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Restaurant survival prediction using customer-generated content: An aspect-based sentiment analysis of online reviews

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ABSTRACT

Business failure prediction or survival analysis can assist corporate organizations in better understanding their performance and improving decision making. Based on aspect-based sentiment analysis (ABSA), this study investigates the effect of customer-generated content (i.e., online reviews) in predicting restaurant survival using datasets for restaurants in two world famous tourism destinations in the United States. ABSA divides the overall review sentiment of each online review into five categories, namely location, tastiness, price, service, and atmosphere. By employing the machine learning–based conditional survival forest model, empirical results show that compared with overall review sentiment, aspect-based sentiment for various factors can improve the prediction performance of restaurant survival. Based on feature importance analysis, this study also highlights the effects of different types of aspect sentiment on restaurant survival prediction to identify which features of online reviews are optimal indicators of restaurant survival.

1. Introduction

The number of active internet users worldwide reached 4.66 billion in early 2021. This figure has climbed consistently over time and now accounts for 59.5% of the world's population (Statista, 2022). As a common form of electronic word-of-mouth (eWOM), user-generated content (UGC) serves as an important source of information about hospitality products; such insight conveys consumers' experiences and profoundly affects both potential consumers' purchase behavior and businesses' online reputations (Anagnostopoulou et al., 2020). The rapid development of the internet has allowed online reviews to reach countless consumers with enduring impact (Sparks et al., 2016). Online reviews—many of which are posted by prior consumers—can increase prospective buyers' certainty about acquiring desired products or services (Zhang, Liang, et al., 2019).

Growth in consumers' reliance on and companies' marketing efforts related to online reviews has aroused intense scholarly interest: numerous studies have addressed associated topics in the hospitality field (Li, Ji, et al., 2022). For example, the significant and positive effects of online reviews on hotel performance (e.g., sales, revenue per available room, and financial profitability) are well documented (Anagnostopoulou et al., 2020; Nieto et al., 2014; Phillips et al., 2017). The volume of online reviews is positively correlated with consumers' satisfaction with, and the reputation and profitability of, lodging establishments (Nieto et al., 2014). Review scores are also significantly associated with hotel occupancy, revenue per available room, sales, and booking transaction value (Torres et al., 2015; Viglia et al., 2016; Ye et al., 2009). Despite extensive research regarding various facets of online customer reviews, little work has focused on the effects of these reviews on businesses' survival (Zhang & Luo, 2022). UGC significantly influences hospitality organizations' financial performance, and many studies have stressed the importance of the customer experience on these businesses' success (Aakash & Gupta Aggarwal, 2022; Fernandes et al., 2021). UGC is thus likely to be tied to service organizations' success or failure and could potentially predict these businesses' survival.

Restaurant failure and survival are inherently complex. These outcomes can be attributed to numerous factors and explained from diverse perspectives, such as marketing, managerial, financial, organizational, ecological, and economic concerns (Kalnins & Mayer, 2004; Parsa et al., 2011, 2021). Social media is regarded as one of the most efficient and effective marketing tools to create awareness and spread WOM (Nizam,

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2017). Multiple dimensions covering myriad factors can inform restaurants' survival. Customers also assign varying weights to restaurant attributes, such as service, ambience, price, and taste (Mahmood & Khan, 2019; Ryu & Lee, 2017). However, it remains unknown whether fine-grained consumer sentiment (expressed via certain aspects of UGC of a focal restaurant) can better indicate restaurant survival and how different features predict survival. The present study therefore refers to UGC to clarify the role of aspect-based sentiment in restaurant survival prediction and compares its predictive power with conventional overall sentiment analysis in terms of prediction performance. This research also aims to identify optimal features of online reviews for predicting restaurant survival, thus offering meaningful implications for restaurants to thrive in today's market.

This study presents several novel theoretical contributions by adopting aspect-based sentiment analysis (ABSA) of online reviews to predict restaurant survival using the machine learning–based conditional survival forest (CSF) model. In addition, this research also makes an early attempt to compare the prediction performance of restaurant survival based on online reviews without review sentiment, with overall review sentiment, and with review aspect–based sentiment. Findings yield practical implications for numerous stakeholders. Restaurant investors and owners can better understand their businesses' circumstances based on ABSA of UGC. Practitioners can identify their firms' competitiveness compared with close competitors and modify their business and marketing strategies accordingly. Lastly, by ranking the importance of different aspects in predicting restaurant survival, catering establishments can allocate resources to prioritize the factors that most strongly influence their businesses' prosperity.

2. Literature review

2.1. Overview of business survival/failure prediction

Business failure represents the point at which a company must cease all business operations or go out of business, following from business distress (Amankwah-Amoah, 2016). Distressed businesses usually display features such as depleted financial or human resources. Some of these businesses ultimately collapse (i.e., fail) (Amankwah-Amoah & Wang, 2019). Businesses fail for an array of reasons, such as the size and type of a company or industry, entrepreneurs' characteristics, and financial distress (Liahmad et al., 2021; Mayr et al., 2021; Ucbasaran et al., 2013). Boyle and Desai (1991) introduced a four-quadrant matrix to conceptualize the apparent causes of business failure, including internal-administrative, internal-strategic, external-administrative, and external-strategic reasons. Financial states, organizational structure, and human resources were attributed to internal-administrative failure causes. Regarding financial performance, Parker et al. (2002) found that financially distressed companies were nearly 2.5 times more likely to eventually go bankrupt when their CEOs were replaced by outsiders, suggesting that the turnover of a firm's top management team was highly associated with business failure. In a hotel context, although many businesses may struggle, the instances of failure are far fewer (Li & Sun, 2012). A direct examination of failure causes is thus warranted. Aside from conceptualizing failure causes from a firm-specific perspective, a business's success is largely associated with the industry in which it is situated (Agarwal & Gort, 1996; Audretsch & Mahmood, 1995; Opstad & Valenta, 2022). Specifically, the restaurant and airline industries have relatively shorter survival times and poorer survival rates than companies in other sectors, such as technological and pharmaceutical firms (Hensler et al., 1997). Honjo (2000) pointed out that companies in industries with a high entry rate and high geographical concentration usually have lower survival rate; the restaurant industry is an example (English et al., 1996). Consequently, competition has also been identified as a core factor in restaurant failure (Wu et al., 2021). Many restaurant operators without sufficient competitive advantages are thus highly susceptible to business failure.

Financial firms have fervently studied business failure or bankruptcy prediction since the 1960s. A number of conventional statistical models have accordingly been developed to predict business failure (e.g., Dimitras et al., 1996; Gepp & Kumar, 2008; Kumar & Ravi, 2007; Li et al., 2022; Wieprow & Gawlik, 2021). Traditionally, business failure prediction (BFP) models, such as discriminant and logit analysis, employed a set of financial ratios from internal monetary report (e.g., net income and loss accounts) and covariates to estimate the probability of corporate bankruptcy (Bunyaminu et al., 2019; Gepp & Kumar, 2008; Luoma & Laitinen, 1991; Smiti & Soui, 2020). By using statistical analysis, BFP can help organizations understand their business circumstances and make better-informed decisions (Lee, 2014; Wieprow & Gawlik, 2021; Yang et al., 2011). However, the business operation status is usually loosely classified by just active or in liquidation, which focused more on the financial management but offered limited insights for operation strategies that might be more efficient to save a distressed company at risk. Departing from forecasting business bankruptcy, survival analysis, as an alternative with BFP technique, can be used to analyze the time frame of business failure and suggest an enterprise's lifespan (Gepp & Kumar, 2008; Luoma & Laitinen, 1991; Naumzik et al., 2022). Representatively, Naumzik et al. (2022) studied review ratings as a proxy of customer satisfaction and predicted the likelihood of failure and risk state of restaurants. Prediction performance was improved using survival analysis with a hazard function compared with previous discriminant and logit analysis. Despite the prevalence of hazard function in survival analysis, the model requires the data to strictly meet the assumptions before generating reliable prediction (Moncada-Torres et al., 2021); therefore, methods that are more flexible to deal with massive online data are needed.

2.2. Survival/failure in the restaurant industry

Research has identified factors that are essential to business survival across industry, such as the macro environment (i.e., national conditions) (Audretsch & Mahmood, 1995; Carroll, 1983), a firm's age, management teams, work experience, and luck (Wadhwa et al., 2009). Specifically, in the restaurant settings, Lee (1987) discussed several characteristics driving success and failure in the food service industry, including food quality, standardization, franchising, adaptability, marketing, advertising, and management. English et al. (1996) extended the study by a longitudinal one and uncovered that ongoing investment in advertising and marketing was positively correlated with restaurants' business success. Promotion and marketing have been frequently mentioned as vital to restaurants' success as well (English et al., 1996; Kotler et al., 2022). Nizam (2017) further identified sound marketing strategies as key, especially for small independent restaurants which are especially vulnerable to failure. In addition, effectively involving consumers and catering to their preferences and needs is critical to drive the restaurant companies' growth (Wang & Kim, 2021) considering that restaurants are market-driven and rely heavily on consumers' experiences and perceptions. Given the importance of customers' experiences in restaurants, Cant and Erdis (2012) performed an exploratory study using a survey to identify restaurant-related success factors from consumers' points of view. Findings outlined cleanliness, value for money, service level, and the quality of food served as core criteria to increase customer satisfaction and establish customer relations, ultimately enhancing these businesses' profitability and survival. Parsa et al. (2005) also found that the most successful restaurants are those who can change dynamically and quickly adapt to market trends. Later, they carried out a restaurant survival analysis by applying the Kaplan–Meier technique and Cox's hazard regression models (Parsa et al., 2011), two prominent survival analysis approaches in the medical and business domains. The authors uncovered significant effects of location, affiliation, and size on restaurants' failure and survival. Failure rates have also been shown to vary significantly by location: restaurants in urban areas generally have higher failure rates than those in the suburbs (Parsa et al., 2005, 2011). Chain restaurants have much higher survival rates and longer lifespans than independent restaurants, largely due to the superior internal and external advantages of chain corporations over independent operators—greater financial resources, more established brands, a broader customer base, and more sophisticated management strategies (Camillo et al., 2008; English et al., 1996). Moreover, restaurants with a larger size and greater operational complexity also have better survival rates (Parsa et al., 2011, 2015).

2.3. The importance of online customer reviews and their roles in restaurant survival prediction

Hospitality organizations generally agree on the importance of consumers' experiences and subsequent WOM. Scholars have discussed these topics at length. Leading hospitality companies such as Marriott, Hilton, and Starbucks have implemented effective customer experience management, and many of their business strategies revolve around the customer experience (Kandampully et al., 2018).

Hospitality organizations previously use customer surveys to obtain analytical data on consumers' satisfaction, experiences, and general feedback to improve service quality and operational performance (Naumzik et al., 2022). More recently, the rise of social media marketing has made online platforms easily accessible. These sites enable customers to leave reviews that can express themselves instantly, which reflects actual customer needs and thus serves as a large data pool for analytical purpose (Calheiros et al., 2017; Naumzik et al., 2022). Several hospitality researchers have thus investigated the role of online consumer reviews from various angles, such as marketing strategies, consumers' purchase intentions, and hotel performance (Kim et al., 2015; Kwok et al., 2017; Su et al., 2022). In the prediction domain, Kim and Park (2017) evaluated the effectiveness of traditional customer surveys versus online customer reviews and ratings in predicting hotel performance. They found that online reviews and ratings could predict hotel performance more powerfully, including the average daily rate, revenue per available room, and total revenue per available room. Building on the discovery that review characteristics (e.g., review volume and length) can influence online sales (Chevalier & Mayzlin, 2006), recent work has sought to extract volume-based indicators from UGC and has confirmed their predictive power in business survival prediction (e.g., Zhang & Luo, 2022). Content-related valence-based data (i.e., review sentiment) remains under-explored, which provides great opportunities to exploit useful information from UGC to a greater extent (Li, Liu, & Zhang, 2020).

Moreover, given the significance of online reviews and e-WOM, hospitality researchers have analyzed UGC sentiment for different purposes (Calheiros et al., 2017; Guerreiro & Rita, 2020; Lee et al., 2018; Li et al., 2017; Zhang et al., 2021). In a hotel-based case study, Calheiros et al. (2017) employed text mining and latent Dirichlet allocation modelling to classify the sentiment of customer-generated content by different topics. Findings revealed consumers held positive or negative perceptions towards certain hotel attributes, which implies the significance of decomposing the aspect-based sentiment for in-depth insights and concrete suggestions. Akhtar et al. (2017) similarly carried out ABSA on online reviews to reveal customers' perceptions of multiple hotel characteristics. He et al. (2017) discovered that review sentiment scores were positively correlated with overall hotel ratings; additionally, they found that extremely positive and negative reviews both often described a hotel's room, food, location, service, and staff. More recently, Ray et al. (2021) proposed a hotel recommendation system based on sentiment analysis and aspect-based review categorization, stressing the utility of online customer reviews.

Recent works that attempted survival prediction with UGC cemented its capacity to predict business survival. Representatively, Zhang and Luo (2022) focused on the predictive power of review photos, while also used topic extraction/categorization from reviews and calculated the overall sentiment of a focal review; however, the authors did not address sentiment in terms of multiple topics or aspects in each online review. Consumers' dense review information thus has yet to be fully exploited. Online restaurant reviews are multifarious, capturing various facets of consumers' perceptions and experience but certain attributes, such as food quality and location, are considered especially important to restaurants' success (Liu et al., 2022; Mandabach et al., 2011; Zhang et al., 2021). Haghighi (2012) argued that food quality, service quality, the restaurant environment, and price level each strongly affect consumer satisfaction, which require more investment and efforts to maintain satisfactory consumers. In addition, most studies on sentiment analysis have solely considered overall review sentiment, which thus leaves the different aspects of restaurants' operations and their respective decisive power that contribute to restaurant survival under-researched. This limitation has constrained managerial implications intended to enhance restaurants' performance and survival. To this end, this study conducted ABSA on individual online reviews to scrutinize consumers' preferences/sentiments associated with different restaurant features (i.e., location, tastiness, service, price, and atmosphere) and then investigated the incremental improvements in predicting restaurant survival via ABSA versus models with overall customer sentiment. This study is one of the first to conduct a longitudinal analysis of restaurant survival from an ABSA perspective.

3. Methodology

3.1. Framework and data

Fig. 1 illustrates our framework integrating online ABSA-based reviews in a restaurant survival prediction system. The analytical process consisted of four steps: (1) collecting restaurant online review data from Yelp; (2) cleaning and preprocessing the data; (3) specifying the model; and (4) evaluating the model's prediction performance.

The data of our study was collected from a metropolitan city in the United States, which is also a famous tourist destination. The city hosts a prosperous hospitality and restaurant industry, which is a key component of tourism-related economic activity; only restaurant industry contributes around 15% of taxable sales citywide and is the second-largest segment for tourism spending. The city's restaurants attract millions of visitors and residents for regular consumption and inject vigor into online review communities featuring consumers' experience sharing. In the first step, we obtained this city's restaurant online reviews (1,158,351 reviews across 974 restaurants in total). All online review data before year 2019 (i.e., from October 2004 to December 2018) were obtained. We specifically gathered information on restaurant characteristics and review characteristics. Restaurant characteristics included chain status, price level, and number of competitors; review characteristics included review ratings; the number of "funny," "useful," and "cool" votes on each review; and the review text.

Next, we cleaned and preprocessed the data. Table 1 describes the variables used in our analysis. We cleaned the data as follows: 1) filtering and removing duplicate and irrelevant data (e.g., non-English words and meaningless symbols) from reviews that might yield inaccurate insights for prediction; 2) converting non-uniform data into a standard format (e.g., standardizing date data such as "the first day of September this year" to "01/09/2017"); and 3) handling missing values (e.g., replacing the missing value for "funny" in specific reviews with 0). We then compiled data at the "month $\times$ restaurant" level, ranging from October 2004 to December 2018. Hutzschenreuter et al. (2021) noted that a firm's competitors affect its profitability; a restaurant's competition can therefore influence its survival. First, to measure the number of competitors per month for each restaurant, we calculated the dynamic restaurant competitor density in each month based on the number of restaurants in the same zip code using Zhang and Luo's (2018) method. We extracted the dates of all restaurant closures (to be explained in the following subsection) and the number of open restaurants in the same zip code per month to identify a focal restaurant's dynamic competitor

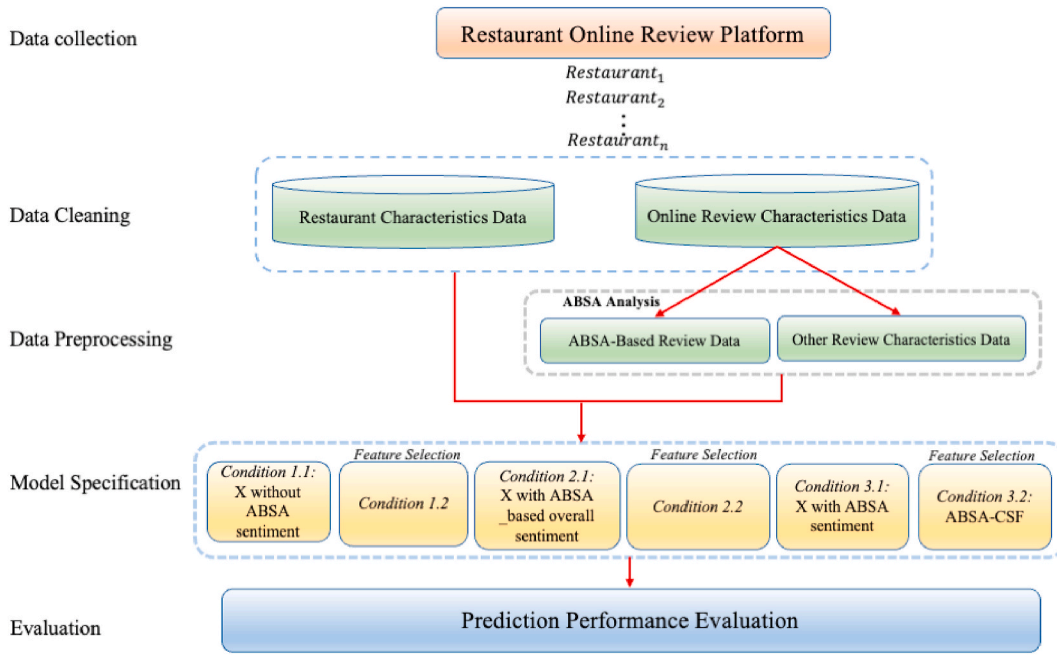

Fig. 1. Online ABSA-based restaurant survival prediction system.

Table 1
List of variables & summary statistics.

Restaurant characteristics	Review characteristics
Avg. number of competitors per month	Avg. review length to date
Price level	Avg. number of customer engagements per month
Chain status	Avg. rating to date
	Avg. number of reviews per month
	Avg. overall review sentiment to date
	Avg. location sentiment to date (Aspect 1)
	Avg. tastiness sentiment to date (Aspect 2)
	Avg. service sentiment to date (Aspect 3)
	Avg. price sentiment to date (Aspect 4)
	Avg. atmosphere sentiment to date (Aspect 5)

Variable	Count	Mean	St.d.	Min.	Max.
Price level	1,158,351	2.121	0.725	1.000	4.000
Chain status	1,158,351	0.185	0.388	0.000	1.000
Review length	1,158,351	106.007	99.679	1.000	1446.000
Engagement	1,158,351	1.723	5.932	0.000	655.000
Rating	1,158,351	4.041	1.112	1.000	5.000
Overall review sentiment	1,158,329	0.505	0.333	0.000	0.999
Location sentiment	1,158,329	0.517	0.310	0.001	0.999
Tastiness sentiment	1,158,329	0.443	0.393	0.000	0.999
Service sentiment	1,158,329	0.521	0.411	0.000	0.999
Price sentiment	1,158,329	0.512	0.406	0.000	0.999
Atmosphere sentiment	1,158,329	0.534	0.369	0.000	0.999

volume. Second, according to restaurants' per-person price listed on Yelp, price was classified into four levels: $ (under $10/person), $$ ($11–$30/person), $$$ ($31–$60/person), and $$$$ (>$61/person). Third, we used ABSA to calculate five aspects of consumer sentiment based on the literature (Haghighi, 2012; Mandabach et al., 2011; Parsa et al., 2005; Parsa et al., 2011): the average sentiment score of the location to date, the average sentiment score of tastiness to date, the average sentiment score of service to date, the average sentiment score of price to date, and the average sentiment score of the atmosphere to date. To understand the central tendency of sentiment in each review, we also computed the mean value of these five scores as a proxy of overall review sentiment. Fourth, customer engagement was defined as the sum of a review's "funny," "useful," and "cool" votes, which are not random or whimsical signals to attract click engagement, but are as good measures of quality (Bakhshi et al., 2015). We thus calculated the average amount of customer engagements per month. Furthermore, the average number of reviews per month was also calculated. Descriptive statistics for all variables are summarized in Table 1.

The third step involved model specification. To determine whether fine-grained sentiment polarity analysis (with a focal restaurant via ABSA) could improve survival prediction accuracy compared with general sentiment analysis, we referred to six groups of data (i.e., taking different variables as input) to compare prediction performance for restaurants. Table 2 presents the input variables used in the prediction model. The baseline prediction model of the six groups is the CSF model, and X refers to the input variables. The input variables X in the six groups include factors without review sentiment, with overall review sentiment, and with aspect-based review sentiment. In brief, Condition 1.1 covers (1) restaurant characteristics, including the average number of competitors per month, price level, and chain status; and (2) review characteristics, including the average review length to date, average number of customer engagements per month, average review rating to date, and average number of reviews per month. Based on Condition 1.1, the input variables X in Condition 2.1 include the average overall review sentiment to date; those in Condition 3.1 include aspect-based sentiment review variables (i.e., average location sentiment to date, average tastiness sentiment to date, average service sentiment to date, average price sentiment to date, and average atmosphere sentiment to date). Condition 3.2 specified the same input variables X as Condition 3.1; however, to optimize CSF prediction, we filtered the input variables X and proposed an ABSA-CSF model with feature selection technology, specifically the exhaustive search method. This approach can choose the model with optimal accuracy by reviewing all possible feature combinations (Nersisyan et al., 2022). It thus does not ignore feature sets that might display optimal prediction performance. The exhaustive search method can also overcome shortcomings of other typical feature selection methods; for example, the Pearson correlation method is only sensitive to linear relationships between variables, and the embedded technique cannot work with other classifiers when making classifier-dependent selections (Hira & Gillies, 2015). Finally, two input variables—chain status and average atmosphere sentiment to

Table 2
Prediction models and included variables.

Category	Variable	Condition 1.1: X without ABSA_based sentiment	Condition 1.2:	Condition 2.1: X with ABSA_based overall sentiment	Condition 2.2:	Condition 3.1: X with ABSA sentiment	Condition 3.2: (ABSA-CSF)
Restaurant characteristics	Avg. number of competitors per month	✓	✓	✓	✓	✓	✓
	Price level	✓	✓	✓		✓	✓
	Chain status	✓		✓		✓	
Review characteristics	Avg. review length to date	✓	✓	✓	✓	✓	✓
	Avg. number of customer engagements per month	✓		✓		✓	✓
	Avg. rating to date	✓	✓	✓		✓	✓
	Avg. number of reviews per month	✓		✓		✓	✓
	Avg. overall review sentiment to date			✓	✓		
	−Avg. location sentiment to date					✓	✓
	−Avg. tastiness sentiment to date					✓	✓
	−Avg. service sentiment to date					✓	✓
	−Avg. price sentiment to date					✓	✓
	−Avg. atmosphere sentiment to date					✓	
Feature selection			✓		✓		✓

date—were further excluded from input variables in the ABSA-CSF model. To obtain the optimal accuracy for each model and ensure a fair comparison, we applied feature selection technology (i.e., the exhaustive search method) in Condition 1.2 (from Condition 1.1) and Condition 2.2 (from Condition 2.1).

In the fourth step, the concordance index (C-index) and the integrated brier score (IBS) were used to evaluate the performance of the above models. The C-index and IBS were also applied to calculate relative improvement.

3.2. Conditional survival forest model

Many regression models are available to evaluate restaurant survival. Yet such approaches can be plagued by data problems. For instance, the Cox proportional hazards model is not appropriate for large-scale omics problems (Wright et al., 2017). Moreover, Cox regression model has restrictive assumptions such as linearity and hazards proportionality, and if these assumptions cannot be met, then the prediction based on Cox regression model might be unreliable (Breiman, 1996). It is thus necessary to adopt methods that do not require numerous assumptions and can solve large volume of data–related problems to enhance survival prediction. Machine learning methods, such as random forest models, are increasingly popular survival prediction alternatives. Using random survival forests for survival analysis is valuable. The method is data-driven and totally nonparametric: the restrictive assumption is not required, and nonlinear effects and high-level interactions among variables can be evaluated automatically (Zhang, Tang, et al., 2019). We therefore employed a CSF model to predict restaurant survival and examine the relationship between restaurant survival and online review characteristics. It applied maximally selected rank statistics to calculate the optimal cutpoint during dividing data into two components (Wright et al., 2017). Considering n observations, this method applies log-rank scores defined as $a_1, a_2, \ldots\ldots a_n$ (Hothorn & Lausen, 2003) with time Z_i and δ_i which denotes the censoring indicator:

$$a_i = a_i(\mathbf{Z}, \boldsymbol{\delta}) = \delta_i - \sum_{j=1}^{\gamma_i(\mathbf{Z})} \frac{\delta_j}{(n - \gamma_j(\mathbf{Z}) + 1)}$$

where $\mathbf{Z} = (Z_1, \ldots, Z_n)'$ is the survival time vector and $\delta_i = (\delta_1, \ldots, \delta_n)'$ is the censoring indicator vector. The observation volume is $\gamma_j(\mathbf{Z}) = \sum_{i=1}^{n} 1_{\{Z_i \le Z_j\}}$, whose survival time is up to Z_j. More details about this method could be found in the study of Wright et al. (2017).

3.3. Aspect-based review sentiment analysis using deep learning technologies

We performed sentiment analysis to uncover consumers' opinions about restaurants. In particular, we calculated consumers' attitudes based on the information contained in online textual reviews, using ABSA to compute sentiment score for different aspects. To identify review sentiment at the aspect level with high accuracy, we applied two methods to extract sentiment: BERT-based aspect-based sentiment analysis and graph convolutional network (GCN)–based aspect-based sentiment analysis. These methods are described in the following subsections.

3.3.1. Review aspect–based sentiment analysis with BERT-based technology

Fig. 2 depicts the process of calculating the aspect-based sentiment of each review with BERT-based technology. First, based on keywords used by Ekawati and Khodra (2017), we defined tastiness, service, location, and price as important aspects to be analyzed for restaurants. We decided to use the term "tastiness" instead of "food" because "tastiness" can more succinctly describe customers' satisfaction. Scholars have also considered "tastiness" an operational definition of the pleasantness of food (Hackel et al., 2018). We specifically used aspect-based sentiments to make predictions; therefore, rather than using "food," we focused on the sub-attribute (i.e., food tastiness) to better reflect the perceived quality of food and consumers' associated sentiment (Padillo et al., 2021). We also defined the "atmosphere" aspect with a data-driven inductive approach. This term does not fall under the above-mentioned four aspects but has appeared more than 80,000 times in reviewers' comments. An excellent overall dining experience via exemplary food, in conjunction with a good atmosphere and high-quality service, is required for consumer satisfaction (Ryu et al., 2012). Thus, we defined "tastiness," "service," "location," and "price" together with "atmosphere" as aspect terms in this stage.

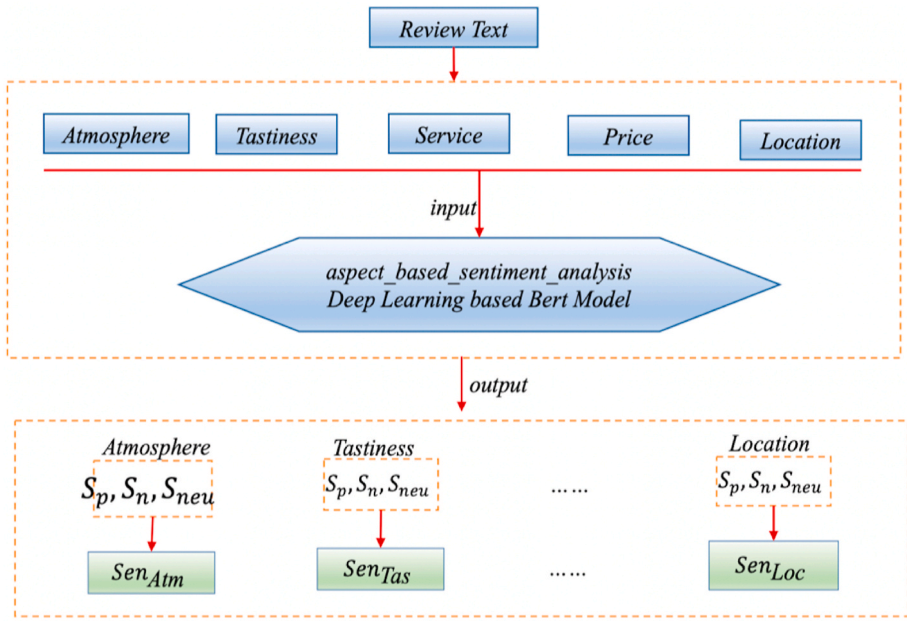

Fig. 2. Sentiment calculation based on ABSA

Next, we used the review text and aspect terms as input for BERT-based sentiment analysis. The ABSA task was conducted with a BERT language model–based Python package named "aspect_based_sentiment_analysis"; this package includes multiple state-of-the-art sentiment analysis methods such as ABSA-BERT-pair (Sun, Huang & Qiu, 2019), LCF-BERT (Zeng et al., 2019), and pipeline-based analysis approaches. The pipeline method was employed in this study. It provides a ready-to-use interface to make predictions, which can be directly applied to a dataset for immediate use. We used SemEval restaurant data, a popular open-source dataset (Pontiki et al., 2014), to verify the inherent pipeline method's performance on ABSA tasks. The confusion matrix performance was 0.8518 for this method. The sentiment polarity of different aspect terms was obtained at the individual review level instead of at the document level. More than one million reviews were used as input to run the trained BERT language model. The model output comprised three scores per aspect: $S_p, S_n,$ and S_{neu} denote the positive sentiment score, negative sentiment score, and neutral sentiment score, respectively. Each score ranges from 0 to 1, with higher scores indicating stronger sentiment. Then, we defined the final sentiment of each aspect as $Sen_{aspect} = \frac{S_p}{S_p+S_n+S_{neu}}$. A higher Sen_{aspect} value suggests a more positive sentiment in the review text.

3.3.2. *Review aspect–based sentiment analysis with graph convolutional network–based technology*

GCN (Welling & Kipf, 2016) has demonstrated outstanding performance in artificial intelligence. GCNs can handle graph structure data better than convolutional neural networks (Krizhevsky et al., 2017). Corresponding models have shown promise with a variety of natural language processing tasks, such as text categorization (Huang et al., 2019), relation extraction (Zhang et al., 2018), and Chinese named entity recognition (Gui et al., 2019). Zhang, Li, and Song (2019) was the first to use GCN for ABSA task to acquire syntax and long-run word dependencies. The network was later adopted in numerous studies for sentiment analysis (Ke et al., 2021; Sun, Zhang, Mensah, Mao & Liu, 2019; Zhao et al., 2020, 2022). To verify the accuracy of aspect-based review sentiment using BERT technology, a SenticNet-based GCN algorithm (Sentic GCN) (Liang et al., 2022) was implemented to uncover review sentiment at the aspect level. SenticNet 6 (Cambria et al., 2020) was used as the commonsense knowledge base to adorn the graph and enhance the sentiment representations in Sentic GCN algorithm. This algorithm was also used as a robustness check of prediction performance.

Sentic GCN is a novel method for building graph neural networks by incorporating SenticNet affective knowledge to improve sentence dependency graphs. To acquire contextual representations, LSTM layers were used in Sentic GCN, and GCN layers were developed to identify connections between contextual words in specific aspects (Wang et al., 2022). This approach considers the dependencies of contextual terms and aspect terms as well as the affective information between opinion terms and aspect terms. Another benefit of Sentic GCN is that it can provide exact sentiment characteristics that correlate with multiple aspects. Three steps were conducted in Sentic GCN to capture sentiment-related dependencies between contextual words and a given aspect with high accuracy (Liang et al., 2022). To start, a dependency graph was constructed under each sentence via a dependency tree, which was used to extract the sentence's syntactical information. Next, the graph generation fused information from external affective common sense knowledge to discern emotion-related dependencies between aspect terms and contextual terms. Finally, the GCN-based model integrated the affective improved dependency graph as input to calculate the sentence's graph representations.

Fig. 3 depicts the process of calculating each review's aspect-based sentiment using Sentic GCN. We first trained the Sentic GCN model with the restaurant domain of SemEval series data (Pontiki et al., 2014, 2015, 2016). Detailed accuracy information about this model appears in Liang et al. (2022). Subsequently, aspect terms in the aforementioned dataset and review text served as input variables for the trained model. The model output consisted of aspect terms with sentiment polarity (i.e., negative sentiment, neutral sentiment, and positive sentiment). Lastly, we manually classified aspect terms (e.g., "staff" and "meats") into aspect categories (e.g., service and tastiness).

3.4. *Restaurant closures*

Restaurant survival was the key attribute of our survival analysis. We needed to know whether restaurants had officially gone out of business, and if so, when exactly they closed. We combined keyword matching with manual verification (Zhang & Luo, 2022) to determine restaurants' closing dates (if applicable) and thus survival. Yelp displays a banner indicating that an establishment is closed; However, the platform does

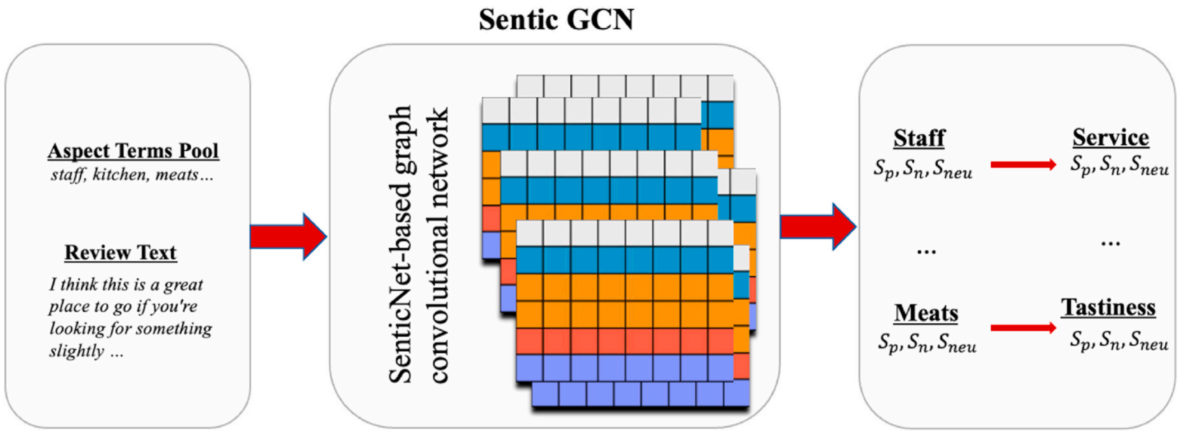

Fig. 3. Sentiment calculation based on sentic GCN

not indicate precisely when the location went out of business. We conducted keyword matching to identify closing dates. We first used Python to filter out reviews containing closure-related keywords; if no review mentioned a closure, then we took the date of the restaurant's last review as its closing date. We created a list of keywords (e.g., "open," "close," "shut down") indicating closure based on information collected from randomly chosen reviews of closed restaurants. For instance, the closing time of a restaurant was determined to be August 1, 2017, per the review "I was so excited to go to this place, but when I arrived there, the waiters told me that they would close from 1st August permanently!"; the keyword for this review was "close" (permanently). Next, as a robustness check, we recruited a research assistant to manually check the earliest review with keywords along with reviews containing keywords 3 years before the last review date. Again, if a reviewer mentioned the restaurant's closing date in the review, we took that date as the closure; the date of the earliest review containing closure-related keywords was considered the closing date otherwise. If no review mentioned closure, the latest review was regarded as the restaurant's approximate closing date. In summary, 136 restaurants were closed and 838 restaurants were open; the overall rate of restaurant failure during the study period was 14%.

3.5. Variable importance (VIMP), survival function, and risk score

Typically, the more important a feature, the greater its predictive ability. Feature importance values inform the top features that help to predict the outcome variable. The importance of each feature represents the gap between the perturbed and unperturbed error rate (Ishwaran, 2007). To determine which variable(s) were more important and predictive, we calculated the importance of all variables in our model based on variable importance (VIMP). The importance of a variable x was calculated by dropping the out-of-bag cases from the in-bag survival tree (Ishwaran, 2007). Each time that variable x was split, a daughter node was assigned randomly, after which the ensemble cumulative hazard function of the tree was extracted and averaged. Next, the VIMP value for variable x was calculated based on the prediction error difference between the original ensemble and the new ensemble randomly assigned by x (Breiman, 2001; Ishwaran, 2007).

We further sought to understand how the ABSA-CSF model (Model 3.2) predicted restaurant survival. In particular, we identified survival situations and risk score differences by comparing chain and independent restaurants, high- and low-priced restaurants. We adopted the ABSA-CSF model to estimate each restaurant's survival function from its entry year to the tenth year (i.e., 120 months). Since Yelp does not display a restaurant's opening day, we took the date of the first Yelp review of each restaurant as its entry day. We defined 10 years as the time horizon from a data-driven perspective: nearly 43% of restaurants have survived for more than 10 years, 78% for more than 5 years, and 92% for more than 3 years. Researchers normally take 3, 5, or 10 years as the timeframe for survival analysis (Balkenhol et al., 2007; Grimmett, 2016; Maajani et al., 2020). Given that nearly 80% of restaurants have been in business for more than 5 years, it is difficult to discern a clear difference in survival with a time horizon of less than 5 years. We thus used 10 years as the time frame for survival analysis.

The survival function $S(t)$ returns the probability that an object or event of interest has not occurred by time t. The survival T denotes the waiting period until an event occurs. $F(t)$ denotes the probability density function (p.d.f.) of T, and the cumulative distribution function (c.d.f.) is given by $F(t) = \Pr[T < t] = \int_{-\infty}^{t} f(u)du$. The survival function can then be computed as $S(t) = 1 - F(t) = \Pr[T \geq t]$.Corresponding to the survival function, the risk score of a sample x is $r(x) = \sum_{j=1}^{J} H(t_j, x)$, where J indicates the number of the part for subdividing the time axis; it is derived from $h(t)$ (the hazard function), which denotes the conditional probability that the event might occur in the future in $[t, t+dt)$ under the condition that it has not occurred before.

$$h(t) = \lim_{dt \to 0} \frac{\Pr[t \leq T < t + dt | T \geq t]}{dt} = \frac{f(t)}{S(t)} = -\frac{d}{dt}\log S(t)$$

Therefore, the hazard function and survival function are connected by $S(t) = \exp\left(-\int_0^t h(u)du\right)$, where $H(t) = \int_0^t h(u)du$ denotes the cumulative hazard function. The risk score of a sample x is then obtained by dividing the time into J sections as in $r(x) = \sum_{j=1}^{J} H(t_j, x)$.

3.6. Prediction accuracy evaluation

To evaluate the prediction performance of our proposed model and to test whether the ABSA of online reviews would improve the survival model's accuracy, we split our data into two groups (88% reserved for training with 12% for testing) (Shahhosseini et al., 2019). The rate of restaurant survival in the training and test sets was approximately 85.2% and 92.3%, respectively. In the testing phase, the C-index (Uno et al., 2011) and the IBS (Graf et al., 1999) were applied to evaluate prediction performance. The C-index is the generalization of the space under the receiver operating characteristic (i.e., area under curve), which can consider censored data. This index also represents a general assessment approach to determine the discriminatory power of different models. This is the ability of a model in right providing a reliable ranking of the survival times based on the individual risk scores. Its value ranges from 0 to 1, with 1 reflecting the best model prediction and 0.5 reflecting random prediction; the higher the C-index, the better the model prediction. The C-index is calculated using the following equation:

$$C - index = \frac{\sum_{i,j} 1_{T_j < T_i} \cdot 1_{\eta_j > \eta_i} \cdot \delta_j}{\sum_{i,j} 1_{T_j < T_i} \cdot \delta_j}$$

Where unit *i* represents the restaurant, and η_i indicates the risk score of *i*. If $\mathrm{T_j}$ is smaller than $\mathrm{T_i}$, then the value of $1_{\mathrm{T_j}<\mathrm{T_i}}$ is 1; if not $1_{\mathrm{T_j}<\mathrm{T_i}}$ is 0. For η_j, if $\eta_j > \eta_i$, then $1_{\eta_j > \eta_i} = 1$; otherwise its value is 0 as well.

The IBS measures a model's overall performance calculation at all available times. This metric is based on the general BS, which has been used to assess survival performance involving censored samples (Graf et al., 1999). The BS(t) is $\frac{1}{N}\sum_{i=1}^{N}\left(1_{T_i>t} - \widehat{S}(t, \vec{x}_i)\right)^2$ in the absence of right censoring, where N denotes the number of samples in a dataset, and $\forall i \in [[1, N]]$. The datapoint format is represented as $(\vec{x}_i, \delta_i, T_i)$ with the forecasted survival function $\widehat{S}(t, \vec{x}_i)$, $\forall t \in \mathbb{R}^+$. When there are right-censored data in a sample, the BS(t) is $\frac{1}{N}\sum_{i=1}^{N}\left(\frac{(0-\widehat{S}(t,\vec{x}_i))^2 \cdot 1_{T_i \le t, \delta_i = 1}}{\widehat{G}(T_i^-)} + \frac{(1-\widehat{S}(t,\vec{x}_i))^2 \cdot 1_{T_i > t}}{\widehat{G}(t)}\right)$. Here, $\widehat{G}(t) = P[C > t]$ with censoring time C, which is used to estimate the conditional survival function of censoring times via the Kaplan-Meier approach. Then the IBS $(t_{max}) = \frac{1}{t_{max}}\int_0^{t_{max}} BS(t)dt$. The lower the IBS, the higher the model's prediction accuracy.

The relative improvement between models can be measured as follows, taking the C-index as an example:

$$Improvement_{model_n}^{C-index} = \frac{C - index(model_n) - C - index(model_{n-1})}{C - index(conditon_{n-1})} * 100\%$$

$$Improvement_{model_n}^{IBS} = \frac{IBS(model_{n-1}) - IBS(model_n)}{IBS(model_{n-1})} * 100\%$$

4. Empirical results using BERT-based ABSA

4.1. Prediction performance

Table 3 lists the results of restaurant prediction performance using BERT-based sentiment analysis. We initially compared model performance when predicting restaurant survival without feature selection (i.e., Models 1.1, 2.1, and 3.1). First, according to the C-index, $\mathbf{Improvement_{C-index}}$, IBS, and $\mathbf{Improvement_{IBS}}$, the prediction accuracy increased sequentially from Model 1.1 to Model 3.1. Specifically, the C-index value consistently rose from the input X variables without review sentiment (Model 1.1: 0.5562) to the model including the overall review sentiment variable (Model 2.1: 0.6568) and then to the model with aspect-based sentiment variables (Model 3.1: 0.7370). Second, the IBS continually decreased from Model 1.1 (0.0398) to Model 3.1 (0.0387). Third, compared with the predictive accuracy of Model 1.1, the $\mathbf{Improvement_{IBS}}$ and $\mathbf{Improvement_{c-index}}$ of Models 2.1 and 3.1 were each greater than 0, further indicating an improved prediction performance from Model 1.1 to Model 3.1.

We then compared the model performance when predicting restaurant survival with feature selection (i.e., Models 1.2, 2.2, and 3.2). First, according to the C-index, the prediction accuracy increased sequentially from the input X variables without review sentiment (Model 1.2: 0.6418) to the model including the overall review sentiment variable (Model 2.2: 0.6977) and then to the model with aspect-based sentiment variables (Model 3.2: 0.7715). Second, the IBS continually decreased from Model 1.2 to Model 3.2. Third, compared with the predictive accuracy of Model 1.2, the $\mathbf{Improvement_{IBS}}$ and $\mathbf{Improvement_{c-index}}$ of Models 2.2 and 3.2 were each greater than 0, further indicating better prediction performance from Model 1.2 to Model 3.2. In summary, the proposed model (Model 3.2: ABSA-CSF) with feature selection technology demonstrated the best prediction performance among all models; the accuracy of the CSF model without any sentiment variable and without using feature selection technology (i.e., Model 1.1) had the lowest C-index and the highest IBS.

4.2. Analysis of VIMP, survival function, and risk score

In this stage, we compared and investigated VIMP in restaurant survival prediction along with the survival functions and risk scores across restaurant types using the proposed ABSA-CSF model (i.e., Model 3.2). This comparison by restaurant type can uncover valuable information based on restaurants' unique business characteristics. We divided restaurants according to whether they were either chain or independent and either high-priced ($$$ and $$$$) or low-priced ($ and $$). Our sample contained 143 chain restaurants, 831 independent restaurants, 768 low-priced restaurants, and 206 high-priced restaurants. Table 4 shows the descriptive statistics for different types of restaurants.

4.2.1. VIMP analysis

In the main analysis, we used the ABSA-CSF model with BERT-based sentiment analysis because its prediction performance was better than GCN-based sentiment analysis. Table 5 indicates the importance of restaurant features using BERT-based sentiment analysis. In terms of sentiment variables, customers' sentiments about a restaurant's service embodied the primary predictor (5.089) of survival, followed by tastiness sentiment, location sentiment, and price sentiment. The number of

Table 4
Summary statistics by restaurant type.

	Variable	Count	Mean	Std	Min	Max
Chain	Review length	214,554	100.66	92.55	1	1446
	Engagement	214,554	1.61	6.17	0	636
	Rating	214,554	4.05	1.08	1	5
	Price level	214,554	2	0.55	1	4
Independent	Review length	943,797	107.22	101.19	1	1167
	Engagement	943,797	1.75	5.88	0	655
	Rating	943,797	4.04	1.12	1	5
	Price level	943,797	2.15	0.76	1	4
Low-priced	Review length	909,210	99.83	90.96	1	1446
	Engagement	909,210	1.68	5.73	0	655
	Rating	909,210	4.04	1.11	1	5
	Price level	909.210	1.81	0.39	1	2
High-priced	Review length	249,141	128.54	123.92	1	1167
	Engagement	249,141	1.88	6.63	0	636
	Rating	249,141	4.05	1.14	1	5
	Price level	249,141	3.27	0.44	3	4

Table 3
Restaurant predictive performance using BERT-based technology.

Condition	C-index	$\mathbf{Improvement_{C-index}}$	IBS	$\mathbf{Improvement_{IBS}}$	Feature Selection
Model 1.1	0.5562		0.0398		x
Model 2.1	0.6568	18.09%	0.0392	1.46%	x
Model 3.1	0.7370	12.21%	0.0387	1.24%	x
Model 1.2	0.6418		0.0395		✓
Model 2.2	0.6977	8.72%	0.0390	1.22%	✓
Model 3.2	0.7715	10.57%	0.0385	1.23%	✓

Note: C-index and IBS were calculated using the average accuracy of the model with seed values (1–100), and they were kept to four decimal places varying by ± 1%.

Table 5
VIMP analysis using BERT-based technology.

Feature	Importance	Pct_importance
Service sentiment	5.089	0.191
Number of competitors	5.079	0.190
Tastiness sentiment	4.355	0.163
Location sentiment	3.856	0.144
Number of reviews	3.367	0.126
Rating	2.539	0.095
Price level	1.218	0.046
Review length	1.111	0.042
Price sentiment	0.098	0.004
Customer engagement	−0.482	0.000

competitors was another leading indicator (5.079) among restaurant characteristics, reflecting its importance for survival. Other review features, such as number of reviews, review rating, and review length, also possessed strong power in predicting restaurants' survival.

4.2.2. VIMP comparison among different types of restaurants

We next compared VIMP for chain and independent restaurants separately to identify pertinent distinctions. We also compared high- and low-priced restaurants. Table 6 displays the feature importance for variables in the ABSA-CSF model among these four restaurant types using ABSA-CSF model with BERT-based sentiment analysis. Several findings were striking. First, consumers' sentiments about a restaurant's price and tastiness, and the number of competitors were the optimal predictors for both chain and independent restaurants. Second, the predictive power of consumers' sentiment about service differed between chain and independent restaurants: it was not strong for chains (−0.92) but strongest for independent establishments (6.017). Third, the average rating (1.639) and consumers' sentiment about service (0.045) were leading predictors for high-priced restaurants; other indicators (i.e., number of competitors) did not hold strong predictive power. For low-priced restaurants, all indicators except customer engagement (−0.9) and review length (−0.99) own high predicting ability for future survival. Finally, number of competitors represented a crucial predictor for most restaurants (e.g., chain, independent, and low-priced).

4.2.3. Risk score analysis and survival function estimate

Fig. 4 presents a comparison of the risk score distribution between restaurant types using the ABSA-CSF model with BERT-based sentiment analysis, while Fig. 5 displays the estimated survival function. Low-priced and independent restaurants in our sample were more likely to close than high-priced and chain restaurants. Risk scores for high-priced restaurants ranged from 5 to 10, and those for most high-priced restaurants (30%) were around 5. However, scores for low-priced restaurants exceeded 25—significantly greater than high-priced restaurants. Chain restaurants' risk scores ranged from 5 to 15; those of independent restaurants were between 15 and 40. Chains were therefore more likely to survive than independent restaurants.

5. Robustness checks

5.1. Robustness check using Synthetic Minority Oversampling Technique

In machine learning field, the dataset is typically resampled by adding additional or removing data manually (e.g., over-sampling or under-sampling) to achieve equal data dispersion. Considering that the rate of restaurant survival was unbalanced in our data (85.2% in the training dataset), we applied the widely used Synthetic Minority Oversampling Technique (SMOTE) to balance the survival rate. As an advanced over-sampling technique, SMOTE could generate new minority-class data near the minority-class sample (Chawla et al., 2002). The benefit of SMOTE is that it does not create duplicates; alternatively, it generates synthetic data points that deviate significantly from the originals. This synthetic method randomly picks sample A (the minority) and its nearest neighbour B, and the newly created minority sample is the sample between samples A and B (Zhang & Chen, 2021). After conducting data balancing with SMOTE, there were 1460 restaurants in the training dataset with a survival rate of 50%.

Table 7 showed the six models' prediction performance with BERT-based sentiment analysis using the SMOTE-based balanced training data. Table 7 indicates a similar trend as shown in Table 3. The C-index revealed that the accuracy increased sequentially from Model 1.1 (0.5893) to Model 2.1 (0.6705), and then to Model 3.1 (0.7199). According to the IBS, the model with aspect-based sentiment variables (Model 3.1: 0.0411) also achieved better performance than Model 1.1 and Model 2.1. When predicting restaurant survival with the feature selection technology (i.e., Models 1.2, 2.2, and 3.2), the $\mathbf{Improvement}_{\mathbf{C-index}}$ and $\mathbf{Improvement}_{\mathbf{IBS}}$ also showed that Model 3.2 performed the best among the three models.

5.2. Robustness check using GCN-based ABSA

Next, we considered whether the results of Table 3 would remain consistent when using a different sentiment analysis approach. We specifically conducted a robustness check using GCN-based sentiment analysis to compare the six models' prediction performance. Table 8 lists the restaurant prediction performance using this method. In terms of predicting restaurant survival without feature selection technology (i.e., Models 1.1, 2.1, and 3.1), Table 8 indicates a similar trend as shown in Table 3. The C-index revealed that accuracy increased sequentially from Model 1.1 (0.5560) to Model 2.1 (0.5970) and then to Model 3.1 (0.6597). According to the IBS, the model with aspect-based sentiment variables (Model 3.1: 0.0390) outperformed Model 1.1 (0.0398) and Model 2.1 (0.0400). When predicting restaurant survival with feature selection technology (i.e., Models 1.2, 2.2, and 3.2), the C-index showed that accuracy increased sequentially from the input X variables without review sentiment (Model 1.2: 0.6526) to the model including the overall review sentiment variable (Model 2.2: 0.6553) and then to the model with aspect-based sentiment variables (Model 3.2: 0.7247). Further, the IBS continually decreased from Model 1.2 (0.0397) to Model 3.2

Table 6
VIMP comparison using BERT-based technology.

Feature	Importance [rank] of certain type of restaurants			
	Chain	Independent	Low-priced	High-priced
Number of competitors	1.01948762 [1]	5.98900496 [2]	6.36369927 [1]	−0.1751978 [3]
Tastiness sentiment	0.98102231 [2]	1.17876341 [7]	2.54175849 [6]	−0.9176212 [6]
Price level	0.89891297 [3]	0.73160031 [8]	–	–
Price sentiment	0.23910528 [4]	2.53242193 [5]	1.6361214 [7]	−1.34156 [8]
Service sentiment	−0.9208961 [5]	6.01743904 [1]	5.33452545 [2]	0.04507154 [2]
Rating	−1.0053051 [6]	2.52802319 [6]	3.16201277 [4]	1.63886766 [1]
Location sentiment	−1.0780219 [7]	2.95302555 [4]	3.82470609 [3]	−1.1674815 [7]
Number of reviews	−1.1037293 [8]	3.03629724 [3]	2.84062515 [5]	−2.0264049 [9]
Customer engagement	−1.1354728 [9]	0.63107355 [9]	−0.9001848 [8]	−0.5171215 [5]
Review length	−1.8475268 [10]	0.41932575 [10]	−0.9884558 [9]	−0.4229589 [4]

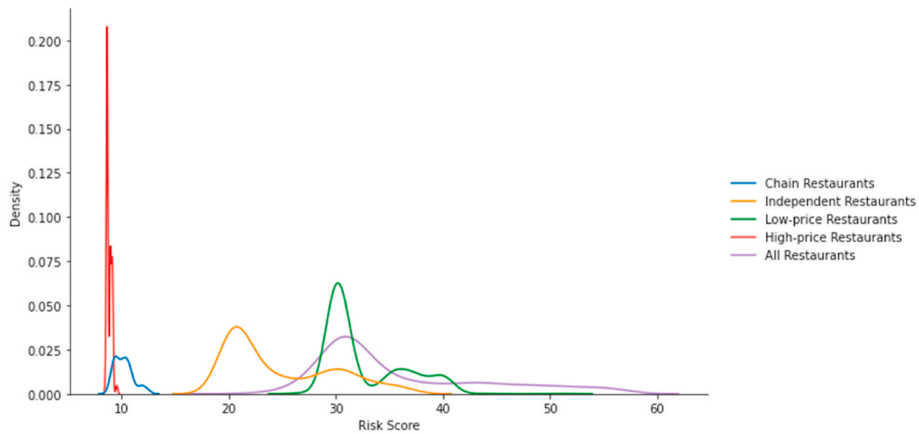

Fig. 4. Risk score distribution of different restaurants using BERT-based technology.

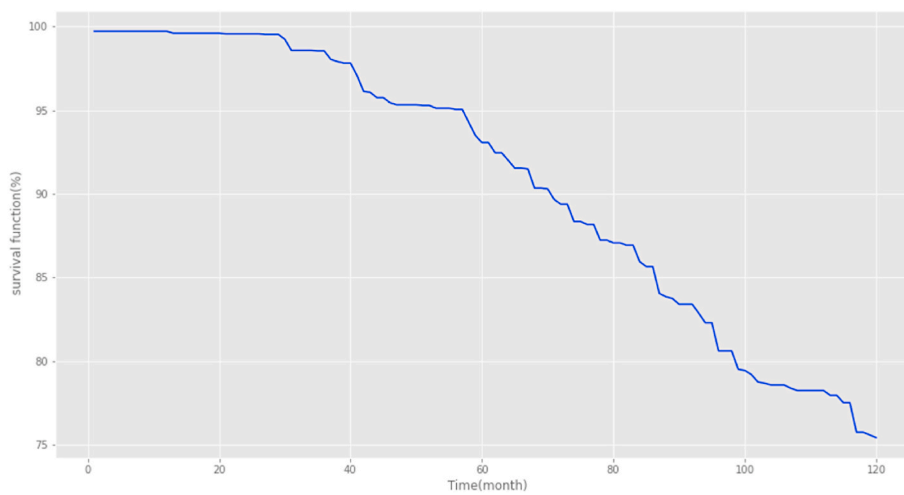

Fig. 5. Survival function estimate.

Table 7
Restaurant predictive performance using BERT-based technology (data balance).

Condition	C-index	**Improvement$_{C-index}$**	IBS	**Improvement$_{IBS}$**	Feature Selection
Model 1.1	0.5893		0.0449		x
Model 2.1	0.6705	13.78%	0.0425	5.24%	x
Model 3.1	0.7199	7.37%	0.0411	3.25%	x
Model 1.2	0.6656		0.0439		✓
Model 2.2	0.7326	10.06%	0.0411	6.56%	✓
Model 3.2	0.7684	4.89%	0.0409	0.48%	✓

Note: C-index and IBS were calculated using the average accuracy of the model with seed values (1–100), and they were kept to four decimal places varying by ± 1%.

Table 8
Restaurant predictive performance using GCN-based technology.

Condition	C-index	Improvement$_{C-index}$	IBS	Improvement$_{IBS}$	Feature Selection
Model 1.1	0.5560		0.0398		x
Model 2.1	0.5970	7.38%	0.0400	−0.38%	x
Model 3.1	0.6597	10.49%	0.0390	2.38%	x
Model 1.2	0.6526		0.0397		✓
Model 2.2	0.6553	0.41%	0.0398	−0.11%	✓
Model 3.2	0.7247	10.58%	0.0384	3.49%	✓

Note: C-index and IBS were calculated using the average accuracy of the model with seed values (1–100), and they were kept to four decimal places varying by ± 1%.

(0.0384). The results regarding restaurant survival with feature selection technology are therefore also similar to those in Table 3.

Fig. 6 depicts a comparison of the risk score distribution among different restaurant types using GCN-based sentiment analysis. The pictured trend confirms the comparison from the ABSA-CSF model using BERT-based sentiment analysis wherein low-priced and independent

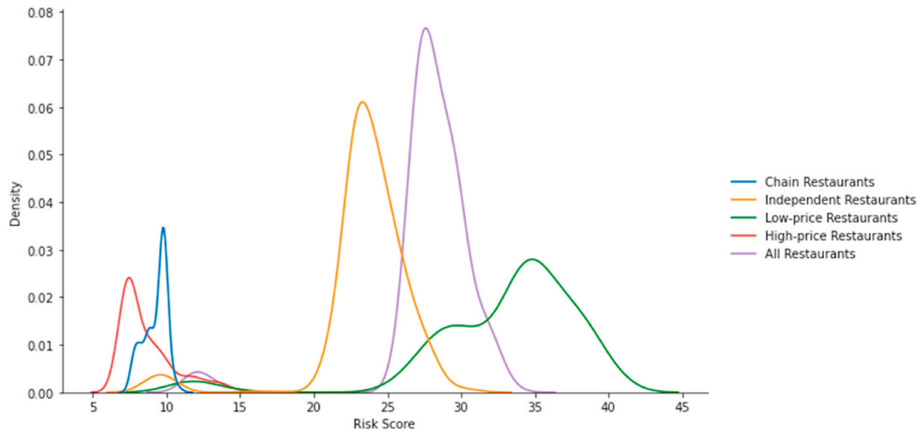

Fig. 6. Risk score distribution of different restaurants using GCN-based technology.

restaurants were more likely (vs. high-priced and chain restaurants) to face higher risks and to close.

5.3. Robustness check based on restaurants from Another City

Next, we considered whether the results of Tables 3 and 8 have external validity, specifically by performing a robustness check comparing the six groups of models in another world famous tourism destination/city in the United States, i.e., Las Vegas. We obtained the business-related and online review data for 300 restaurants in this city (401,294 reviews). Review dates ranged from January 2005 to December 2018. Among these restaurants, there were 110 closed restaurants and 190 that were open, totalling a 63.3% survival rate during the study period. Nearly 64.7% and 53% of surviving restaurants respectively appeared in the training and test sets. Table 9 provides an overview of different models' prediction performance using BERT-based sentiment analysis and GCN-based sentiment analysis, respectively. Similarly, it was found that the prediction performance of ABSA-CSF model with BERT-based sentiment analysis surpassed that wit GCN-based sentiment analysis.

According to Table 9, the prediction performance with BERT-based sentiment analysis, based on findings for the C-index, $\mathbf{Improvement}_{\mathbf{c-index}}$, IBS, and $\mathbf{Improvement}_{\mathbf{IBS}}$, indicated that prediction accuracy without feature selection technology (i.e., Models 1.1, 2.1, and 3.1) rose from Model 1.1 to Model 3.1. The C-index increased from 0.6604 to 0.7277 with an improvement rate of around 10%. The IBS improvement rate was 3.5% between Model 1.1 (0.1790) and Model 3.1 (0.1728). Meanwhile, the prediction accuracy of models with feature selection technology (i.e., Models 1.2, 2.2, and 3.2) rose from Model 1.2 to Model 3.2 as well. Regarding prediction performance with GCN-based ABSA technology, the model using aspect-based sentiment variables with feature selection (Model 3.2) also outperformed the model using overall review sentiment variable (Model 2.2) in the C-index and IBS. These results are consistent with those in Tables 3 and 8 in our main analysis. Overall, the prediction accuracy of models with ABSA technology significantly exceeded that of models without such technology. Model 3.2, with feature selection technology, demonstrated the optimal prediction performance of all models.

In the following analysis, we only showed the results of the ABSA-CSF model with BERT-based sentiment analysis because its prediction performance was better than that with GCN-based sentiment analysis. Table 10 demonstrates the VIMP Analysis for restaurant survival prediction in Las Vegas, while Fig. 7 displays the estimated survival function based on the ABSA-CSF model. According to the VIMP analysis results, some indicators were identically indicative of survival prediction between the two cities. For instance, the importance of competitors was 3.530 for Las Vegas, which informed its importance as part of the restaurant characteristics in predicting restaurant survival. Similarly, in terms of consumer sentiment, the restaurant's tastiness and location were leading indicators of restaurant survival. The number of reviews was the leading driver of restaurant survival in Las Vegas.

Table 10
VIMP analysis for restaurants from another city.

	Feature	Importance	Pct_importance
BERT-based Technology	Number of reviews	8.660	0.480
	Number of competitors	3.530	0.195
	Tastiness sentiment	3.173	0.176
	Location sentiment	2.693	0.149

Table 9
Predictive performance for restaurants from another city.

	Condition	C-index	$\mathbf{Improvement}_{\mathbf{C-index}}$	IBS	$\mathbf{Improvement}_{\mathbf{IBS}}$	Feature Selection
Using BERT-based Technology	Model 1.1	0.6604		0.1790		X
	Model 2.1	0.6917	4.74%	0.1774	0.88%	X
	Model 3.1	0.7277	5.20%	0.1728	2.59%	X
	Model 1.2	0.7133		0.1714		✓
	Model 2.2	0.7328	2.74%	0.1706	0.50%	✓
	Model 3.2	0.7698	5.05%	0.1631	4.37%	✓
Using GCN-based Technology	Model 1.1	0.6598		0.1792		X
	Model 2.1	0.6579	−0.29%	0.1800	−0.41%	X
	Model 3.1	0.6771	2.92%	0.1784	0.88%	X
	Model 1.2	0.7150		0.1708		✓
	Model 2.2	0.6946	−2.86%	0.1749	−2.42%	✓
	Model 3.2	0.7235	4.16%	0.1732	0.99%	✓

Note: C-index and IBS were calculated using the average accuracy of the model with seed values (1–100), and they were kept to four decimal places varying by ± 1%.

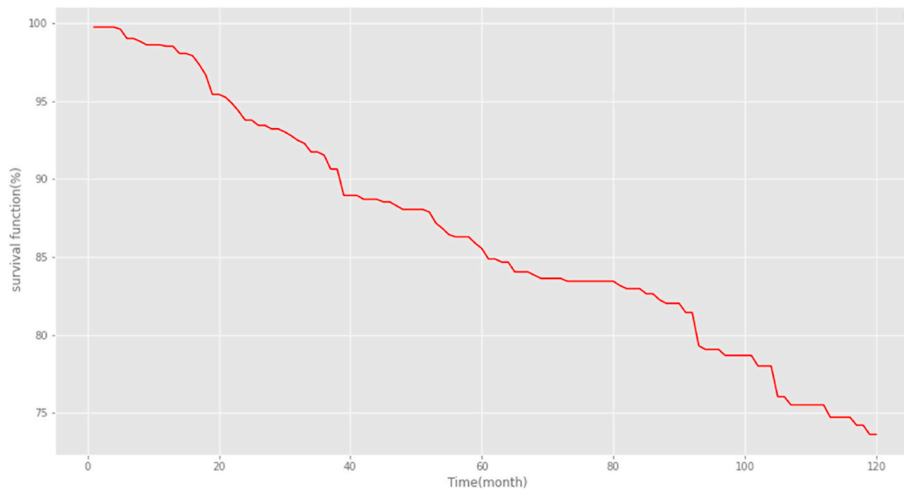

Fig. 7. Survival function estimate for restaurants from another city.

6. Conclusion and discussion

By employing the CSF model, we confirmed the feasibility of using customer-generated content to predict restaurant survival and investigated whether modelling with ABSA demonstrates stronger predictive power versus models using overall online review sentiment. Specifically, online review sentiment was found to significantly improve the prediction performance of restaurant survival. In this regard, we specified models without sentiment, with overall sentiment, and with aspect-based review sentiment to compare their prediction performance on restaurant survival. The results turn out that aspect-based review sentiment significantly outperformed models with overall review sentiment and models without sentiment in terms of prediction accuracy.

In addition, we calculated the feature importance of different aspect-based sentiments in restaurant survival prediction. Sentiment related to a restaurant's location and tastiness of food were essential for predicting restaurant survival. This outcome is congruent with Parsa et al. (2005) and Parsa et al. (2011), who indicated significant effects of location and food quality on restaurant survival. We then went a step further and considered how features of different importance informed prediction for different types of restaurants. We conducted feature importance analysis separately after the sample was subset by independent/chain and low/high price level. We found tastiness sentiment was important aspect for chain restaurant survival prediction. Conversely, service, location, and price sentiment appeared to be especially impactful for independent restaurants. This finding may be attributable to chain organizations' established brand identities, greater customer loyalty, and more effective marketing strategies, all of which reduce these restaurants' location dependence (Camillo et al., 2008; English et al., 1996). Independent restaurants, in contrast, are more likely to enjoy benefits from superior locations, value for money and good service. Observation from visualized survival function suggested that chains were more likely to survive than independent restaurants during the whole course of our analysis. Comparisons of low- and high-priced restaurants revealed that higher-priced restaurants were more likely to survive for longer than low-priced restaurants (i.e., low-priced restaurants had a lower average survival rate than high-priced ones). The intensive capital investment, larger size, and greater operational complexity of high-priced restaurants may explain this outcome (O'Neill & Duker, 1986; Parsa et al., 2011, 2015). Moreover, the number of competitors remains a leading indicator for predicting independent and low-priced restaurants' survival, and also exerts a strong influence on the chain restaurants' survival.

6.1. Theoretical implications

By using online reviews to predict restaurant survival, this study contributes to the literature in a few ways. First, this research is one of earliest efforts in tourism and hospitality to predict restaurant survival based on real online review data. Unlike previous research that utilized small sample size collected by survey or financial indicators disclosed by limited entities, we analyzed restaurant online review data from Yelp to extract informative indicators and demonstrated a good performance in predicting restaurant survival. In addition, this study is one of the earliest attempts to conduct a longitudinal study that collects data of 15 years and covers 10-year horizon for survival analysis after the restaurant's entry at a monthly interval. The analysis horizon and granularity offer insights from a long-term perspective compared to the majority that only focused on the upcoming 5 years at most.

Second, we made an initial attempt to apply ABSA to online reviews to predict restaurant survival. Our work marks an early effort to compare review analyses without sentiment, with overall sentiment, and with aspect-based sentiment in predicting restaurant survival. Although review information has shown predictive power in relation to restaurant survival (Zhang & Luo, 2022), no other study appears to investigate the incremental predictive power of fine-grained ABSA in restaurant survival. Unlike previous research that used consumer overall sentiment, we decomposed the sentiment by important aspects that were pre-identified and extracted the associated sentiment for each aspect from their review text. Consumers are not viewing each aspects of the experience equally important; certain aspects outweigh others which requires additional focus and constant optimization that instantly cater to consumers' feedback. Introducing ABSA into prediction modelling paves way for granular analysis of the sentiment of certain aspect and implies concrete operation strategies to the business owners for a more reasonable resource allocation.

Third, we have expanded the methodology of restaurant survival analysis. This study is one of the first to employ conditional survival forest for business survival analysis in tourism and hospitality and propose ABSA-CSF based on feature selection for optimizing the prediction performance. Previous studies firstly started with traditional qualitative methods (e.g., Camillo et al., 2008) or quantitative approaches such as proportional hazard regression models (e.g., Parsa et al., 2011; Zhang & Luo, 2018), survey methods (Cant & Erdis, 2012) or mixed methods (Parsa et al., 2015) and then introduced machine learning techniques that are more distribution-free, efficient and robust (e.g., Kim, 2011; Li & Sun, 2012). In addition, prior works devoted to predicting business failure mainly came from the finance domain, which commonly matched each failed sample with a corresponding non-failed sample that has the nearest total asset (Li & Sun, 2012) to create balanced dataset for fitting conventional statistical model; the choice-based sample bias is inevitable (Kim, 2011). In contrast, this study not only utilized real-world online data for the survival analysis of restaurants in order to maintain data authenticity and fidelity, but also used the data balance technology to guarantee the validity and stability of our method. Despite a number of works has demonstrated the superiority of using machine learning models that include support vector machine and artificial neural network over conventional statistical models (e.g., multiple discriminate analysis) to predict firm bankruptcy (e.g., Kim, 2011), we proposed a state-of-the-art machine learning–based model, ABSA-CSF, based on the CSF algorithm. Our model overcomes the large-scale data problems and proportional hazards assumption issue of traditional survival models (e.g., the Cox proportional hazards model or regularized Cox models). By automatically identifying which factors are most crucial for restaurants' survival prediction, the model is built with the optimal feature combinations that contributes to better prediction performance. Empirical results demonstrate that the proposed model can use large-scale online UGC to predict restaurant survival effectively and efficiently.

6.2. Managerial implications

This study provides several practical implications for the restaurant industry and relevant stakeholders. First of all, catering establishments should recognize the role of online customer reviews in business survival. Restaurant managers should monitor online platforms especially closely to improve business performance based on consumer feedback. Second, our results provide insight into the relative importance of multiple aspects in business survival. Restaurants can apply our model to identify which factors are most essential to its survival. In particular, because features hold differential importance across restaurant types and price levels, restaurant managers can better allocate their resources and attend to aspects that are more influential for business survival. Restaurants can then improve their performance accordingly. Third, based on the algorithm of the restaurant survival function, we could compute the risk score for each restaurant at a specific time. Risk management is critical for companies to prevent business failure (Piatt, 1992). By using the proposed algorithm (i.e., the conditional random forest survival model), practitioners can better understand their businesses' risk levels and make corresponding strategic adjustments.

6.3. Limitations and future research

Similar to other studies, our work suffers from a few limitations. First, due to the data availability limitation, additional factors such as restaurants' marketing tactics, managerial practices, and financial status could be investigated in the future to make better-informed survival predictions. These characteristics should be included when such data are available. Second, fraudulent or manipulated reviews are increasingly common: companies may defame their competitors by posting negative reviews while publishing positive reviews for themselves (Li, Meng, et al., 2020). The credibility of some reviews is therefore suspect. Subsequent work can exclude reviews with low credibility by constructing indices to generate more accurate results. Third, we only used data on restaurants in two U.S. cities; researchers can apply the same method to investigate other regions and different types of hospitality products. Lastly, the catering industry is highly susceptible to external environmental conditions. Hospitality establishments also have much higher survival rates during economic booms (Gemar et al., 2019). The COVID-19 pandemic has subjected many restaurants to sharp decreases in sales and even bankruptcy (Song et al., 2021). It is therefore important to explore the predictive effects of online customer reviews on restaurant survival during this time.

Author contribution statements

Hengyun Li, Huicai Gao, Bruce X.B. Yu designed the research framework and derived the models, as well as contributed to the manuscript writing. Gang Li provided suggestions for improvement of the research design, and made a major revision on the manuscript.

Impact statement

This study investigates the effect of customer-generated content (i.e., online reviews) in predicting restaurant survival. Restaurant investors and owners can better understand their businesses' circumstances based on aspect-based sentiment analysis involving customer-generated content. The impacts of this study are summarized as follows:

- **First of all,** catering establishments should recognize the role of online customer reviews in business survival. Restaurant managers should monitor online platforms, and identify their firms' competitiveness compared with close competitors and shift their business and marketing strategies accordingly.
- **Second**, catering establishments can apply our model to identify which factors are most essential to its survival, and allocate resources to prioritize the factors that most strongly influence their businesses' prosperity.
- **Third**, by using the proposed algorithm (i.e., the conditional random forest survival model), practitioners can better understand their businesses' risk levels at certain time and make corresponding strategic adjustments.

Declaration of competing interest

None.

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