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Predicting and interpreting digital platform survival: An interpretable machine learning approach

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A R T I C L E I N F O

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A B S T R A C T

Despite the substantial economic impact of digital platforms, research on platform risk evaluation has been sparse. In this study, we investigate whether online content can serve as leading indicators of digital platform survival. We employ machine learning techniques to extract features from three types of online content, that is, user generated content, platform generated content, and third party generated content and examine their utilities in predicting platform survival. Using a predictive XGBoost algorithm and data crawled from a leading web portals of digital platforms for online lending in China, we find online content are strong predictors of platform survival. Furthermore, we use casual forest models to reveal the differences among the three type of online content in terms of predictive utility. Interestingly, we find the presence of third-party generated content indicates lower probability of platform survival while the platform with more user generated content has higher chance to survive. The relationship between platform generated contents and platform failure is not significant. Based on the results, we provide practical implications for market managers and platform owners.

1. Introduction

In recent years, the boom in the digital platform economy has spawned a large number of platform-type firms. Platform-type firms, as opposed to traditional businesses, are embedded in a large amount of information and high-frequency communications supported by digital technology, thus attracting a diverse set of actors involved. It expands the boundaries of platform governance beyond the scope of traditional organizations and evolves into an ecosystem with multiple relationships centered on the platform (Jacobides et al., 2018; Rolland et al., 2018). If successful, the ecosystem can provide the platform with ongoing social and economic value, but it also exposes the platform to complexity, making it fragile and prone to failure (Jacobides et al., 2018; Wang, 2021). Reeves et al. (2019) demonstrate that less than 15 percent of the platforms could survive in the long run, and called on researchers to study the problem of high platform failure rate.

However, current research focuses primarily on successful platforms that can be easily observed at the top of the industry, leaving a large number of failed cases in the dark. Drawn on platform ecosystems literature, researchers demonstrate that factors influencing the success of a digital platform are the continuous contribution of developers in platform ecosystems (Parker and Van Alstyne, 2005), the actors' commitments to the platform (Jacobides et al., 2018), and the coordination of actors' interests in the platform (Kretschmer et al., 2020). These studies underline the importance of actors in platform success and the fact that actors are a double-edged sword to the platform. Because they are trapped in their qualitative analysis of certain star platform cases, the research on how actors are related to platform failure in a broader scenario is nascent.

Online content generated by actors is knowledgeable and influential (Goh et al., 2013; Song et al., 2019; Timoshenko and Hauser, 2019; Kilanioti and Papadopoulos, 2023), and actors expose content about platforms with interrelated social or economic purposes (Adner, 2017; Gulati et al., 2012; Kapoor, 2018). For example, customers share their experiences, platform marketers attract and sustain customers, and third-party media exhibit their expertise to gain followers. It is a great challenge for the platform to manage and coordinate such multiple online contents because it complicates the platform information environment and may mislead both customers and platforms. Therefore, we argue that the contents generated by the platform's key actors, such as

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1567-4223/© 2024 Elsevier B.V. All rights reserved, including those for text and data mining, AI training, and similar technologies.

customers, platforms, and third parties, have strong relationships with digital platform survival, which is rarely studied by researchers.

To fill in these research gaps, we use interpretable machine learning approaches to investigate the problem of platform failure with various types of online content and try to figure out which kinds of platforms are more likely to survive. We start by extracting text features from multi-source online content using several text mining techniques. Second, we demonstrate the importance of each feature by using the XGBoost technique to build a platform failure prediction model based on extracted text features. Finally, in order to better understand the relationships between multiple online contents and platform failure, we use an interpretable causal forest technique to analyze in which feature condition the platform has a high probability of failing.

This study makes several contributions to extant literature. First, this research contributes to the digital platform survival literature to study platform survival from a multiple online content lens. Second, we are the first to look into platform survival drawing on the view of the platform ecosystem, combining the platform fundamentals with the multi-types of online content generated by various actors. Unlike previous studies that focused solely on a subset of online content, we analyze the entire online content in the platform ecosystem and provide a view of online content effects on platform survival from four dimensions. Third, owing to our interpretable approach, we are able to illuminate heterogeneous relationships between textual features and platform failure among samples, which may enlighten future research.

Our study has significant practical implications for digital platform risk management with our online content prediction models and remarkable feature analysis. From the perspective of platform customers, our study provides a guideline for identifying reliable platforms and avoiding platform failures. From the perspective of platform managers, our study highlights the importance of monitoring the platform's external information environment, which includes not only the attitudes of customers and third-party media but also the topics they discussed. We also present a demo to notify platform managers of the impending failure of the platform. Moreover, this study is also of great reference value to managers because causal trees can provide specific guidance for managers to strategically formulate management strategies.

2. Literature review

2.1. Platform ecosystem and platform survival

Digital ecosystems refer to connections between a loosely coupled set of autonomous actors and the central platform (Wang, 2021) in order to foster entrepreneurial actions following the direction of platform owners coordinately (Wareham et al., 2014) or to match transactions among distinct groups of actors (Cennamo and Santalo, 2013). Platform owners, users, and stakeholders, such as content producers and advertisers, are among platform actors (Perks et al., 2017; Qiu et al., 2017). Stakeholders and users are willing to share dynamic opinions and knowledge about products, services, and so on. Not all of them are beneficial to platforms. Many platforms struggled and failed due to the failure to deal with actor relationships (Wang et al., 2021). It is crucial for platform owners to direct the content generated by actors in a way that benefits the platform.

The extant research investigates the determinants of the success of several well-known digital platforms through qualitative analyses. For example, Parker and Van Alstyne (2005) argue that the continuous contributions of developers in platform ecosystems give platform firms more chances at success. Jacobides et al. (2018) demonstrate that the commitments among actors are critical factors affecting ecosystem emergence. Kretschmer et al. (2020) point out that successful platform ecosystems require coordination among multiple participants with conflicting interests. These studies underline the importance of actors in platform success and the fact that actors are a double-edged sword to platform survival. Actors and their generated contents have the power to induce platform failure, while research on actors and platform failure is still lacking.

2.2. Multiple online contents

One of the unique characteristics of digital platforms is the simultaneous appearance of a large number of online content created by multiple actors. Several researchers study online content in different digital platform contexts. User-generated content (UGC), the most common type of online content, has been widely studied in social networks, e-commerce, online brand communities, etc., and has demonstrated a significant effect on economic outcomes, such as product sales (Choi et al., 2019; Rosario et al., 2016), firm value (Chen et al., 2012; Tirunillai and Tellis, 2012) and so on. Blankespoor et al. (2013) find that firm-generated contents are linked to market liquidity. Recently, researchers gathered UGC and MGC to evaluate their integrative effects. According to Goh et al. (2013), UGC and MGC have a strong impact on customer purchases. UGC and MGC are compared in terms of their impact on box office revenue (Song et al., 2019) and brand performance (Gopinath et al., 2014). In addition, news produced from third-party media is regarded as a standard signal for the movement of listed companies' stock prices. Although these three types of online content are excellent indicators of business success, it is unclear how such online contents from multiple actors relate to platform survival. Instead of focusing on business success, this study undertakes a series of analyses to predicate platform failure by integrating multiple online contents and then resolve the role of online content features in platform survival.

2.3. Interpreting machine learning methods

2.3.1. Overview

Although earlier prediction studies adopt black-box approaches, such as machine learning approaches and neural networks, more recent work has begun to adopt interpretable approaches to serve academic explanations better. For academic research, the provided explanations can help scholars easily understand the paper and extend the latent theoretical contributions for research. Interpretable machine learning techniques can be divided into two categories based on when the interpretability is obtained: intrinsic interpretability and post-hoc interpretability (Du et al., 2019). Intrinsic interpretability is achieved by creating self-explanatory models, also known as a glass box, that incorporates interpretability directly into their structures. This category includes decision trees, rule-based models, linear models, and attention models. The post-hoc method, on the other hand, necessitates the development of a second model to provide explanations for an existing model. The first interpretation model is more popular in the academic area because it can provide accurate and true interpretation, so it is called a glass box, while the post-hoc interpretation model can only open part of the black box, according to the explanation demand such as sensitive analysis (Rai, 2020). Hence, we adopt XGBoost and causal forest, two kinds of decision tree-based machine learning approaches, to predict and interpret platform survival from multiple online content perspectives.

2.3.2. Extreme gradient boosting

The XGBoost model, which stands for Extreme Gradient Boosting, is a decision-tree ensemble machine learning algorithm that utilizes gradient boosting with multiple Classification and Regression Trees (CART) (Chen and Guestrin, 2016). It builds a model with higher accuracy by combining multiple tree models with lower classification accuracy, Training an XGBoost is an iterative procedure that computes at each step the best possible split for the trees and enumerates all the possible trees still available at that point in the path. Given the loss function, gradient boosting seeks to minimize the overall error by measuring the loss function's local gradient for the available set of parameters, iteratively tweaking them in the direction of the descending gradient.

XGBoost has been used in detecting and predicting research in recent research. Tadesse et al. (2018) adopted XGboost to detect individuals' personality traits based on user behavior on Facebook. XGBoost is regarded as the base classifier for predicting the bankruptcy of Small-Medium Enterprises (Kou et al., 2021) and scoring the performance of online workers in reputation systems (Kokkodis, 2021). This study chooses the XGBoost approach because it offers several advantages in our research context. First, in our dataset, the content types owned by a focal platform are not all the same, and missing data often occurs. XGBoost can address missing values in the dataset and scale to meet the dataset's size fluctuations. Also, XGBoost performs well in various competitions and studies (Torlay et al., 2017). Furthermore, it can provide an important ranking of features, allowing us to open the black box and make our research more interpretable.

2.3.3. Causal forest

The causal forest is an advanced machine learning method for estimating heterogeneous treatment effects (Wager and Athey, 2018). Similar to random forests (Breiman, 2001), causal forests attempt to find neighborhoods in the covariate space, also known as recursive partitioning. While a random forest is built from decision trees, a causal forest is built from causal trees, where the causal trees learn a low-dimensional representation of treatment effect heterogeneity. Importantly, the splitting criterion optimizes for finding splits associated with treatment effect heterogeneity and finding leaves where the treatment effect is constant but is different from other leaves. The benefit of this is obvious, the model can learn and split the data to decompose the global average treatment effect in the population into various sub-population local treatment effects without making any assumptions about possible linear, non-linear, or interactive model specifications. Luo et al. (2019) provide an example of employing causal forests in business analysis. In their research content, the customers they studied are different in their purchase history, and their purchase reactions to e-commerce cart targeting manipulation are different. Causal forest excels at splitting the heterogeneous reactions of sub-samples and providing heterogeneity effects among individuals in the sample, rather than a roughly pro/con effect between independent and dependent variables. Taking advantage of the causal forest technique, we apply an additional analysis after the prediction to interpret the effects of online content features and allow us to provide specific implications for the industry.

3. Data and variables

3.1. Data

This study utilizes a unique dataset from Wangdaitianyan, a popular online P2P lending community in China. This community ensembles information generated by multiple actors of platforms, including customer-generated content, platform marketer-generated content, and third-party media reporting. The community captures complete external information contents about each platform because when the information appears in other channels, the community also crawls and filters it. Our data is collected from the backend database. This dataset contains 5045 platforms and 573,435 text records generated by customers, marketers, and third-party media from 2011 to 2018. It tracks the platforms' metadata and multiple sources of online content from infancy to maturity. In detail, UGCs are short reviews from the review section and long essays from the forum section of the community; MGCs are contents generated by platform marketers, such as advertising and promotion notifications; third-party contents are news, investigative reports, expert notes, etc.; the platform fundamentals are integrated with platform voluntary disclosure and policy requirements. The numeric summary of online content from various actors is shown in Table 1.

Table 1
Summary of online contents from multiple sources.

	UGC		Platform generated content	Third-party generated content
	Short	Long		
Total volume	357,604	201,392	5017	9422
# of platform has	2687	1984	287	830

3.2. Platform basic variables

According to the platform ecosystem framework, both internal and external platform features influence the development of digital platforms. Here, we collect the platform's basic attributes from the platform's initial information, endorsement, and operation, as shown in Table 2. Other relevant platform studies have considered similar factors as the fundamentals of platforms. For example, Wang et al. (2016) consider the platform region; Li et al. (2010) focus on the firm operations. As Milian et al. (2019) suggested, we also add the policy effect into our control. The external platform attributes from online content are depicted in section 4.1.

4. Analysis approaches

In this section, we describe the components of our framework to predict and understand digital platform survival from multiple online content perspectives. This study presents two interpretable machine learning approaches, XGBoost, and causal forest, to predict and understand platform survival from a platform ecosystem perspective. This study develops the variables engineered by mining the specific features extracted from multiple sources of online content and collecting platform attributes within the organization. By leveraging a series of platform features, this study begins by predicting platform survival using the XGBoost method and identifying the influential features from a set of platform features. Then a causal forest is built on the identified key features to mine the potential causal relationships between features and platform survival, which helps us understand in which conditions the platform is more likely to fail. The research framework of our analysis is depicted in Fig. 1.

Table 2
Summary of platform basic variables.

Variable	Meaning	Mean	Std. dev
$Rugulations_j$	The number of regulations issued monthly	0.853	1.277
$Location_i$	Location of platform i	1.904	2.087
Log $RegistFund_i$	The logarithm of registration fund of platform i	0.806	0.123
$LaunchYear_i$	The year of platform i launch online	0.774	0.076
$LaunchMonth_i$	The month of platform i launch online	6.794	3.107
IPO_i	Whether platform i has listed parent company	0.017	0.129
VC_i	Whether platform i got venture capital.	0.036	0.187
$BankDepos_i$	Whether platform i have monetary depository with third party bank	0.099	0.298
$Associa_i$	Whether platform i joined official Internet Financial Association in China	0.030	0.170
$StateOwned_i$	Whether platform i has a state-owned parent company	0.026	0.158
$Rate_i$	The average rate of loans	12.932	6.560
$Period_i$	Loan periods (Ordinal variable)	3.002	0.789
$LoanType_{i,k}$	Loan type k of Platform i	1.681	1.739
$GuaranteeType_{i,k}$	Risk guarantee type k of Platform i	0.908	0.939
$DebtTrans_i$	Whether the loan can be sold in the secondary market	0.136	0.342

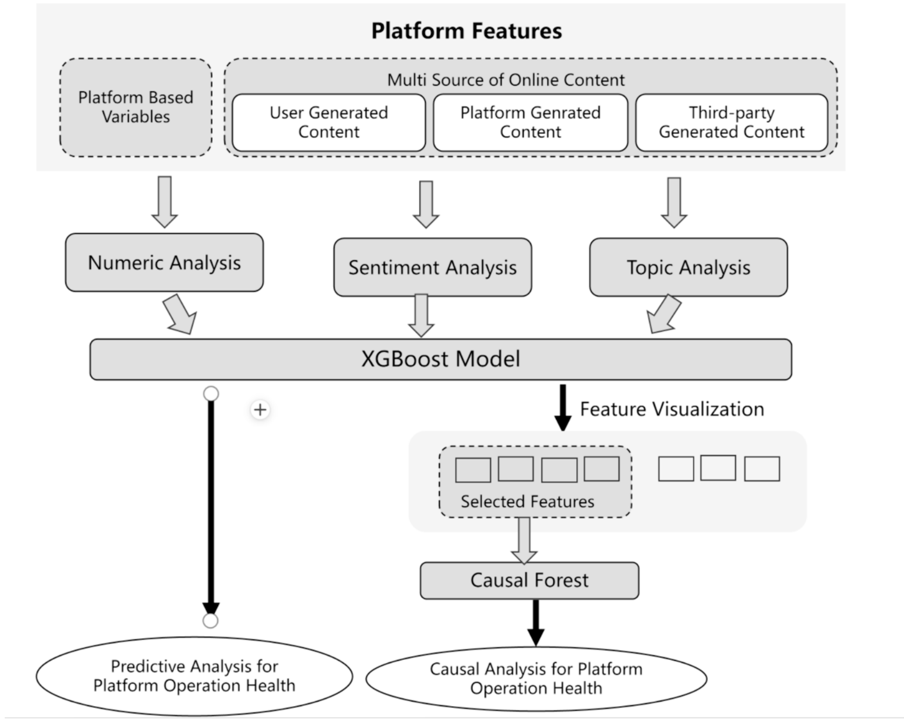

Fig. 1. Research framework.

4.1. Online content feature generation

This section describes the procedure of mining the features extracted from multiple sources of online content. The three types of online content are processed by numeric analysis, sentiment analysis, and topic analysis (shown in Fig. 2).

In numeric analysis, we first check whether the focal platform has short reviews, long essays, platform-generated content, and third-party content or not, respectively. If the focal platform has one of them, we computed the total number of each type of content and its average length of documents. We also collect some type-specific features, such as the average comment number of third-party content and long essays and the average view volume of reviews and essays, because the Wangdaitianyan does not collect for other types.

In sentiment analysis, following the sentiment extraction approach (Zhang et al. 2022), we compute the positive, neutral, negative, and hostile sentiments for each type of online content. To address the challenges of sentiment analysis for extracting contextual semantic meanings, we integrate a domain-related corpus, the word embedding technique (Word2Vec), and the bidirectional long-short-term memory (Bi-LSTM) to extract user sentiment towards platforms. We obtain the sentiment labels identified by the platform to train the model based on the contextual-aware recurrent neural networks (Word2vec and Bi-LSTM). For the platform with more than fifty documents, we compute

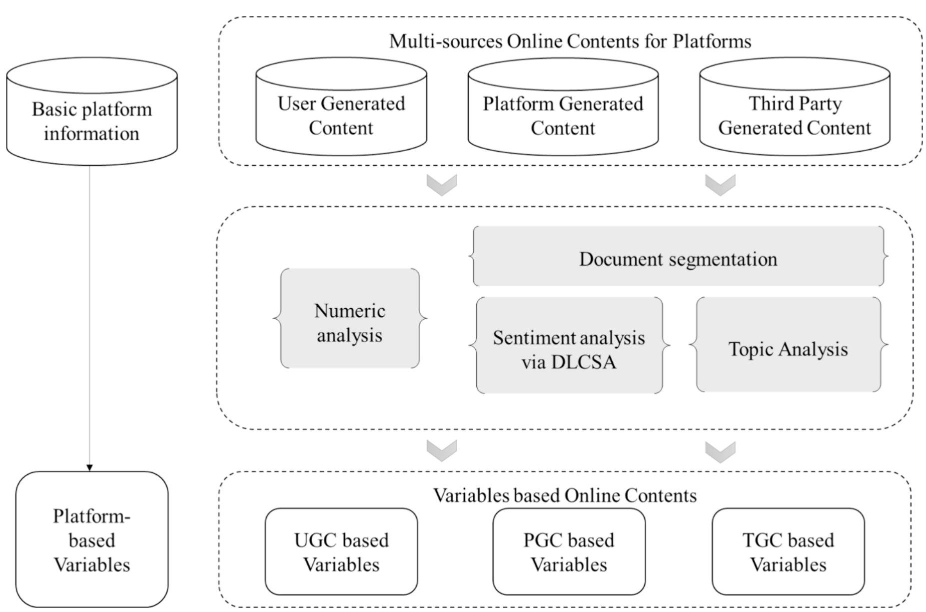

Fig. 2. Variables of platform failure prediction.

the valence of each sentiment. The framework for sentiment analysis is in Fig. 3.

In topic analysis, we first segment all documents into sequences of words and phrases by Jieba,[1] a popular Chinese segmentation tool. The term frequency-inverse document frequency, namely TF-IDF, is used to transform documents into numbers (Aizawa, 2003). The intuition of TF-IDF is to weigh the words (also phrases in Chinese) by evaluating how relevant a word or phrase is to documents in a collection of documents. To extract the topics of documents, a common method, Linear Discriminant Analysis (LDA), is used (Blei et al., 2003). LDA aims to find topics that the document belongs to based on words and phrases within it. It assumes that documents with similar topics will use a similar group of words. LDA enables the documents to map the probability distribution over latent topics and topics are probability distribution. The combined application of IF-IDF and LDA is the most popular method for performing topic modeling. Table 3 represents the results of our topic modeling and the major topics in Wangdaitianyan are seven. By summarizing the meaning of the most weighted words in a topic, we name the seven topics as Platform status, Marketing for attracting new customers, Risk of the platform itself, Marketing for Retaining extant customers, Risk of platform products, Illegal cases, Positive impression and transform them into Categorical variables. In addition, we also follow the method introduced by and calculate the similarity of each document and average them in each type of content for a focal platform.

4.2. Leveraging multiple online content to predict platform survival via XGBoost model

We leverage the platform's basic attributes and online content features to predict platform survival using XGBoost. The main reasons for using the XGBoost model in our paper are twofold. First, XGBoost is an ensemble machine learning algorithm based on decision trees. It constructs a high-accuracy model by combining multiple tree models, each with lower classification accuracy. Training an XGBoost model is an iterative process where, at each step, it calculates the best possible split for a tree and exhaustively enumerates all possible trees on available nodes along the path. XGBoost attempts to minimize the overall error by iteratively adjusting in the direction of gradient descent, measuring the local gradient of the loss function under the given loss function conditions. Second, in our dataset, the platform possesses different types and quantities of content, often leading to situations with uneven data scales. XGBoost is well-suited to address the issue of imbalanced datasets and can scale according to fluctuations in dataset size.

Referring to the general method of machine learning, XGboost divides the data into training and testing sets, training the classifier model on the training set and predicting on the testing set using the model trained on the training set. Cross-validation is used to assess the performance of the model. In terms of tuning parameters of the XGBoost model, we adopt grid search to find the optimal values of hyper-parameters. The grid search helps to loop through predefined hyper-parameters, fit the model on the training set, and select the optimal parameters from the listed hyper-parameters. The optimal parameters were determined by the area under the curve (AUC) of the receiver operating characteristic (ROC) (Bradley, 1997). We also recall (R), precise (P), and F-score (F1) to evaluate the performance of the XGBoost model.

Furthermore, the XGBoost package provides a function for calculating main importance metrics, which quantify the importance of all features trained on by the model. There are three methods to compute the feature importance, "weight," "gain," and "cover'. Rather than defining "gain" and "cover" to evaluate algorithm performance, weighted importance is defined with economic meanings. The definition of weighted feature importance is the number of times a particular feature crops up in the trees (Shi et al. 2019). We incorporate this function to identify the key features of the platform failure.

4.3. Understanding platform survival with causal forests model

The unique advantage of the causal forest model is that identify the estimates of treatment variables rather than maximizing the prediction performance. The causal forest model can infer the treatment effects by building causal trees similar to propensity score matching (Wager and Athey, 2018). It is an excellent tool for extracting the effects of interested variables on the outcomes. Different from the XGBoost model, which is built on a single independent variables group, the causal forest model has three types of variable groups, the independent variable group, the confounding variables group, and the treatment variable group (Athey et al., 2018). The confounding variable group consists of control variables that eliminate the heterogeneity between subsamples, just like the confounding variable in propensity scoring matching. The treatment variable group is the treatment of the potential outcomes. The assumption that treatment variables should be independent of potential outcomes conditional on controls is acquired (Wager and Athey, 2018). The independent variable group contains the variables that the researchers are interested in.

Based on the top 30 important variables we identified by the XGBoost prediction model, we built a causal forest model to explain the relationships between multiple online contents and platform failure. As we mentioned in the literature review, whether and how online contents are related to platform failure is our research question. To address it, we define whether a focal platform generated content by itself, generated content by third parties, or generated short reviews and long essays by users, respectively, and estimate the effect of each treatment vatable with a separate causal forest model. The important features form the independent variable group, and the remaining variables are in the confounding variable group.

5. Results

5.1. Performance of XGBoost prediction

We find the model performs best when the max depth is nine and the minimum child weight is four. Table 4 shows the cross-validation results of three-fold, five-fold, and ten-fold. We also employ the decision tree and random forest model as the baseline model. We show the comparison result of these models in Table 5. We find that the AUC of our XGboost model is 0.020 and 0.030 higher than the decision tree and random forest model, respectively. In the literature, a 0.01 improvement in AUC can be considered a noteworthy gain (Iyer et al., 2016). To test the stability of prediction accuracies, we produce the cross-validation ten times in these three models and show that XGBoost steadily outperforms other tree-based methods, as shown in Fig. 4. Therefore, the XGBoost model performs better prediction power than the baseline model. The consistent results are shown in the confused matrix of XGBoost and the Logistic model that involves platform fundamentals and online content features (see Fig. 5).

More importantly, the importance of online content in digital transaction platform failure is verified. We compare the performance of the models obtaining online content features and without the online content features. The results show that by involving online content features, the AUCs of the three prediction models have improved by 0.349, 0.389, and 0.371, respectively. All of them demonstrate that the features from online content have a great accuracy improvement for digital transaction platform failure.

5.2. Feature importance from XGBoost

XGBoost provides a function to obtain main importance metrics to

[1] Jieba is one of the best Python Chinese word segmentation modules. https://github.com/fxsjy/jieba.

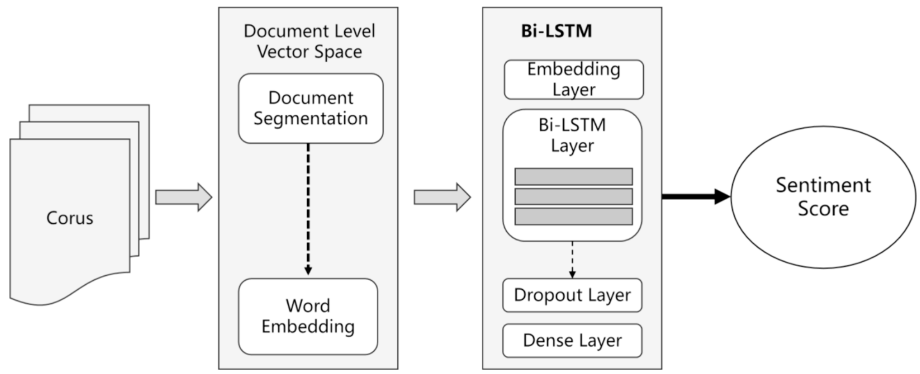

Fig. 3. Deep learning based sentiment analysis.

Table 3
Results of topic modeling.

Topic No.	Topic	The List of Topics
0	**Platform status**	是否, 失联, 跑路, 老板, 怎样, 提现困难, 担保, 抓, 是否是, 谁 Whether, missing, running away, boss, how, cash withdrawal difficulties, guarantee, catch, whether, who
1	**Marketing for attracting new customers**	登录, 奖励, 元, 活动, 红包, 新人, 注册, 您, QQ, 帐号 Login, reward, yuan, activity, financial stimuli, newcomer, registration, you, QQ, account number
2	**Risk of platform itself**	怎么样, 哪些, 安全, 如何, p2p, 可靠, 网贷, 理财产品, 收益, 是否 How, which, safe, how, p2p, reliable, online lending, financial products, benefit, whether
3	**Marketing for Retaining extant customers**	福利, 赢, 倍, 大礼包, 享, 礼包, 好礼, 发标, 礼, 泄露 Well-being, Win, Double, Big Gift Bag, Enjoy, Gift Bag, Good Gift, Biding, Gift, Leak
4	**Risk of platform products**	多少, 贷款, 怎么样, 多久, 理财平台, 理财产品, 逾期费, 靠谱, 回款, 到期 How much, loan, how, how long, investment platform, investment products, overdue fees, reliable, repayment, maturity
5	**Illegal cases**	警方, 非法, 通报, 吸收, 涉案, 公众, 嫌疑人, 案件, 分局, 涉嫌 Police, illegal, notification, absorption, involved, public, suspect, case, sub-bureau, suspected
6	**Positive impression**	不错, 很, 好, 我, 感觉, 挺, 投, 收益, 比较, 还是 Not bad, very, good, I, feel, quite, investment, income, relative, as well

Table 4
Performance of XGBoost.

# of Folds	Recall (R),	Precise(P)	F-score(F1)	AUC
3	0.984	0.997	0.942	0.942
5	0.984	0.9999	0.941	0.942
10	0.984	0.9999	0.941	0.942

quantify the importance of all features trained on by the model. The weighted feature importance is computed as the number of times a particular feature crops up in the trees (Shi et al. 2019), which represents the important extent of the feature to the dependent variables. We incorporate this function with the well-trained model and show the importance ranking of the top 30 features in Fig. 6. These features are from platform fundamentals, online reviews, essays, platform-generated

Table 5
Performance comparison.

Model		Recall	Precise	F-score	AUC
Decision Tree	Basic features	0.838	0.812	0.825	0.591
	Basic features + Online content features	0.977	0.982	0.979	0.964
SVM	Basic features	0.856	0.816	0.837	0.616
	Basic features + Online content features	0.981	0.985	0.981	0.969
Random Forest	Basic features	0.953	0.804	0.872	0.585
	Basic features + Online content features	0.988	0.984	0.985	0.974
GBDT	Basic features	0.959	0.787	0.873	0.639
	Basic features + Online content features	0.987	0.996	0.989	0.991
LightGBM	Basic features	0.956	0.785	0.866	0.642
	Basic features + Online content features	0.986	0.992	0.986	0.987
XGBoost	Basic features	0.961	0.799	0.873	0.645
	Basic features + Online content features	0.988	0.999	0.994	0.994

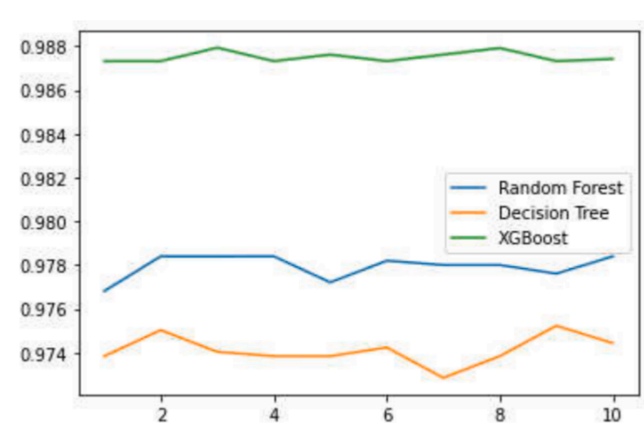

Fig. 4. Cross-validation of the Random Forest, Decision Tree, and XGBoost Model.

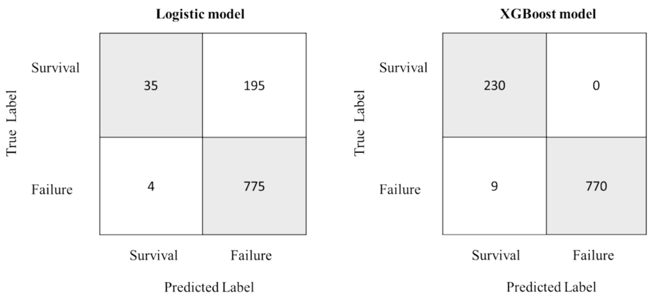

Fig. 5. Confusion matrix of the logistic model and XGBoost model.

content, and third-party-generated content. The results are consistent with our argument that the factors generated by actors around the platform are related to platform survival. Not only are platform fundamental variables related, but the online contents generated by various external actors also play powerful roles in predicting platform survival. To be specific, the F-scores for the three major categories of online content—user-generated content, platform-generated content, and third-party-generated content—all exceed the value of 1, thereby demonstrating the strong predictive capability of online content concerning operational risks for digital platforms.

5.3. Results of causal forests

5.3.1. Treatment effects

From the preceding section, we know the important features in platform failure prediction while still unknown the effects of these variables on platform failure. This section builds causal forest machine learning models to estimate the relationships between online content and platform survival. We estimate each treatment effect separately by treating the focal variable as a treatment variable and present the results in Table 6. A positive effect means a positive relationship with platform failure. We find that the presence of essays on a focal platform, as well as the presence of third-party-generated content, has a positive relationship with platform failure. In contrast, the presence of reviews has a negative relationship with platform failure; in other words, the platform with online reviews generated is more likely to survive. The relationship between the presence of platform-generated content and platform failure is not significant; there is no evidence to show that platform-generated contents are related to platform failure.

We draw upon signaling theory to explain how different types of online content can predict platform operational health. Signaling theory provides a useful framework to explain how entities send signals to convey information to others by reducing information asymmetry and building trust (Wells et al. 2011; Salge et al. 2022). First, user-generated content can serve as the platform signals of user engagement, user loyalty, and user trustworthiness. Specifically, user-generated content reflects the engagement and activity of the platform's user base (Zeng et al., 2013). Besides, Users who are actively engaged in generating content are more likely to recommend the platform to others, which shows their trust and endorsement. In sum, a growing volume of content indicates an active and vibrant platform (Aggarwal et al., 2012). Second, platform-generated content has algorithmic biases and profit motives (Hukal et al., 2020). As a result, it is often perceived as less trustworthy than user-generated content for prediction. Third, third-party-generated content serves as quality and responsibility signals (Song et al., 2019). An increase in third-party content may indicate that the platform is relying heavily on external sources, which can raise questions about the quality and reliability of the content. Users may perceive a higher risk of encountering low-quality or untrustworthy content, which undermines their trust in the platform. Besides, an influx of third-party content may give the impression that the platform is relinquishing control over its content, which can raise concerns about accountability and content moderation. Users may fear that the platform is not adequately monitoring or curating the content, leading to a higher risk of harmful or inappropriate material (Guo et al., 2021).

5.3.2. Heterogeneity of treatment effects

To further interpret the heterogeneity relationships in the causal forest, we draw the splitting of the causal tree that treats the presence of user-generated content and third-party-generated content as the treatment variables respectively. Fig. 7 presents the heterogeneity treatment effects of the presence of user-generated content in conditional subsamples. In the subsample that contains 3111 platforms with the condition that the platforms have less than 0.885 normalized registered funds (the second leaf in the second layer of the figure), the ATE of the presence of review is −2.094. It means that the presence of reviews has more impact on platform failure. After splitting the node, the ATE of the presence is −2.62 when the subsample has negative reviews. It suggests that negative reviews have a strong relationship with platform failure when the registered funds of platforms are relatively less. With further splitting, in the subsample containing 553 platforms all of them have launched in less than 6.5 months, the ATE of the presence of reviews is −2.963. While the subsample contains 954 platforms that are older than 6.5 months, the ATE of the presence of reviews is −2.421. It suggests that the presence of reviews has a stronger impact on platform failure when a platform is young has less equity, and contains negative reviews. In the subsample in the leftist node in the third layer, the condition is the view number of essays; it sheds light on the complemental function of essays when a platform has no negative reviews.

Fig. 8 presents the heterogeneity treatment effects of the presence of third-party generated contents in conditional subsamples. The leftist leaf in the third layer is the condition of essays. It shows that when the normalized registered funds of platforms are relatively less, and the platforms have no negative third-party-generated content, the essays are complemented to some extent. Concretely, if the score of topic 3 (Marketing for Retaining Extant Customers) is less than 0.929, the ATE of the presence of third-party-generated content is 3.042, showing a strong impact on platform failure. When the score is more than 0.929, the ATE of the presence of third-party-generated content is 2.064. It denotes that if a customer generates content with the purpose of persuading other customers to stay on the platform, the function of third-party content is weakened. The subsample containing 398 platforms (the second leaf in the third layer) shows the ATE of the presence of third-party generated contents is 0.776 when there are negative third-party contents exist. This result is intuitive; the presence of negative third-party content could weaken the impact of the presence party is questionable. The negative content generated by third parties is trustless and with the purpose of confusing customers. The results of the causal tree are finely divided. It allows us to observe the results of subsamples taking into account heterogeneity. For researchers, it is conducive to understanding research questions and exploring research ideas. Such results are also of great reference value to practice because causal trees can provide specific guidance for managers to strategically formulate management strategies.

To be specific, our finding shows platforms with more user-generated content have a higher likelihood of survival. It indicates that the success of a platform is closely tied to user engagement and community building (Song et al., 2019). Our result also reveals a negative correlation between third-party-generated content and platform survival. As a result, managers should review and monitor third-party content to ensure it does not harm the platform's reputation or user experience. Even though the research did not find a significant relationship between platform-generated content and platform failure, this type of online content can complement the platform ecosystem, and its quality and relevance should be maintained.

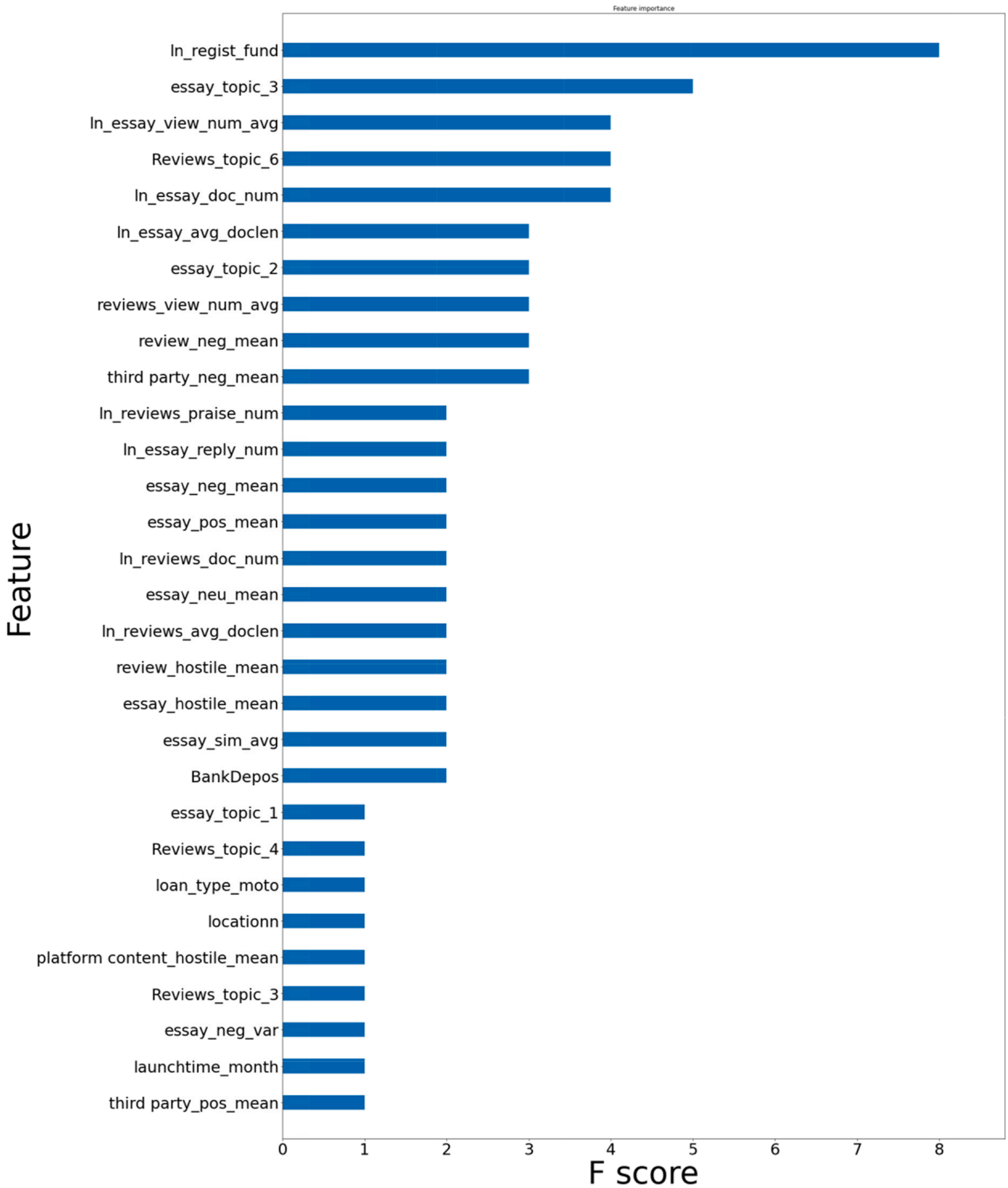

Fig. 6. Top 30 important features of platform failure.

6. Discussion and conclusion

In this study, we employ random forest machine learning methods to predict and interpret platform failure from multiple online content perspectives. Our study extracts the features from online content and leverages them with platform fundamentals to predict platform failure by the XGBoost model. To make the research more interpretable, we identify the top thirty important features of platform failure prediction and build causal forests to interpret the relationships between the presence of online content and platform failure. The results show a significant improvement in predicting accuracy by leveraging online content features with the XGboost model. Furthermore, the importance analysis donates the importance of involving features from online content. By building causal forests, we find that the presence of essays and third-party-generated content has a positive relationship with platform failure. In contrast, the presence of reviews has a negative relationship with platform failure. Through analyzing the causal tree of the treatment variable, we explain the heterogeneity of the average treatment effects among subsamples on platform failure.

Our findings have several important implications for research and practice. This study contributes to both digital platform failure literature and platform ecosystem literature. First, by leveraging online content features, this study provides a new lens for studying digital platform survival. The advantage of this lens is that online content is easy to

Table 6
Results of causal forests.

	Treatment Variables	Average treatment Effects	Standard Error
User-generated content	Reviews_dummy	−1.402**	0.622
Platform generated content	Platform_content_dummy	−0.012	0.016
Third-party generated content	Third_party_dummy	1.385***	0.659

Note: *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

touch. Due to the majority of platforms being SMEs, information like annual reports is not required to be made public. Second, we are the first to look into platform survival drawing on the view of the platform ecosystem, combining the platform fundamentals with the multi-types of online content generated by various actors. Unlike previous studies that focused solely on a subset of online content, we analyze the entire online content in the platform ecosystem and provide a comprehensive view of online content effects on platform survival. Third, owing to our interpretable approach, we are able to illuminate heterogeneous relationships between textual features and platform failure among samples, which may enlighten future research.

Our study has significant practical implications for digital platform risk management with our online content prediction models and remarkable feature analysis. From the perspective of platform customers, our study provides a guideline for identifying reliable platforms and avoiding platform failures. From the perspective of platform managers, our study highlights the importance of monitoring the platform's external information environment, which includes not only the attitudes of customers and third-party media but also the topics they discussed. At last, this study is also of great reference value to the practice because

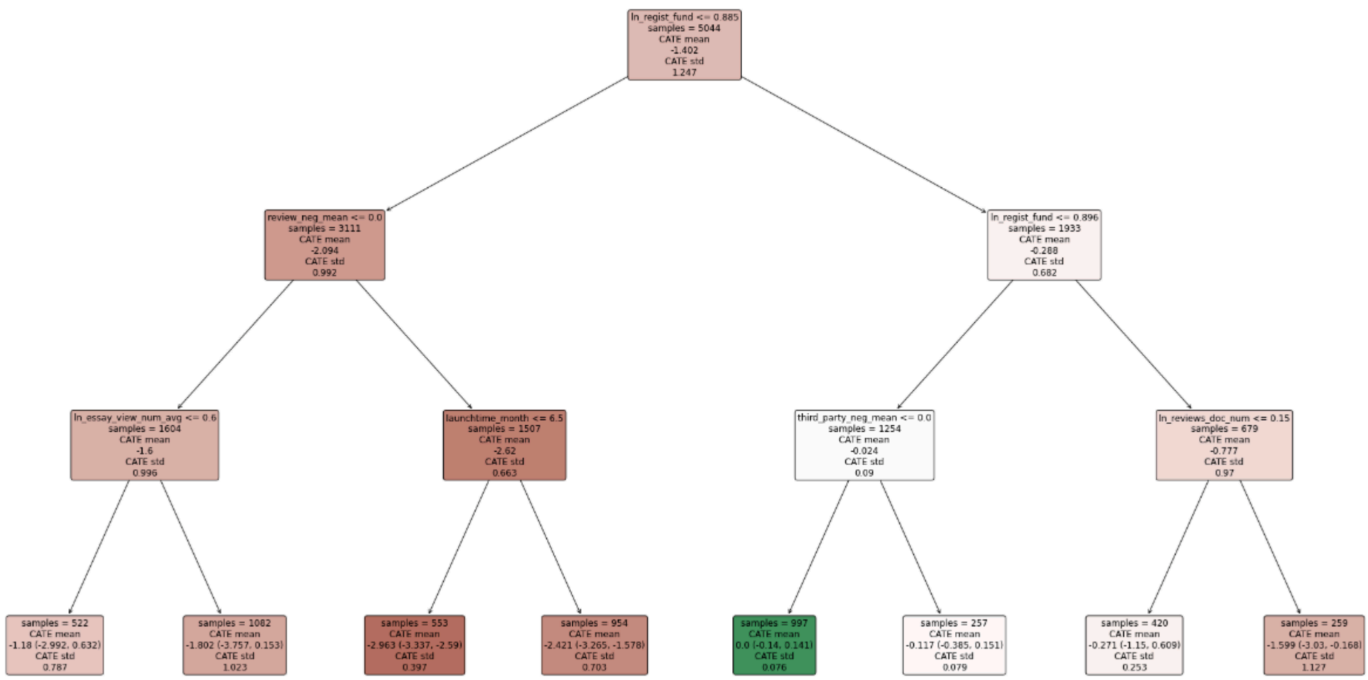

Fig. 7. Causal tree of the presence of user-generated content.

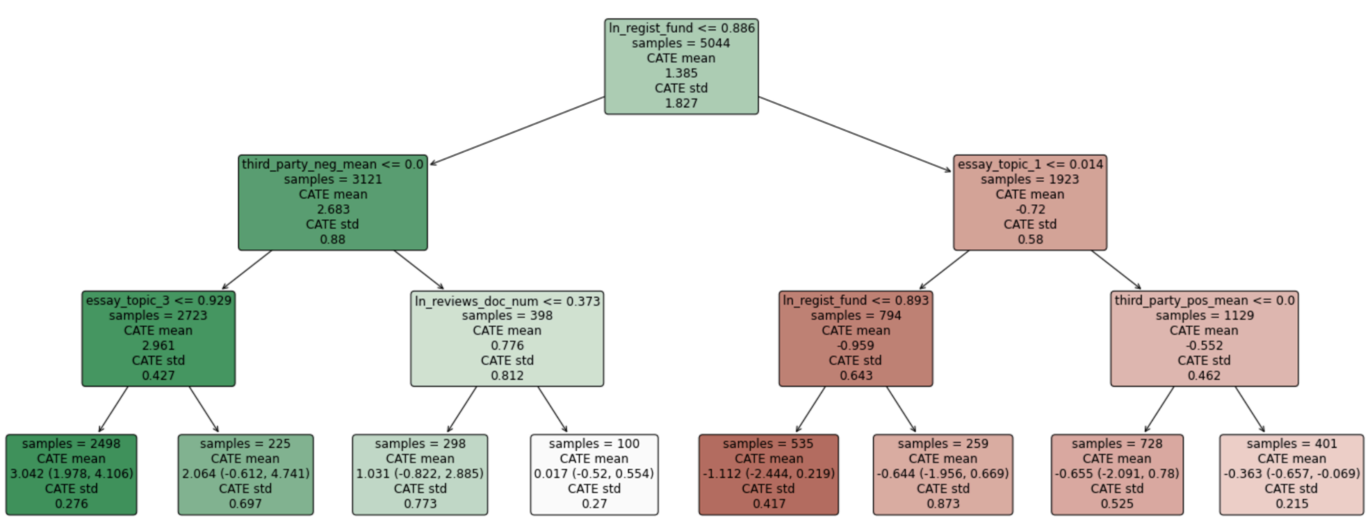

Fig. 8. Causal tree of the presence of third-party-generated content.

causal trees can provide specific guidance for managers to formulate management strategies strategically.

In conclusion, we aim to predict and interpret the platform survival by leveraging multiple online contents in the third study. We find that our prediction methods have a significant improvement in predicting accuracy by integrating the online content features and platform basic attributes with the XGBoost model. The feature analysis provides evidence that online contents play an important role in platform failure prediction. Moreover, by building causal forests, the presence of online content is confirmed that it is strongly associated with platform failure. To be specific, the presence of essays and third-party-generated content has a positive relationship with platform failure; the presence of reviews has a negative relationship with platform failure. Our research has significant implications for digital platform risk management. For researchers and practitioners, it provides an online content lens for understanding platform failure. The results of our causal forest analyses may enlighten future research by revealing heterogeneous effects among subsamples, as well as provide specific guidance for managers in strategically formulating management strategies.

CRediT authorship contribution statement

Xinyu Zhu: Writing – original draft, Validation, Software, Methodology, Investigation, Conceptualization. **Qiang Zhang:** Writing – review & editing, Visualization, Resources, Investigation, Formal analysis. **Baojun Ma:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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