan memnuniyetin birincil kaynakları olarak ortaya çıkmaktadır. Ayrıca algılanan değer odaklı memnuniyetsizlik artan prestijle birlikte (yıldız seviyesine göre) yoğunlaşmaktadır. Diğer taraftan çalışma bulguları, pandemi sonrası dönemde konukların genel duygu durumunda belirgin bir kötüleşme gözlemlendiğini ortaya koymaktadır. Nitekim olumsuz yorum oranları 2020 öncesindeki %5'in altındaki seviyelerden 2025'te %14,2'ye yükselmiştir. Bulgular, Michelin yıldızlı fine-dining restoranlarda kusursuz memnuniyeti engelleyen unsurun çoğu zaman mutfak performansı yerine deneyimin diğer boyutlarında gizlendiğini ortaya koymaktadır.

Anahtar Kelimeler: Lüks gastronomi deneyimi, müşteri memnuniyeti, boyut/özellik tabanlı duygu analizi (ABSA), Michelin yıldızlı restoran, Beklenti-Onaylanmama Teorisi

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Introduction

The concept of luxury has evolved over time to encompass not only exclusivity but also the capacity to deliver meaningful and memorable experiences, with contemporary luxury increasingly taking on an experiential character (Yeoman & McMahon-Beattie, 2018). This transformation has led the luxury dining sector to extend beyond product attributes to holistic experiential dimensions (Lee et al., 2020). In this context, dining has shifted from being a biological necessity to an experience in its own right (Tsai & Wang, 2017). Accordingly, fine-dining restaurants represent the upper echelon of the food and beverage industry, where the experience is the dominant value driver.

Fine dining constitutes an immersive consumption experience shaped by venue authenticity, exclusive ingredients, narrative storytelling, and sensory engagement (Batat, 2022). Luxury marketing strategies are grounded in the promise of a “unique experience” (Michael & Fusté-Forné, 2022), which extends beyond food quality to include atmosphere, service, and overall dining environment (Yu & Sun, 2019). Thus, gastronomic experiences are evaluated as integrated wholes rather than as isolated dishes (Jeannot et al., 2022), reinforcing experience as a central construct in luxury gastronomy marketing (Waqas et al., 2021). Importantly, these multi-faceted experiential dimensions do not merely construct the consumption environment; they operate as critical touchpoints where pre-dining expectations interact with perceived performance. In high-stakes luxury environments, customer satisfaction is dynamically determined by the degree of alignment or disjunction between these elevated expectations and actual experiential performance across each individual dimension.

Despite carefully designed service systems, customer satisfaction in fine dining restaurants is not guaranteed. Even with high-quality cuisine and service standards, achieving customer satisfaction remains complex because luxury dining guests hold exceptionally high, multi-dimensional expectations regarding food quality, service, price, and

dining attributes (Lo et al., 2024). Grounded in Expectation-Disconfirmation Theory (EDT), customer satisfaction is determined through a cognitive and emotional evaluation comparing these initial expectation benchmarks with actual perceived performance (Park, 2019; Schiebler et al., 2026). In high-stakes luxury dining environments, when perceived operational or experiential performance falls short of guests' elevated reference standards, negative disconfirmation occurs, directly impairing overall satisfaction, customer loyalty, and establishment reputation (Lo et al., 2024; Oh et al., 2022). As a result, understanding the experiential determinants of satisfaction has become increasingly important, particularly given the rapid growth and economic significance of upscale gastronomy (Daries et al., 2021). Consequently, identifying the factors that influence satisfaction among highly discerning customers is critical (Green, 2020). To address this need, this study aims to identify the factors that prevent fine-dining guests from achieving full satisfaction aligned with their expectations.

Despite carefully designed service systems, customer satisfaction in fine dining restaurants is not guaranteed. Even with high-quality cuisine and service standards, consumer preferences fluctuate in highly competitive environments (Jamaludin & Hashim, 2025). As a result, understanding the experiential determinants of satisfaction has become increasingly important, particularly given the rapid growth and economic significance of upscale gastronomy (Daries et al., 2021). Accordingly, identifying the factors that influence satisfaction among highly discerning customers is critical (Green, 2020). Accordingly, this study aims to identify the factors that prevent fine-dining guests from achieving full satisfaction aligned with their expectations.

While traditional structured survey instruments provide valuable standardized insights, many existing studies relying on them face methodological limitations. Surveys conducted post-consumption often suffer from recall bias—where post-experience perception alters the recollection of initial ex-

expectations—as well as self-reporting bias and constraints associated with limited sample sizes. In contrast, user-generated online reviews provide unfiltered, spontaneous, and unprompted expressions of real-time consumer experiences across the full consumption timeline, offering a rich and complementary data source to explore multi-faceted guest perceptions (Oh et al., 2022). TripAdvisor, one of the largest travel platforms, offers extensive user-generated content that enables deep insights into consumer perceptions (Lee & Ko, 2022). Reviews are typically rated on a 1–5 scale, where 1–2 reflect dissatisfaction, 4–5 reflect satisfaction, and 3 represents an intermediate state of partial or ambivalent satisfaction.

Within the framework of Expectation-Disconfirmation Theory, three-point reviews occupy a critical conceptual position. On TripAdvisor's standardized rating taxonomy, a 3-point review is explicitly classified as "Average" (distinct from 1–2 as "Terrible/Poor" and 4–5 as "Good/Excellent"). Rather than reflecting outright dissatisfaction or failure, a 3-point rating in two- and three-Michelin-starred restaurants represents a unique "threshold zone"—a state of moderate or ambivalent satisfaction where guests' core baseline expectations are largely met, yet specific experiential shortfalls prevent them from transitioning to full satisfaction. In ultra-luxury dining environments where baseline expectations are inherently set at excellence, an "Average" evaluation indicates a state of partial disconfirmation. Therefore, systematically analyzing three-point reviews provides a nuanced opportunity to identify the precise friction points that cause this gap, offering actionable insights into what inhibits completely positive disconfirmation in fine-dining experiences.

Aspect-Based Sentiment Analysis (ABSA) offers a suitable methodological framework for analyzing nuanced textual data. Unlike traditional sentiment analysis, ABSA identifies multiple aspects within a text and assigns sentiment polarity to each dimension (Zarandi & Mirzaei, 2023). For instance, a single review may express a positive sentiment toward cleanliness while simultaneously expressing a negative sentiment toward food quality. This

granularity enables more precise insights into customer evaluation (Hammad et al., 2025).

By decomposing sentiment at the aspect level, ABSA supports more effective decision-making than holistic sentiment models (Kuppusamy & Selvaraj, 2023). Its growing relevance stems from the increasing availability of opinion-rich digital content (Hua et al., 2024). Moreover, ABSA allows the identification of specific underperforming dimensions within a service experience, making it particularly suitable for analyzing ambiguous mid-scale reviews. In this study, ABSA was employed to examine three-point reviews, where positive and negative evaluations coexist within the same narrative.

Grounded in Expectation Disconfirmation Theory, this study addresses the following research question: What aspect-level factors prevent guests of two- and three-Michelin-starred restaurants from achieving full satisfaction in their three-point TripAdvisor reviews? The sub-questions are as follows: (1) Which aspects (e.g., food quality, service, ambiance, and value for money) generate negative sentiment in three-point reviews? (2) Do these factors differ between two- and three-star restaurants? (3) Are there cross-country differences between France, Spain, and Italy?

Existing research on gastronomy and hospitality has extensively utilized user-generated online reviews to examine overall customer satisfaction, service quality attributes, and dining experiences (e.g., Barrera-Barrera, 2023; Lee & Ko, 2022; Rita et al., 2023). However, most studies have predominantly focused on holistic evaluations or extreme ratings (positive vs. negative disconfirmation), leaving the specific determinants of partial or incomplete satisfaction under-researched. This study addresses this critical empirical gap by disaggregating the micro-level experiential factors that prevent near-satisfactory dining experiences (i.e., 3-point "Average" ratings) from becoming fully satisfactory in two- and three-Michelin-starred restaurants. By zooming in on this specific rating band through the lens of Expectation-Disconfirmation Theory, the study advances current understanding beyond aggregate satisfaction metrics.

Practically, the findings offer actionable managerial insights for ultra-luxury restaurant operators to systematically bridge the gap between "near satisfaction" and "full admiration."

To address the research aim, this study conducts a comparative analysis focusing on two- and three-Michelin-starred restaurants across France, Spain, and Italy. These destinations were selected primarily due to their overwhelming dominance in top-tier European gastronomy, hosting a total of 110 (France), 53 (Spain), and 53 (Italy) two- and three-starred establishments respectively, which collectively represent the vast majority of Europe's highest culinary accreditations (Michelin Guide, 2026). Incorporating these distinct geographical markets into the research framework enriches the analytical scope of the study by capturing a broader diversity of luxury dining settings, operational models, and service dynamics. Rather than examining guest nationalities, this multi-destination comparison allows for a macro-level investigation into how experiential friction points manifest across different leading market environments. Consequently, this multi-country approach enhances the external validity of the findings and provides broader, transferable insights into the determinants of partial satisfaction in the luxury restaurant sector.

Theoretical Framework

Fine Dining, Michelin Stars and Customer Experience

Although fine dining, upscale, and luxury restaurants are occasionally used interchangeably in hospitality literature, subtle conceptual distinctions exist among them. Fine dining establishments are primarily defined by culinary creativity, globally influenced techniques, small portions, seasonal or local sourcing, and a dominant focus on atmosphere (Top & Yarmaci, 2021). Upscale restaurants are recognized for their premium pricing, fine food, attentive service, and elevated overall dining experience (Lo et al., 2024). Meanwhile, luxury restau-

rants occupy the pinnacle tier of the market, characterized by meticulously crafted physical environments, exclusive aesthetics, superior food and beverage quality, and an all-encompassing combination of prestige and hedonics (Chen et al., 2015; Hwang & Hyun, 2012). Crucially, two- and three-Michelin-starred restaurants represent the precise conceptual intersection of these three domains. Because these ultra-luxury establishments inherently operationalize high culinary artistry, premium market positioning, and exclusive experiential luxury simultaneously, these terms are examined together in this study to capture their unified impact on guest perceptions.

The definitions of fine-dining restaurants converge on key attributes such as impeccable service, expensive menus, high-quality food, and superior physical settings (Lee & Hwang, 2011). This definition further includes refined cuisine, full table service, aesthetic presentation, and a sophisticated atmosphere shaped by decor, lighting, and furnishings (Yang & Mattila, 2016). Within this structure, luxury restaurants include haute cuisine venues, Michelin-starred establishments, and bistronomic formats that reinterpret traditional gastronomy in more accessible ways (Jeannot et al., 2022).

Michelin-starred restaurants occupy a central position in luxury gastronomy, acting as key representatives of haute cuisine and contributing to gastronomy tourism and regional economies (Castillo-Manzano & Zarzoso, 2023). Michelin stars function as strong quality signals that shape and elevate consumer expectations (Bang et al., 2022).

Customers of such restaurants typically seek unique and memorable gastronomic experiences that extend beyond consumption, enabling the discovery of new tastes and cultural dimensions (Björk & Kauppinen-Räsänen, 2017). To achieve this "beyond satisfaction" state, restaurants engage customers across the sensory, emotional, cognitive, behavioral, and relational dimensions (Bonfanti, Bagnato, & Vigolo, 2025). In this context, food quality, service quality, physical environment, menu variety, and hygiene are the core compo-

nents of a luxury dining experience (Almohammimed, 2017; Bonfanti, Bagnato, Rossato, et al., 2025).

Although food taste is a key determinant of experience quality (Liu et al., 2020), service effectiveness and atmospheric design are equally critical in shaping overall satisfaction and perceived value (Green, 2020). Accordingly, the dining experience is evaluated holistically, where overall judgment emerges from the integration of all experiential components (Tsaur & Lo, 2020). Therefore, a well-designed experience-based offering is a strategic competitive asset that enhances differentiation, word-of-mouth communication, loyalty, and reputation (Souki et al., 2023). Consequently, customer satisfaction in Michelin-starred establishments cannot be viewed as a static outcome of culinary output alone; rather, it is the cumulative result of expectation-performance disconfirmation occurring across both core and peripheral experiential dimensions.

Fine Dining and Online Reviews (eWOM)

The widespread use of the Internet and social media has transformed consumer decision-making processes. Consumers increasingly rely on friends and acquaintances and the broader communities of prior users when evaluating products and services (Rita et al., 2023). In this context, electronic word-of-mouth (eWOM) has become a central component of decision-making, particularly in tourism, where experiential and high-risk services make peer-generated information highly influential (Tran & Kumar, 2026). In the restaurant sector, online reviews and ratings are important information sources that shape consumer choices (Harrington et al., 2013).

Although Michelin ratings strongly influence restaurant selection and serve as reliable quality signals (Özen et al., 2025), online reviews continue to play a critical role in final pre-consumption decision-making. Consumers heavily rely on eWOM to reduce perceived purchase risks in high-involvement service contexts (Chang & Ko, 2017; Bang et

al., 2022). More broadly, consumer behavior research indicates that individuals demonstrate a higher willingness to talk about and share experiential consumption (e.g., dining, travel) compared to material purchases, as experiences foster social connection and storytelling utility (Kumar & Gilovich, 2015). Furthermore, luxury purchases are often shared on social media as a form of status signaling and symbolic self-expression (Kemper et al., 2022). Situated at the intersection of high experiential value and luxury status, Michelin-starred dining experiences inherently prompt consumers to share their evaluations on online platforms (Lee & Ko, 2022). Within this high-expectation environment, negative or ambivalent eWOM—when perceived as highly credible—substantially amplifies perceived risk and diminishes consumer intention (Pooja & Upadhyaya, 2025).

Luxury consumers not only use luxury goods as status signals but also invest effort in understanding and experiencing their attributes (Wang, 2022), increasing the importance of peer-generated information. Customers frequently post reviews immediately after dining experiences on dedicated platforms (Ransbotham et al., 2019). The dining experience is often considered complete only after being shared online (Daries et al., 2024).

Within this framework, this study focuses on three-point TripAdvisor reviews as a distinctive form of user-generated content. These reviews represent neither clear satisfaction nor explicit dissatisfaction but rather ambivalent evaluations reflecting incomplete satisfaction with Michelin-starred dining experiences. Analyzing this “grey zone” of eWOM provides deeper academic insight into how luxury dining experiences are articulated online and offers practical implications regarding which dimensions of the experience fail to meet guest expectations.

Expectation Disconfirmation Theory

Expectation Disconfirmation Theory (EDT) has been recognized as a dominant framework for explaining consumer satisfaction for over four decades (Schiebler et al., 2026). The theory is built on

four core constructs: performance expectations, perceived performance, disconfirmation (the gap between expectations and perceived performance), and consumer satisfaction (Schiebler et al., 2026). According to the EDT, satisfaction results from a comparison between pre-consumption expectations and actual perceived performance (Oliver, 1977, 1980). Satisfaction occurs when performance meets or exceeds expectations, whereas dissatisfaction emerges when it falls short (Zhang et al., 2022).

The EDT is particularly suitable for analyzing customer evaluations in high-expectation contexts, such as Michelin-starred restaurants. These establishments represent the highest level of gastronomy tourism, where expectations are extremely high (Lau et al., 2026). In this setting, three-star ratings can be interpreted as cases of negative disconfirmation, where the perceived performance fails to fully meet the expectations shaped by the restaurant's prestigious status across one or more dimensions of the dining experience.

Therefore, identifying the sources of negative disconfirmation in three-point reviews is crucial for understanding why Michelin-starred experiences fail to achieve complete customer satisfaction.

Sentiment Analysis and ABSA (Aspect Based Sentiment Analysis)

Sentiment analysis is a computational approach used to identify and interpret opinions, emotions, and evaluations expressed in textual data, enabling a systematic understanding of consumer perceptions and satisfaction levels (Hammad et al., 2025). In its basic form, sentiment analysis typically operates at the document or sentence level, where the overall polarity of a text is classified as positive, negative, or neutral. However, such aggregate-level approaches often fail to capture the multidimensional nature of consumer evaluations, particularly in experiential service contexts, such as restaurants.

To address this limitation, Aspect-Based Sentiment Analysis (ABSA) has been developed as a more granular extension of sentiment analysis in

the field of natural language processing. ABSA enables the identification of specific experiential dimensions (aspects) within a text, such as food quality, service, or ambiance, and assigns sentiment polarity to each dimension separately (Hua et al., 2024; Zarandi & Mirzaei, 2023). This allows researchers to move beyond overall evaluations and examine how different components of the service experience are individually perceived.

In the context of luxury dining, ABSA is particularly relevant because a single review may simultaneously contain both positive and negative evaluations of different aspects of the same experience. This makes it possible to disentangle complex consumer judgments and provides a more nuanced understanding of satisfaction formation in multidimensional service environments. Accordingly, ABSA offers a suitable analytical lens for examining fine-dining experiences, where overall satisfaction is shaped by the interaction of multiple experiential attributes, rather than a single dominant factor. Specifically in this study, ABSA is directly operationalized to extract and classify sentiments across nine distinct experiential dimensions relevant to luxury gastronomy (i.e., food quality, service and staff, ambiance, value, wine/beverages, reservation/waiting, location, dietary flexibility, and hygiene). As detailed in the Methodology section, mapping customer sentiments directly onto these nine specific dimensions enables a granular examination of how discrete service attributes drive partial satisfaction.

Material ve Method

Research Design

This study adopts a qualitatively oriented computational research design based on online reviews to examine the aspect-level determinants of incomplete satisfaction among guests of Michelin-starred fine-dining restaurants. While traditional structured survey instruments offer substantial practical value in systematically measuring customer satisfaction and testing established theoretical frameworks, they may rely on predefined

scale items that might not capture the full, unprompted complexity of experiential evaluations (Yan et al., 2015). To complement survey-based approaches, this study leverages naturally occurring online review data. This non-intrusive approach enables the analysis of consumer sentiment in an organic form, helping to reduce potential framing and recall biases while capturing fine-grained, self-selected dimensions of luxury dining experiences.

The analytical framework was structured across three analytical levels. At the first level, Aspect-Based Sentiment Analysis (ABSA) is used to identify the distribution of positive, negative, and neutral sentiments across the core dimensions of the fine-dining experience. At the second level, a cross-establishment (star-level) comparison examines whether aspect-level dissatisfaction differs between two- and three-star Michelin restaurants. At the third level, a cross-country analysis investigates the systematic differences between France, Spain, and Italy. Together, these levels allow the study to move beyond aggregate indicators and assess whether patterns vary by restaurant prestige and the national culinary context.

Data Collection and Sampling

The data for this study were obtained from TripAdvisor, one of the world's largest travel review platforms (Lee & Ko, 2022), using an automated visual web scraping software. The data extraction process was configured with specific parameters to target three-point (3/5) reviews for two- and three-Michelin-starred restaurants in France, Spain, and Italy. The extracted data fields included the establishment name, review title, publication date, review rating, and full text body. To maintain linguistic consistency and support English-based ABSA models, the scraping parameters were restricted strictly to reviews published in English. To ensure data integrity and prevent potential data loss during the automated extraction, a rigorous cross-verification protocol was applied: the total number of English reviews displayed on each restaurant's official TripAdvisor page was systematically cross-

checked against the scraped dataset to ensure complete data retrieval before analysis.

The target population of this study comprised all two- and three-Michelin-starred restaurants across France (110), Spain (53), and Italy (53). However, due to the complete absence of user reviews on TripAdvisor for certain establishments, these were excluded, resulting in a final dataset of 189 restaurants across the three countries. The French sample consisted of 95 restaurants (26 three-star and 69 two-star), the Spanish sample included 49 restaurants (16 three-star and 33 two-star), and the Italian sample comprised 45 restaurants (12 three-star and 33 two-star). In total, 2,330 three-point reviews were collected: 1,088 from France, 820 from Spain and 422 from Italy. The reviews covered the period between 2010 and 2026. However, because of the extremely limited number of observations in 2010 and 2026 (two and three reviews, respectively), these years were excluded from the analysis.

Identification of Experiential Dimensions (Aspects)

One of the key methodological decisions in ABSA studies is the definition of aspect categories used to structure the sentiment analysis. In this study, nine experiential dimensions were identified based on the fine-dining literature and the structure of the review dataset to form an analytical framework for classifying reviews. The selection was primarily guided by prior research on luxury gastronomy, customer experience and satisfaction.

The existing literature consistently highlights food quality, service, staff behavior, and ambiance as central determinants of restaurant experiences, while also identifying waiting time, cost, and portion size as major sources of dissatisfaction (Özen et al., 2025). Similarly, studies on Michelin-starred restaurants emphasize service quality, ambiance, and staff behavior as key drivers of customer satisfaction (Baykal & Yazıcı Ayyıldız, 2024). Additional research has expanded these dimensions to include wine and beverage service, particularly in high-end restaurants where sommelier expertise

is integral to the experience (Stöckl et al., 2025), as well as ambiance elements such as lighting, décor, and furniture (Barrera-Barrera, 2023).

Large-scale clustering and qualitative analyses further support dimensions such as food quality, service, environment, value for money, time risk, wine, chefs, staff, and price as the dominant evaluative categories (Kim et al., 2025; Saydam et al., 2022). In addition, post-pandemic studies indicate a shift in consumer expectations toward hygiene, cleanliness, and communication, reflecting a transformation in luxury dining expectations after Covid-19 (Lo et al., 2024). This shift was also considered in the dimension development process to ensure its contemporary relevance.

The final set of dimensions was refined based on expert evaluations provided by three academics specializing in services marketing, consumer behavior, and gastronomy management. The experts were selected based on two criteria: holding a Ph.D. in a relevant domain and having a strong track record of publishing on customer experience, fine dining, or eWOM analysis in high-impact, peer-reviewed journals. Based on their evaluations regarding content validity and category distinctiveness, dimensions were intentionally kept separate rather than merged to preserve analytical granularity. For example, dietary flexibility was not subsumed under food quality to avoid masking distinct dissatisfaction signals. Similarly, location and accessibility, hygiene and cleanliness, and reservations and waiting were confirmed as independent, standalone categories.

Accordingly, nine experiential dimensions were defined: food quality, service and staff, ambiance and atmosphere, perceived value, wine and beverages, reservation and waiting, location and accessibility, dietary flexibility, and hygiene and cleanliness. These categories capture both core culinary elements and peripheral but important experiential factors, combining the tangible and intangible dimensions of fine dining. This structure enables a more detailed identification of experiential “tipping points” that lead to three-point reviews of Michelin-starred restaurants.

Analysis Process

The analytical process in this study consisted of four sequential stages: data preprocessing, overall sentiment analysis, aspect-level sentiment extraction, and complaint mining. All analyses were conducted in Python using Google Colaboratory (Google Colab), a cloud-based environment that enables reproducible data-analysis workflows.

In the first stage, the raw data were pre-processed using the Pandas library. The review texts were cleaned by removing extra whitespace, line breaks, and irregular characters. The review titles and body texts were merged into a single analytical unit when available. Additionally, a year variable was extracted from the review dates to enable temporal comparisons.

In the second stage, overall sentiment scores were calculated using TextBlob, a widely used lexicon-based sentiment analysis tool (Aljedaani et al., 2022; Nariman, 2025). TextBlob assigns polarity scores ranging from -1 to +1. Based on these scores, reviews were classified as negative (below -0.05), neutral, or positive (above 0.10), providing a general overview of sentiment distribution before the aspect-level analysis.

The third stage represents the core of the analysis and involves keyword-based aspect extraction, following ABSA principles. Instead of a deep learning-based model, a lexicon-based approach was used, in which predefined keyword lists were created for nine experiential dimensions. The representative keywords used for each dimension are presented in Table 1. The reviews were segmented into sentences, and sentences containing aspect-related keywords were automatically identified and assigned to the corresponding dimensions. This rule-based approach was preferred because of its interpretability, suitability for structured fine-dining discourse, and computational efficiency. Aspect-level sentiment scores were then computed using TextBlob polarity values for the extracted sentences, capturing the sentiment within each experiential dimension.

Table1. Representative Keyword Examples Used in Dimension/Aspect Definition

Dimension / Aspect	Representative Keywords
Food Quality (FQ)	food, dish, cuisine, taste, ingredient
Service & Staff (S&S)	service, staff, waiter, sommelier, hospitality
Ambience & Atmosphere (A&A)	ambience, atmosphere, decor, lighting, noise
Value & Price (V&A)	price, bill, value, expensive, over-priced
Wine & Beverage (W&B)	wine, wine list, champagne, pairing, beverage
Reservation & Waiting (R&W)	reservation, booking, waiting, delay, slow
Location & Access (L&A)	location, parking, access, entrance, reachable
Dietary Flexibility (DF)	vegetarian, vegan, allergy, gluten, special menu
Hygiene & Cleanliness (H&C)	hygiene, cleanliness, dirty, hair, smell

Note: In the following tables, the abbreviations of the dimensions presented in this table are used.

In the final stage, complaint mining was conducted on the negatively scored reviews. Unigram, bigram, and trigram frequency analyses were performed using CountVectorizer to identify dominant complaint expressions, both overall and within each aspect category. This enabled the systematic identification of recurring negative language patterns and provided detailed insights into the specific experiential weaknesses underlying three-point reviews of Michelin-starred restaurants.

Reliability and Validity

Various measures were taken to ensure the validity and reliability of the analytical process. First, the study's exclusive focus on three-point reviews constitutes a sampling decision grounded in the research question rather than an arbitrary filtering choice, thereby supporting the construct validity of the analysis. The standardized keyword-based extraction procedure applied uniformly across all nine categories ensured that the review texts were treated consistently throughout the dataset. Furthermore, the sentiment classification thresholds adopted for TextBlob polarity scores — below -0.05 for negative and above 0.10 for positive — were established to minimize the misclassification of borderline neutral texts, thereby reducing the

measurement error in the sentiment categorization process. Finally, the large and geographically diverse dataset encompassing 2,330 reviews obtained from 189 restaurants across three countries enhances the external validity of the findings and strengthens the generalizability of the study's results within the context of the fine-dining segment.

Findings

Descriptive Overview of the Dataset

The dataset consisted of 2,330 customer reviews collected from 189 Michelin-starred restaurants across Spain, France, and Italy. In terms of geographical distribution, most reviews originated from France (n=1,088), followed by Spain (n=820), and Italy (n=422). The sample included 135 two-Michelin-star and 54 three-Michelin-star restaurants. Regarding review distribution, 1,257 reviews belong to two-star restaurants and 1,073 to three-star restaurants, indicating a relatively balanced distribution across star categories, although two-star establishments are more heavily represented than three-star establishments.

The reviews cover the period between 2010 and 2026; however, owing to minimal observations in the boundary years, the effective analysis period is 2011–2025, as specified in the methodology section. A key characteristic of the dataset is its homogeneity in the rating structure, as all reviews correspond to a score of 3. This design allows the analysis to focus on textual content rather than rating variation, enabling the identification of nuanced dissatisfaction and ambivalent evaluations in three-point reviews.

The average review length is 946.8 characters, indicating detailed customer feedback and providing rich textual data suitable for Aspect-Based Sentiment Analysis (ABSA). Sentiment analysis was conducted exclusively on textual content using a lexicon-based method. Based on predefined thresholds, reviews were classified as negative (below -0.05) or positive (above 0.10). Accordingly, 158 reviews were classified as negative and 1,543

as positive, demonstrating variations in emotional tone even within a uniform rating category.

Scope of Dimensions and Sentiment Distribution

The aspect-level analysis revealed substantial variation in the frequency with which different experiential dimensions were addressed across the 2,330 reviews. As shown in Table 2, food quality was the most frequently discussed dimension (97%), followed by service and staff (79.8%), ambiance, and atmosphere (65.5%). These three dimensions represent the core evaluative focus of three-point reviews, highlighting their central role in fine-dining experiences.

Perceived value (50.1%) and wine and beverages (48%) appeared in approximately half of the reviews, indicating that they are important but not universal evaluative criteria. In contrast, reservation and waiting (27.9%), location and accessibility (9.6%), dietary flexibility (5.1%), and hygiene and cleanliness (4.1%) were less frequently mentioned, suggesting that these dimensions are more context-dependent in shaping guest evaluations.

more mixed evaluations than ambiance and location.

Perceived value exhibited the lowest mean sentiment score (0.071) among the frequently referenced dimensions, approaching the neutral threshold and indicating a persistent area of ambivalence in three-point reviews.

Negative Sentiment Intensity by Dimension

Although the overall sentiment remained positive across all aspect categories, negative mention rates revealed a clear variation in dissatisfaction intensity across experiential dimensions, indicating a hierarchy of negative experiences within the dataset.

Despite its low mention frequency (4.1%), hygiene and cleanliness recorded the highest negative sentiment rate (28.4%), highlighting its critical role as a latent but strong source of dissatisfaction in Michelin-starred contexts. Perceived value followed with a negative rate of 26.2% and a low mean sentiment score (0.071), indicating persistent concerns regarding price-value balance and perceived justification of cost.

Table 2. Distribution of Mention Rates and Sentiment Scores by Dimension

Dimension / Aspect	Number of Reviews Mentioned	Mention Rate (%)	Avg. Sentiment Score	Number of Negative Mentions	Negative Review Rate (%)	Number of Neutral Mentions	Number of Positive Mentions	Positive Review Rate (%)
FQ	2,261	97	0.182	213	9.4	553	1,495	66.1
S&S	1,859	79.8	0.220	245	13.2	442	1,172	63
A&A	1,527	65.5	0.224	181	11.9	373	973	63.7
V&P	1,167	50.1	0.071	306	26.2	352	509	43.6
W&B	1,119	48	0.172	167	14.9	355	597	53.4
R&W	649	27.9	0.089	116	17.9	304	229	35.3
L&A	224	9.6	0.259	22	9.8	59	143	63.8
DF	118	5.1	0.131	17	14.4	57	44	37.3
HC	95	4.1	0.058	27	28.4	28	40	42.1

Note: The mention rate was calculated as the percentage of reviews ($n = 2,330$) in which each dimension was referenced. Sentiment polarity scores were computed using TextBlob. Reviews with a polarity score below -0.05 were classified as negative, those above 0.10 were classified as positive, and the remaining reviews were classified as neutral.

In terms of sentiment distribution, all nine dimensions yielded positive mean polarity values, consistent with the overall positive orientation of the dataset (Section 4.1). The service and staff recorded the highest mean sentiment score (0.220), followed by ambiance and atmosphere (0.224), and location and accessibility (0.259). Food quality, despite its near-universal presence, showed a more moderate mean sentiment score (0.182), indicating

Reservation and waiting (17.9%), wine and beverages (14.9%), dietary flexibility (14.4%), and service and staff (13.2%) showed moderate negative sentiment rates, contributing meaningfully to overall dissatisfaction patterns in three-point reviews.

In contrast, food quality, the most frequently discussed dimension, showed a relatively low negative rate (9.4%), with 66.1% of its references be-

ing positive. This indicates that culinary performance is rarely the primary source of dissatisfaction. Instead, negative sentiment is more concentrated in peripheral and organizational dimensions, such as pricing, hygiene, waiting time, and beverage service.

These findings align with the Expectation Disconfirmation Theory, suggesting that negative disconfirmation tends to emerge in dimensions where expectation–performance gaps are most pronounced, particularly in less anticipated aspects of the dining experience.

Complaint Term Analysis by Dimension

A term-level analysis was conducted to identify the main sources of dissatisfaction within each experiential dimension. The most frequently occurring complaint terms are presented in Table 3, enabling a more granular understanding of negative evaluations in three-point reviews.

Table 3. Most Frequent Complaint Terms by Dimension Categories

Dimension / Aspect	Most Frequently Occurring Terms in Negative Reviews (Frequency)
Food Quality	menu (129), dishes (92), disappointed (44), tasting menu (36), taste (45)
Service & Staff	staff (89), served (80), sommelier (47), cold (27), disappointed (23)
Ambiance & Atmosphere	table (101), room (73), tables (39), small (16), decor (15)
Value & Price	expensive (161), price (119), worth (85), bill (40), disappointing (30)
Wine & Beverage	wine (227), sommelier (50), wines (40), expensive (19), pairing (22)
Reservation & Waiting	minutes (46), hours (33), slow (32), long (20), wait (23)
Location & Access	location (9), entrance (6), find (3), gps (3), access (3)
Dietary Flexibility	vegetarian (8), gluten free (3), allergies (4), no vegetarian (2), unfortunately (2)
Hygiene & Cleanliness	dirty (17), smell (8), hair (4), clean (6), unpleasant (3)

Note: Terms were extracted from reviews classified as negative using CountVectorizer (unigrams, bigrams, and trigrams). Frequencies reflect the number of repetitions within aspect-specific negative review sentences. The terms are ranked according to their frequency within each dimension category.

In the perceived value dimension, complaints are primarily concentrated on price perceptions and price–value imbalances. Frequent terms such as “expensive” (n=161), “price” (n=119), and “worth” (n=85), along with “bill” and “cost,” indicate that

guests often question whether the dining experience justifies its cost;

Dissatisfaction with food quality is mainly linked to preparation, consistency, and expectations regarding the tasting experience. Recurring terms such as “menu,” “dishes,” “taste,” and “tasting menu” suggest that criticisms are particularly focused on the tasting menu structure, perceived rigidity, and unmet culinary expectations. The term “disappointed” further reflects expectation–performance gaps in the study.

In service and staff, complaints are operational and interaction-based, with dominant terms such as “served,” “waiter,” “sommelier,” and “cold.” The term “cold” reflects both temperature-related issues and a perceived lack of interpersonal warmth, indicating that even minor service deficiencies influence overall evaluation.

The reservation and waiting dimension is characterized by time-related dissatisfaction, with terms such as “minutes,” “hours,” “slow,” and “long,” highlighting delays and inefficiencies in the service flow. Although less frequent, hygiene and cleanliness complaints are highly negative in tone, with terms such as “dirty,” “smell,” and “hair,” indicating severe breakdowns when they occur. In ambiance and atmosphere, complaints focus on spatial and environmental factors such as “table,” “room,” “decor,” and “view.” Terms such as “small” and “table” suggest that spatial constraints reduce perceived comfort and undermine the sense of exclusivity.

For wine and beverages, dissatisfaction was associated with “wine,” “sommelier,” “pairing,” and “expensive,” indicating concerns related to pricing and expectations of expertise in wine pairing. In terms of location and accessibility, although limited, complaints cluster around navigation issues, with terms such as “entrance,” “find,” and “gps,” suggesting first-arrival difficulties. In terms of dietary flexibility, dissatisfaction was reflected in terms such as “vegetarian,” “gluten free,” “allergies,” and “no vegetarian,” indicating gaps in accommodating specific dietary needs.

Overall, the findings show that dissatisfaction in Michelin-starred restaurants is systematically

structured around recurring, dimension-specific issues rather than random complaints, highlighting clear experiential weak points within mid-range (three-point) evaluations.

Comparative Analysis: Two-Star and Three-Star Restaurants

The comparison between two- and three-Michelin-starred restaurants, built upon the dimension-based patterns identified previously, offers additional insights into how customer evaluations evolve as the level of prestige increases. While the importance structure of the dimensions remains largely consistent across star categories, noteworthy differences emerge with respect to sentiment intensity and dissatisfaction distribution. Table 4 presents the aspect-level sentiment distribution across the two- and three-star categories.

price-value balance becomes more pronounced and is not fully offset by symbolic value.

The differences in services and staff between the two categories were minimal. Although three-star restaurants perform slightly better (mean sentiment: 0.221 vs. 0.219; negative rate: 12.6% vs. 13.6%), the gap is marginal, indicating that service quality remains sensitive to minor deficiencies, regardless of the star level. A similar pattern was observed in reservation and waiting, where three-star restaurants showed slightly lower dissatisfaction (16% vs. 19.5%) but still retained a notable negative sentiment.

Hygiene and cleanliness differ more clearly, with two-star restaurants showing higher negative rates (33.3% vs. 23.4%), suggesting that hygiene-related issues are more prevalent at lower star levels, although their occurrence is generally infrequent in both groups.

Table 4. Aspect-Level Sentiment Distribution by Michelin Star Category

Dimension / Aspect	2 Michelin Star Restaurants					3 Michelin Star Restaurants				
	Mention (%)	Rate	Avg. Sentiment Score	Negative views Rate (%)	Re-	Mention (%)	Rate	Avg. Sentiment Score	Negative views Rate (%)	Re-
FQ	96.9		0.174	10.8		97.2		0.192	7.8	
S&S	79.3		0.219	13.6		80.3		0.221	12.6	
A&A	63.9		0.240	10.8		67.5		0.207	13	
V&P	50.4		0.073	25.4		49.8		0.069	27.2	
W&B	48.5		0.176	13.8		47.4		0.167	16.3	
R&W	27.3		0.079	19.5		28.5		0.099	16	
L&A	10.6		0.286	6.8		8.5		0.220	14.3	
DF	4.4		0.099	21.8		5.9		0.160	7.9	
H&C	3.8		0.012	33.3		4.4		0.105	23.4	

Note: The mention rate was calculated as the percentage of reviews within each star category in which the relevant dimension was referenced. Two-star category: $n = 1,257$ reviews; three-star category: $n = 1,073$ reviews. Sentiment polarity scores were computed using TextBlob.

Food quality remained the most dominant dimension in both categories, with mention rates exceeding 96%. However, three-star restaurants show higher mean sentiment (0.192) and lower negative rates (7.8%) than two-star establishments (0.174 and 10.8%). This indicates that higher prestige is associated with better fulfillment of food-related expectations, resulting in lower levels of dissatisfaction.

In contrast, perceived value showed an opposite pattern, with three-star restaurants exhibiting higher negative rates (27.2% vs. 25.4%) despite similar mention frequencies. This suggests that as prestige increases, dissatisfaction related to the

For ambiance and atmosphere, two-star restaurants show higher sentiment (0.240) and lower negative rates (10.8%), whereas three-star restaurants exhibit lower sentiment (0.207) and higher negativity (13%), indicating that higher expectations at the three-star level may intensify dissatisfaction in this dimension.

Wine and beverages also showed divergence, with three-star restaurants reporting higher negative rates (16.3% vs. 13.8%) despite similar mention rates. This reflects stricter expectations regarding sommelier expertise, pairing quality, and pricing at higher-prestige levels, consistent with complaint-level findings.

Table 5. Aspect-Level Sentiment Distribution by Country

Dimension / Aspect	France			Spain			Italy		
	Mention Rate (%)	Avg. Sentiment Score	Negative Reviews Rate (%)	Mention Rate (%)	Avg. Sentiment Score	Negative Reviews Rate (%)	Mention Rate (%)	Avg. Sentiment Score	Negative Reviews Rate (%)
FQ	96.2	0.169	11.8	97.6	0.197	6.4	98.1	0.187	9.2
S&S	80.1	0.208	15.2	79.1	0.221	11.2	80.3	0.247	11.8
A&A	67.7	0.238	10.7	62.6	0.217	11.1	65.6	0.204	16.2
V&P	51.1	0.058	26.8	46	0.078	27.3	55.5	0.092	23.1
W&B	45.6	0.164	15.7	46.8	0.182	13	56.6	0.171	16.3
R&W	26.9	0.081	20.8	28.9	0.081	16.9	28.2	0.122	12.6
L&A	10.3	0.229	12.5	7.6	0.317	6.5	11.8	0.257	8
DF	5.7	0.167	9.7	4.6	0.132	15.8	4.3	0.005	27.8
H&C	3.9	0.046	3.1	5.4	0.067	25	2.1	0.072	33.3

Note: The mention rate was calculated as the percentage of reviews within each country sub-sample in which the relevant dimension was referenced. France: $n = 1,088$ reviews; Spain: $n = 820$ reviews; Italy: $n = 422$ reviews. Sentiment polarity scores were computed using TextBlob.

Dietary flexibility was evaluated more positively in three-star restaurants (0.160; 7.9% negative) than in two-star establishments (0.099; 21.8% negative), indicating better accommodation of dietary needs in higher-tier restaurants. In contrast, location and accessibility were rated more negatively for three-star restaurants (14.3% vs. 6.8%), likely reflecting more remote or exclusive locations.

Overall, the findings indicate that higher Michelin ratings improve core experiential dimensions, such as food quality and hygiene, while simultaneously increasing sensitivity and dissatisfaction in perceived value, ambiance, and certain operational aspects. Rather than uniformly enhancing satisfaction, increasing prestige reshapes evaluation criteria and intensifies expectations in specific dimensions. These results align with the Expectation Disconfirmation Theory, as dissatisfaction emerges from the dynamic interplay between rising expectations and perceived performance across multiple dimensions.

Comparative Analysis: France, Spain, and Italy

The country-level analysis, built upon the general dimension salience and complaint patterns identified previously, reveals consistent structures and noteworthy differences across France, Spain, and Italy. While the dominance of core dimensions such as food quality and service and staff remains constant across all three countries, the intensity and sentiment of the evaluations differ significantly.

Table 5 presents the aspect-level sentiment distributions for the three countries examined in this study.

Consistent with the overall findings, food quality was the most frequently referenced dimension across all countries, with mention rates exceeding 96%. However, clear cross-country differences emerged in sentiment and negativity levels. Spain shows the most positive evaluations (mean sentiment = 0.197; negative rate = 6.4%), followed by Italy (0.187; 9.2%), while France records the lowest sentiment (0.169) and highest negativity (11.8%), indicating comparatively stronger food-related dissatisfaction in France.

A similar pattern was observed in the service and staff evaluations. Although the mention rates are stable across countries (~80%), Italy records the highest sentiment (0.247), followed by Spain (0.221) and France (0.208). France also showed the highest negative rate (15.2%), suggesting more pronounced service-related shortcomings, consistent with earlier complaint-level findings.

Perceived value remains the most critical dimension across countries. High negative rates persist in Spain (27.3%) and France (26.8%), with Italy being slightly lower (23.1%). Despite minor differences in mean sentiment, the consistent negativity across all countries confirms perceived value as a structural source of dissatisfaction, supporting earlier findings related to price-related complaint terms such as “expensive” and “worth.”

For reservation and waiting, Spain had the highest mention rate (28.9%), followed by Italy (28.2%) and France (26.9%). However, France again recorded the highest negativity (20.8%), compared to

Spain (16.9%) and Italy (12.6%), indicating greater issues in time management and service flow in the French context.

Hygiene and cleanliness show low overall mention rates across all countries (ranging between 2.1% and 5.4%), indicating that hygiene serves as a baseline expectation in luxury dining rather than a primary driver of discussion. While Italy (33.3%) and Spain (25.0%) display higher negativity percentages in this category compared to France (3.1%), these proportional differences should be interpreted cautiously due to the very small absolute number of hygiene-related mentions. Nonetheless, these findings confirm that, although infrequent, hygiene issues represent critical failure points with a strong negative impact when they occur.

In ambiance and atmosphere, sentiment was generally positive across countries, with France recording the highest mean sentiment (0.238). However, Italy showed a higher negative rate (16.2%), suggesting more frequent dissatisfaction with spatial and environmental aspects.

Wine and beverages displayed notable variations across the three countries. France recorded the lowest mean sentiment (0.164) along with a high negativity rate (15.7%), indicating unmet expectations regarding sommelier expertise, pairing choices, and pricing. Notably, Italy exhibited both the highest mention rate (56.6%) and the highest negativity rate (16.3%) in this dimension. This pronounced focus and heightened sensitivity in Italy likely reflect elevated customer expectations tied to its status as a premier global wine-producing context, where guests apply more stringent evaluative standards to wine pairings and beverage service (Stöckl et al., 2025). Spain demonstrated relatively lower negativity (13.0%) and higher sentiment (0.182), suggesting greater guest alignment with beverage offerings.

Peripheral dimensions, such as location, accessibility, and dietary flexibility, showed lower and more variable patterns. Spain performed best in terms of location and accessibility (mean sentiment = 0.317), whereas Italy showed a weaker performance in terms of dietary flexibility (mean sentiment = 0.005; negative rate = 27.8%).

Overall, the country-level analysis indicates that core dissatisfaction drivers—particularly perceived value, food quality, and service—are consistent across contexts, but their intensity varies by country. France exhibits relatively higher dissatisfaction across multiple dimensions, whereas Spain and Italy show more favorable evaluations. These findings highlight the importance of contextual and cultural factors in interpreting fine dining customer experiences.

Trend of Negative Sentiment Over Time

A temporal analysis was conducted to examine how customer evaluation evolved over time. To ensure reliability, years with extremely low observations (particularly 2010 and 2026) were excluded, and the main analysis focused on the post-2012 period, where the data coverage was more consistent.

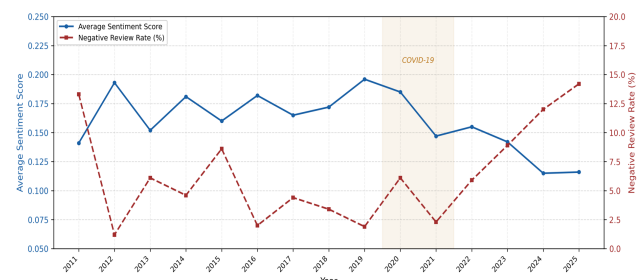


Figure 1. Graph of Negative Review Rate and Sentiment Scores (2012-2025)

As shown in Figure 1, sentiment remained relatively stable between 2012 and 2019, peaking in 2019 (mean sentiment = 0.196). However, a gradual decline emerged after 2022, with sentiment decreasing to 0.115 in 2024 and 0.116 in 2025. In parallel, negative review rates—stable and below 5% before 2020—rise sharply in the post-pandemic period, reaching 8.9% in 2023, 12% in 2024, and 14.2% by 2025. These results indicate an increasing gap between expectations and perceived performance in recent years, representing a shift that may be related to broader post-pandemic developments.

Dimension-level trends further clarify this pattern (Table 6). Food quality shows a marked increase in negativity in 2025 (19%), compared to

Tablo 6. Yearly Distribution of Aspect-Based Sentiment Scores and Negativity Rates (2012-2025)

Year		FQ	S&S	A&A	V&P	W&B	R&W	L&A	DF	H&C
2012	A.S.	0.2	0.3	0.3	0.2	0.1	0.2	0.3	0.2	-0.1
	N.R.	%4.9	%10.9	%8.1	%15.1	%13.2	%8.3	%0	%0	%66.7
2013	A.S.	0.2	0.2	0.2	0	0.2	0.1	0.1	0.2	-0.5
	N.R.	%10.7	%15.2	%17.2	%27.6	%16.9	%17.1	%9.1	%0	%100
2014	A.S.	0.2	0.2	0.2	0.1	0.1	0.1	0.2	0.2	0.1
	N.R.	%4.7	%12.3	%8.3	%22.2	%9.4	%17.4	%0	%12.5	%50
2015	A.S.	0.2	0.2	0.2	0	0.2	0.1	0.3	0.1	0.2
	N.R.	%7.1	%13	%9	%27.9	%9.1	%17.3	%11.1	%14.3	%0
2016	A.S.	0.2	0.2	0.3	0.1	0.2	0.1	0.3	0.2	0.3
	N.R.	%7.1	%15.3	%8.1	%20	%15.1	%23.5	%4.8	%0	%0
2017	A.S.	0.2	0.2	0.2	0.1	0.2	0.1	0.3	0.2	0
	N.R.	%9.1	%11.4	%13.5	%33	%20	%20.3	%0	%5.6	%36.4
2018	A.S.	0.2	0.1	0.2	0.1	0.2	0.1	0.1	0.1	-0.1
	N.R.	%7.5	%11.6	%7.2	%20	%18.5	%20	%23.7	%30.8	%42.9
2019	A.S.	0.2	0.2	0.2	0.1	0.2	0.1	0.2	0.1	0.2
	N.R.	%9.7	%11.4	%9	%26.6	%14.8	%13	%0	%14.3	%0
2020	A.S.	0.2	0.2	0.2	0	0.2	0.1	0.1	0.2	0
	N.R.	%9.1	%17.2	%10	%30.8	%11.1	%22.2	%0	%0	%0
2021	A.S.	0.1	0.2	0.1	0	0.1	0.1	0.2	0.2	0
	N.R.	%9.8	%14.3	%11.8	%38.5	%16.7	%5.9	%0	%0	%0
2022	A.S.	0.2	0.2	0.2	0	0.1	0.1	0.3	0.1	0.1
	N.R.	%8.1	%7.2	%11.8	%37.5	%16.1	%11.4	%0	%0	%37.5
2023	A.S.	0.2	0.2	0.2	0.1	0.1	0.1	0.3	0	0.1
	N.R.	%11	%15.6	%11.9	%27.1	%18.3	%13.6	%0	%50	%0
2024	A.S.	0.2	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.1
	N.R.	%10.4	%13	%10.1	%30.3	%21.1	%15.7	%18.2	%7.7	%12.5
2025	A.S.	0.1	0.2	0.1	0.1	0.1	0	0.2	0.1	-0.1
	N.R.	%19	%15.1	%14	%30.5	%20	%31.1	%12.5	%20	%62.5

***A.S.**= verage Sentiment: Represents polarity scores calculated using the TextBlob library. These scores range from -1 (completely negative) to +1 (completely positive). The concentration of values between 0.0 and 0.3 in this table indicates that, due to the fact that the analyzed reviews are "3-point" (mid-level) ratings, they exhibit a tendency close to neutral but slightly positive. **N.R.**= Negative Rate: Refers to the percentage of reviews within the relevant year that carry a negative sentiment (polarity score below 0) regarding the corresponding aspect. A high percentage is a strong indication that customer expectations were not met in that specific dimension during that year. For example, looking at the Hygiene and Cleanliness row in 2025; the Avg. Sent. value of -0.1 shows that the overall perception shifts into the negative range, while the Neg. Rate value of 62.5% indicates that 6 out of every 10 guests commenting on this issue are directly dissatisfied.

10.4% in 2024 and the dataset average of 9.4%, suggesting a growing difficulty in meeting culinary expectations. Hygiene and cleanliness exhibits the most dramatic shift, reaching 62.5% negativity in 2025, the highest value across all dimensions and years.

The perceived value remains consistently high in negativity throughout the period, exceeding 20% from 2013 onward and reaching 30.3% in 2024 and 30.5% in 2025, confirming its structural role as a source of dissatisfaction. Reservation and waiting also show a strong upward trend, rising to 31.1% by 2025.

The COVID-19 period (2020–2021) appears to be a transitional phase with fluctuations in sentiment and increased sensitivity to value perceptions (30.8% in 2020 and 38.5% in 2021), likely reflecting operational disruptions.

Overall, the temporal patterns indicate not a change in the core sources of dissatisfaction but an intensification of existing issues such as value

for money, service efficiency, and hygiene. This aligns with the Expectation–Disconfirmation Theory, which states that widening expectation–performance gaps generate stronger negative disconfirmation over time.

Discussion

The Structural Nature of Dissatisfaction in the Fine-Dining Food Experience

Within the boundary conditions of this study, the findings suggest that dissatisfaction expressed in three-point fine-dining reviews is not purely incidental but exhibits consistent patterns across a stable set of experiential dimensions. Perceived value, hygiene and cleanliness, reservation and waiting, and wine and beverages consistently emerged as the main sources of negative sentiment across the examined countries, star categories, and time periods. This persistence indicates

that, within this specific mid-range review segment, dissatisfaction is frequently linked to recurring operational and experiential friction rather than isolated service failures. However, as this study focuses exclusively on three-point TripAdvisor ratings, these structural patterns reflect the nuances of partial satisfaction and cannot be directly generalized to the entire fine-dining experience, higher or lower rating categories, or all restaurant scales.

These results are consistent with prior research identifying key experiential drivers such as food quality, service, ambiance, and price-performance ratio (Gan et al., 2017), as well as operational issues such as waiting time and reservation difficulties (Özen et al., 2025). The present study extends this literature by showing that these structural patterns persist even within a homogeneous rating segment (three-point reviews), highlighting that moderate dissatisfaction is a recurring rather than an exceptional phenomenon. In contrast to studies analyzing mixed rating distributions (Bang et al., 2022; Lee & Ko, 2022; Özen et al., 2025), the exclusive focus on three-point reviews allows for a more precise identification of barriers to complete satisfaction.

A notable finding was that food quality, despite being the most frequently mentioned dimension, exhibited relatively low negativity (9.4%). This challenges the assumption that dissatisfaction with fine dining primarily stems from kitchen performance. Instead, environmental and organizational factors, such as pricing, waiting time, hygiene, and beverage service, generate more consistent negative evaluations. This aligns with the broader view that service quality in luxury dining is shaped by both experiential and environmental factors (Chen et al., 2015).

The temporal analysis shows that sentiment remained relatively stable over time but declined after 2022, accompanied by an increase in negative reviews between 2023 and 2025. The COVID-19 period emerged as a transitional phase marked by sentiment fluctuations, which may potentially reflect broader operational adaptations and evolving

post-pandemic service contexts, aligning with observations in prior literature (Pleerux & Nardkulpat, 2023). Dimension-level trends further indicate rising dissatisfaction with perceived value, hygiene, and reservation-related aspects. Overall, these temporal patterns suggest a widening gap between customer expectations and perceived performance in recent years, representing a shift that may be associated with evolving post-pandemic customer dynamics.

The Role of Expectations, Prestige and Perceived Value

A key finding of this study is the persistent role of perceived value as a central source of dissatisfaction across both star categories in all three countries. This is particularly notable in the luxury dining context, where guests typically exhibit low price sensitivity and high willingness to pay (Bang et al., 2022; Kiatkawsin & Han, 2019). This apparent paradox can be explained by the expectation–Disconfirmation Theory, which posits that satisfaction depends on the alignment between expectations and perceived performance rather than price alone (Oliver, 1977). In fine dining, high expenditure is linked to social status and expectations of novelty and experiential justification (Daries et al., 2024). When these expectations are not met, strong negative disconfirmation emerges as perceived value dissatisfaction.

This interpretation is supported by evidence suggesting a reverse U-shaped relationship between price and satisfaction, where price initially signals quality but becomes a source of dissatisfaction beyond a threshold, as the perceived sacrifice outweighs the perceived benefits. In Michelin-starred restaurants, moderate pricing aligned with perceived offerings has been identified as more effective than extreme pricing strategies (Chen & Lin, 2025). Given the wide price range within this segment (Castillo-Manzano & Zarzoso, 2023), pricing strategies must balance cost, authenticity, and perceived experiential value, as relying on Michelin prestige alone risks generating value-based dissatisfaction.

The comparison between two- and three-star restaurants adds further nuance to the study. Three-star establishments show slightly higher dissatisfaction regarding perceived value (27.2% vs. 25.4%), indicating that higher prestige intensifies expectations. Simultaneously, they performed better in terms of food quality (7.8% vs. 10.8% negativity), suggesting that culinary excellence is more consistently achieved at higher levels but is insufficient on its own to ensure full satisfaction. This aligns with evidence that fine-dining consumers are heterogeneous in terms of motivation and context (Lee & Ko, 2022) found that even minor operational issues such as reservation problems or service interactions can disproportionately affect overall evaluation in high-stakes dining experiences.

Theoretical and Practical Contributions

From a theoretical perspective, this study contributes to the luxury dining experience, consumer satisfaction, and sentiment analysis literature in several ways. First, it challenges the dominant assumption that food quality is the primary driver of satisfaction in Michelin-starred fine-dining restaurants. The findings show that dissatisfaction is more strongly associated with organizational and environmental dimensions, particularly service interactions, waiting, billing, and hygiene issues. These results suggest that the main gaps between expectations and perceived performance emerge at critical service touchpoints, offering a revised understanding of how satisfaction is conceptualized in fine dining.

Second, this study makes a methodological contribution by applying a keyword-based ABSA approach to a theoretically defined subset of reviews (three-point ratings). Compared to prior studies that have analyzed aggregated review data (Bang et al., 2022; Lee & Ko, 2022; Özen et al., 2025), this focused design enables a more precise identification of the factors underlying partial satisfaction. The integration of the expectation–Dis-

confirmation Theory further strengthens the interpretive framework and theoretical coherence of the analysis.

From a practical perspective, the findings have clear implications for managers in the fine-dining sector. The persistent importance of perceived value indicates that pricing strategies must carefully balance cost, authenticity, and customer expectations rather than relying solely on Michelin prestige (Kim et al., 2025). Service quality remains critical, as professionalism, politeness, and consistency directly shape overall evaluation (Stöckl et al., 2025). Operational efficiency, particularly reservation systems and waiting management, should also be improved to reduce experiential friction. Finally, hygiene and cleanliness emerged as high-impact factors; although infrequent, failures in this area generated disproportionately strong negative responses and required strict managerial attention.

Limitations and Future Research

This study had several limitations. First, although the keyword-based sentiment extraction approach is computationally efficient and interpretable, it may not fully capture the semantic complexity of natural language and may misclassify sentences in which keywords appear in non-evaluative contexts. Future research could address this limitation by employing deep learning-based ABSA models, such as BERT-based architectures, which offer higher accuracy in aspect detection and sentiment classification.

Second, reliance on English-language reviews introduces a potential sample bias toward international and non-native English-speaking visitors, which may underrepresent local guests' perspectives and culturally grounded evaluations. Third, the geographical scope of the dataset is limited to France, Spain and Italy, which restricts the generalizability of the findings. Future studies could extend this framework to other fine-dining contexts, such as Asia, the Americas, and the Middle East, where culinary traditions and service expectations differ significantly.

Declarations

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Ethical Approval: Ethics committee approval was not required for this study because it did not involve human participants or the collection of personal data.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

AI Disclosure: Gemini was used for language edition, translation support, grammar checking, coding support. The author reviewed, edited, and verified all AI-assisted outputs and takes full responsibility for the content of the manuscript.

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