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Customer Satisfaction-Driven Approach for Predicting Customer Churn in Online Video: Case of Guangxi Province, China

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Abstract

This study explores a customer satisfaction-driven approach for predicting customer churn in online video platforms within Guangxi Province, China. By analysing key satisfaction factors—such as content quality, user experience, and pricing—the research identifies patterns influencing users' decisions to discontinue services. Using machine learning models, it demonstrates how integrating satisfaction metrics enhances churn prediction accuracy. Findings suggest that improving specific satisfaction dimensions significantly reduces churn rates. The study offers practical insights for video service providers to retain customers through targeted satisfaction strategies, contributing to sustainable user engagement and competitive advantage in the dynamic Chinese online video market.

Keywords: Customer Satisfaction, Churn Prediction, Online Video, Guangxi Province

Introduction

In the era of rapid digital transformation, online video service platforms have emerged as a dominant force within China's digital economy, fundamentally transforming the landscape of business operations and driving considerable changes in media consumption and customer interaction patterns. With widespread internet and mobile device usage, consumers now engage with digital video content through diverse channels, fostering highly competitive market conditions among service providers. Among these digital innovations, online video services have experienced unprecedented growth, become an integral part of consumers' daily lives and representing a significant segment of the digital entertainment industry.

However, this remarkable growth has been accompanied by an equally significant challenge: online customer churn, which has emerged as one of the most critical issues facing digital service providers in the contemporary business environment. Customer churn, defined as the phenomenon where customers cease to use a company's digital products or services or discontinue their subscriptions to shift to competitors, represents a fundamental threat to business sustainability in the digital age. Unlike traditional brick-and-mortar businesses, online platforms face unique challenges in customer retention due to the non-contractual nature of customer relationships, the ease of switching between services, and the intensely competitive digital marketplace.

The magnitude of this challenge is evidenced by the 2023 Guangxi China Customer Satisfaction Index (C-CSI), which reveals a stark deterioration in customer satisfaction levels for video streaming platforms, with satisfaction scores plummeting from 81.1 points in 2022 to 64.1 points in 2023. This dramatic decline, occurring within a market of over 36.25 million users, underscores the critical nature of the customer churn challenge facing the online video service industry. The significance of addressing customer churn extends beyond mere revenue protection, as customer acquisition costs are substantially higher than retention costs, making customer churn prediction and prevention a strategic imperative. Research indicates that retaining existing customers is five to seven times more cost-effective than acquiring new ones, particularly in the competitive online video service market where content licensing costs and technological infrastructure investments continue to escalate.

Customer satisfaction has become a central determinant of user retention in online environments and serves as the cornerstone of customer retention strategies (Bashir et al., 2020; Polas et al., 2020). In the context of digital services, satisfaction encompasses multiple dimensions including service quality, technological performance, content value, user experience, pricing, and technological reliability. Satisfied customers are more likely to renew subscriptions, engage in repeat usage, and offer positive recommendations, whereas dissatisfaction can accelerate churn rates. The relationship between customer satisfaction and churn behavior is particularly complex in online video services, where users' expectations continuously evolve with technological advancements and content availability.

The importance of customer satisfaction in the online video service industry is magnified by the subscription-based business model that dominates the sector. Unlike traditional purchase-based transactions, subscription services require sustained customer engagement and continuous value delivery. This model makes customer satisfaction a dynamic, ongoing requirement rather than a one-time achievement, necessitating sophisticated analytical approaches to understand and predict customer behaviour patterns.

Traditional approaches to predicting customer churn have relied on basic statistical analyses, conventional machine learning methods, or rule-based models; however, these methods often struggle to process massive, multifaceted behavioural data generated by modern digital platforms and have proven inadequate for handling the volume, variety, and velocity of data generated by online video platforms. The advent of deep learning (DL) has introduced advanced computational techniques capable of uncovering complex, nonlinear patterns within large datasets and offering unprecedented capabilities to analyse complex behavioural patterns and predict customer actions with remarkable accuracy.

Deep learning models, such as convolutional neural networks (CNN), deep neural networks (DNN), and gated recurrent units (GRU), have demonstrated substantial improvements in predictive performance across various domains. The application of deep learning in customer churn prediction is particularly relevant for online video services, where user behavior generates massive amounts of structured and unstructured data. From viewing patterns and content preferences to interaction sequences and engagement metrics, deep learning models can analyse these multifaceted data sources to identify early warning signs of potential churn. This technological advancement enables businesses to move from reactive to proactive customer retention strategies, intervening before customers actually leave the platform.

Online platforms have created a unique ecosystem where traditional business principles require fundamental re-examination. The digital nature of these platforms introduces specific challenges and opportunities for customer relationship management. The convenience and accessibility of online platforms, while attracting vast user bases, also contribute to reduced switching costs and increased customer volatility. Given the dynamic and competitive nature of the online video industry in China—exemplified by rapid technological upgrades, seasonal user variations, and evolving customer expectations—understanding the distinctive characteristics of online platforms is essential for developing effective churn prediction and retention strategies.

The online video service industry exemplifies the complexities of digital platform management, where factors such as content quality, technological performance, user interface design, and pricing strategies all influence customer retention. The interconnected nature of these factors creates a complex web of customer satisfaction drivers that require sophisticated analytical approaches to understand and manage effectively.

This research addresses these critical challenges by developing an integrated framework that combines customer satisfaction analysis with advanced deep learning techniques to predict and prevent customer churn in online video services. By focusing on the specific context of Guangxi Province's online video service market, this study provides both theoretical insights and practical solutions for understanding and managing customer churn in the digital age. Through systematic data analysis, behavioural modelling, and interdisciplinary perspectives, this research contributes actionable insights that inform both theory and managerial practice for sustainable growth in China's online video service sector, enabling platforms to better anticipate user behaviour, devise proactive retention strategies, and optimize operational efficiency.

Problem Statement

China's online video service industry faces escalating customer churn challenges, with Guangxi satisfaction scores declining from 81.1 to 64.1 points between 2022-2023 (C-CSI, 2023). (as shown in Figure 1.1). This decline is alarming, considering the user base for online video platforms reached approximately 36.25 million by mid-2023(as shown in Table 1.1), accounting for a significant portion of internet users in Guangxi China. The discrepancy between the expanding user base and diminishing satisfaction levels indicates a failure in effectively catering to evolving customer preferences and needs.

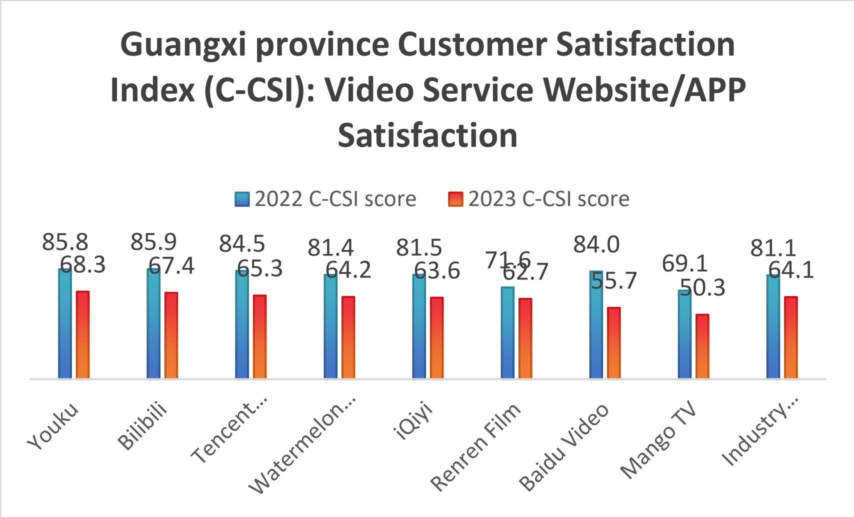

Figure 1.1China customer satisfaction index (C-CSI): video service website/APP satisfaction

Limitations

Key limitation of this study is its regional focus on Guangxi Province, which may restrict generalizability to other regions. Additionally, self-reported satisfaction data may be subject to bias, and the integration of qualitative insights with quantitative models poses challenges in ensuring consistent interpretation and validity.

Literature Review

Several findings are reported including the empirical verification that service quality, service value, and satisfaction may all be directly related to behavioural intentions when all of these variables are considered collectively (Cronin Jr et al., 2000). Some scholars have emphasized that previous empirical research has largely overlooked the establishment of brand attractiveness in the eyes of consumers. After investigating the role of brand attractiveness in fostering customer brand recognition, empirical testing of the conceptual model showed that brand reputation, brand uniqueness, and memorable brand experiences have a significant indirect impact on customer brand recognition through brand attractiveness, while brand social benefits directly promote this recognition.

The research results emphasize the importance of presenting a brand image that is attractive to the target consumers to achieve customer brand recognition (So et al., 2017). In the realm of digital services, scholars have delved into the roots of user satisfaction research, examining its connection to satisfaction research in marketing studies and how these studies are used to inform the information system environment. They have also discussed the evolution and maturation of research on user satisfaction and usage in information system studies over time, identifying antecedents and outcomes of user satisfaction determined in information system research, and providing recommendations for future research (Vaezi et al., 2016). E-commerce shopping has gradually become the norm for consumers to choose shopping channels, and part of this shopping process benefits from advanced technologies, including voice assistants. Researchers have proposed a model to study the construction of the technology acceptance model (perceived ease of use and perceived usefulness) and its impact on the involvement and loyalty between the reason assistant and consumers (Moriuchi, 2019).

Artificial Intelligence (AI) voice assistants continue to gain popularity among consumers. Some brands are now utilizing voice assistants to provide brand-related information and services. Research has aimed to uncover key drivers in enhancing consumer brand engagement through voice assistants. The research results affirm the importance of voice assistants in influencing consumer brand engagement (McLean et al., 2021). Individuals can utilize digital assistants (such as Apple's Siri, Amazon's Alexa, and Google's Google Assistant) to perform basic personal tasks as well as more advanced functions. Functional, social, and psychological factors significantly shape user attitudes toward chatbot usage in emerging markets (Nur, Sahabuddin, Hossain, & Ismail, 2024).

Service quality dimensions play a significant role in shaping brand relationships among Generation Z, with customer perception mediating the link between service quality and brand satisfaction (Polas et al., 2020). In the context of e-banking, customer perceived value mediates the relationship between service quality and overall customer satisfaction (Bashir et al., 2020). Effective customer care service management is essential for sustainable customer retention across industries, contributing to stronger brand loyalty (Afshar et al., 2019). Customer perceived value significantly influences satisfaction, which in turn supports the sustainability of hypermarkets in Malaysia (Polas et al., 2019).

Scholars have examined the relationship between digital assistant services and customer satisfaction, and confirmatory analysis has shown that the interaction experience with digital assistants can meet customer expectations, thereby enhancing customer satisfaction (Brill et al., 2022; Polas et al., 2019). Despite the increased opportunities that virtual agents provide for retailers and consumers, establishing trust with machines remains challenging. Some researchers suggest combining human-computer interaction theory with quasi-social relationship theory to gain deeper insights into how trust and attitudes toward voice assistants are formed. Research findings indicate that while functional factors drive users' attitudes toward using voice assistants, social attributes are a unique prerequisite for developing trust, and also shed light on the relationship between privacy and trust (Pitardi and Marriott, 2021). However, from a consumer perspective, the mobile payment industry, dominated by innovative mobile financial technology payment services such as Apple Pay and Samsung Pay, has recently flourished and is the most important and fastest-growing fintech service.

Consequently, research has investigated the relationships between perceived security, service knowledge, confirmation, perceived usefulness, and satisfaction. The analysis results indicate that knowledge and perceived security in mobile financial technology services significantly impact users' confirmation and perceived usefulness (Lim et al., 2019).

The research in China particularly focuses on adapting to the rapidly changing market environment, such as the rapid development of e-commerce and the quick evolution of consumer preferences. Chinese research extensively applies big data analysis and artificial intelligence technology in customer churn prediction, reflecting the country's technological advancements in these areas. Given the high reliance of Chinese consumers on online and mobile platforms, studies typically concentrate on customer behaviour and churn patterns through these channels. However, they have also benefited from global research, leading to rapid advancements.

In the phase of prediction methods based on traditional statistics, such studies mainly target contract customer churn in industries such as telecommunications and banking, building highly accurate predictive models. Similarly, methods such as the Pareto/NBD model decision trees (Wei and Tang, 2002;), Logistic regression (Zhao et al., 2021), and clustering (Yang et al., 2004; Cao et al., 2015) have been utilized to construct high uplift coefficient churn prediction models, obtaining strong explanatory judgment rules. On the other hand, researchers have effectively extracted customer value features and data probability features from demographic, consumption, and product service data using the RFM model (Chen et al., 2015; Wu and Li, 2021), and the enterprise competition

Delta model has provided effective management explanations. For example, scholars have used decision trees to automate feature extraction methods on fund customers, which significantly improves recall rates. Additionally, some researchers have established big data customer churn prediction models based on high-value customer operations in the telecommunications industry using logistic regression, effectively identifying potential customers and proposing targeted win-back strategies based on empirical research results. They have also analysed customer churn trends and reasons through data mining algorithms, addressing how customer churn occurs, its influencing factors, and how companies can win back customers (Zhao et al., 2021).

Some studies have revealed the impact of the Length, Recency, Frequency, Monetary, and Profit (LRFMP) customer value model on predicting customer churn (Chen et al., 2015). Although many scholars have used the RFM model to study customer churn, few have considered customer value based on churn analysis. Based on this, some scholars have quantified customer value using an improved customer value model, validating it from the perspectives of recency, frequency, monetary value, and asset level, albeit with various boundaries and assumptions. This framework can provide useful insights for commercial banks to better formulate marketing strategies for different customer segments and economically analyse churn, rather than simply a classification problem (Wu and Li, 2021).In the e-commerce field, in order to ensure healthy development in the intense market competition, companies not only need to make their products attractive but also deeply understand user preferences and satisfaction, and deeply explore user behavioural characteristics. Some research has applied decision tree technology to business analysis, predicting the churn of small users within a certain period, thereby implementing retention strategies and reducing churn rates (Liu, 2021).

From a wealth of literature, it is evident that most researchers have used binary classification methods to predict customer churn, including logistic regression and decision trees (Nie et al., 2011). Many scholars have used traditional statistical methods for customer churn prediction, but they face limitations in handling complex data, which are unavoidable in this stage. Due to the limitations of traditional statistical methods, researchers have begun to utilize early artificial intelligence methods for customer churn prediction. They primarily analyse the value characteristics of telecommunications customers and use artificial neural networks (Hwang et al., 2004; Yu et al., 2016) to establish customer churn prediction models, finding them to outperform traditional statistical models.

Additionally, multi-criteria neural networks and partial least squares (Lin et al., 2011) have been used for data feature extraction. The main focus of traditional artificial intelligence methods is to incorporate biological intelligence simulation into traditional methods, such as simulative learning of artificial neural networks (ANN) and rule-based reasoning of expert systems, further advancing research in customer churn prediction (Yu et al., 2016).However, the current methods are unable to accurately describe the characteristics of e-commerce customers, leading to inaccuracies in predicting e-commerce customer churn and low efficiency in forecasting e-commerce customer churn.

In order to improve the prediction of e-commerce customer churn, some scholars have designed a big data-based model for predicting e-commerce customer churn, providing an effective research method for analysing e-commerce customer churn (Wu, 2020). Although traditional artificial intelligence methods have been applied, traditional artificial neural networks require a large amount of data for training, and they also demand high data quality and diversity. Insufficient or poor-quality data may affect the accuracy of the model, and the poor generalization ability of traditional artificial neural networks cannot be avoided. When using traditional artificial neural networks for customer churn prediction, these issues need to be carefully considered

Research Questions
What are the factors that affect online customer satisfaction?

Research Objective
To investigate the factors that affect online customer satisfaction.

Research Methodology
Theoretical sampling was employed to determine the sample size. Theoretical sampling involves selecting participants who can provide rich, relevant, and diverse insights into the phenomenon under study, continuing until data saturation is reached — the point at which no new information or themes are observed in the data (Aguboshim, 2021). Based on preliminary literature review and expert consultations, it was estimated that three focus groups, network video company management personnel group, high usage group and at-risk of churn group, each comprising 10-12 participants, would likely achieve saturation given the study's scope and the complexity of customer churn within network video services. This approach allows for a comprehensive exploration of personal experiences, perceptions, and the nuanced factors contributing to customer churn.

1.Network Video Company Management Personnel Group: Participants in this group are individuals working in management positions within network video companies. They may include executives, decision-makers, and other key personnel responsible for overseeing the operations, content, and strategic direction of the company.

2.High Usage Group: Participants in this group are individuals who are identified as high users of online video services. These may be customers who regularly consume a significant amount of video content through various platforms and have a deep engagement with online video services.

3.At-Risk of Churn Group: Participants in this group are individuals who are identified as being at-risk of churn, meaning they are customers who are likely to discontinue or switch their usage of online video services. These participants may exhibit behaviours or characteristics that indicate a higher likelihood of ending their subscription or reducing their usage of online video platforms.

By categorizing the participants into these distinct groups based on their roles, usage patterns, and churn risk, the focus group interviews can effectively explore the issue of customer churn in online video services from multiple perspectives.

Data Analysis
For the qualitative component, 36 participants were carefully selected through purposive sampling and organized into three distinct focus groups: churned customers who had discontinued their service within the previous six months, retained customers with over two years of active subscription, and management personnel from video service providers. Each group comprised twelve participants, allowing for in-depth exploration of experiences and perspectives. The focus group discussions were conducted following a semi-structured format, with sessions lasting between 90 and 120 minutes, professionally moderated and recorded with participant consent.

The deep learning analysis utilized an extensive behavioural dataset comprising over 23 million interaction records from 600,000 users, obtained through collaboration with major video service providers in Guangxi. This comprehensive dataset encompassed user login patterns, viewing histories, interaction records, and demographic information, all collected and processed in accordance with strict data protection protocols and ethical guidelines. The integration of these three data collection approaches - survey responses, focus group interviews, and behavioural data analysis - provides a robust foundation for understanding the multifaceted nature of customer churn in the online video service industry.

The qualitative analysis component delves into users' personal experiences and perceptions of online video services through focus group interviews. In this study, the focus groups were categorized into three types: management personnel from online video companies, high-usage users, and users at risk of churn, with each group consisting of12 participants. This grouping strategy not only encompasses managerial perspectives from within the industry but also considers users' actual usage experiences and potential reasons for attrition. During the interviews, researcher designed a series of open-ended questions addressing various dimensions, including product and service quality, pricing, interactivity, and technical performance. These questions were aimed at guiding participants to discuss their personal experiences and views in depth, thereby revealing the underlying factors influencing customer churn. The discussions sought to explore users' specific feelings, usage experiences, and potential factors that might lead to service discontinuation.

Through this approach, not only enriched our understanding of customer churn phenomena but also provided comprehensive contextual support for the quantitative analysis results. This qualitative method not only enhanced our understanding of customer attrition but also offered in-depth contextual backing to the quantitative findings, achieving a methodological complementarity. The qualitative data analysis followed a systematic and rigorous process utilizing NVivo software for data management and analysis. Initially, all focus group interviews were independently transcribed by two researchers to ensure transcription accuracy, followed by cross-verification to eliminate potential errors. The analysis process employed a thematic coding approach, beginning with thorough familiarization with the data through repeated reading of transcripts while documenting initial observations.

The hierarchical coding function in NVivo was utilized to organize related codes into themes and subthemes, facilitating the identification of patterns and relationships within the data. Data saturation was carefully monitored throughout the analysis process, with theoretical saturation being confirmed when three consecutive interview groups failed to generate new themes or insights. This methodological rigor was particularly evident in the analysis of technological dimensions, where three main sub-themes emerged through continuous comparative analysis: user experience, improvements, and challenges. The systematic coding and analysis process, combined with the achievement of data saturation, enhanced the credibility and trustworthiness of the qualitative findings, providing a robust foundation for understanding the complex dynamics of customer churn in the online video service context.
Through the analysis presented aim to offer valuable recommendations for online video service providers to enhance customer satisfaction, reduce churn rates, and formulate future development strategies. Our research not only provides practical solutions for online enterprises in Guangxi but also serves as a reference for customer churn management in other industries.

Finding and Conclusion
This study employs focus group interviews to gather feedback from churned customers. Qualitative analysis of the interview data was conducted using NVivo software, which generated thematic distribution diagrams and word clouds to visually present key themes and concepts.

According to the thematic distribution diagram produced by NVivo, the feedback from churned customers can be categorized into six main dimensions: technology, interactivity, overall satisfaction, product, pricing, and service. These dimensions are highly consistent with the theoretical framework of this study, providing a structured foundation for subsequent analyses. Each dimension encompasses several sub-themes, reflecting the multi-layered reasons for customer churn.

The product dimension includes four sub-themes: content, quality, attractiveness, and design. Churned customers commonly report that the content is insufficiently diverse or lacks appeal, and the quality does not meet their expectations, directly impacting their usage experience and willingness to renew subscriptions. One respondent commented, "The content updates too slowly; end up watching the same old things." This highlights the importance of product innovation and content renewal in retaining customers.

The pricing dimension encompasses two aspects: value for money and pricing strategies. Many churned customers believe that the price of the service does not align with their perceived value, particularly when competitors offer more attractive pricing plans. This resonates with Zeithaml's (1988) theory of perceived value, emphasizing customers' sensitivity to the balance between price and value.

The service dimension primarily includes customer service and feedback as its sub-themes. Churned customers generally indicate that customer service response times are slow and problem resolution efficiency is low, which severely affects their usage experience. One customer mentioned, "Every time I encounter an issue, I have to wait a long time to get a response, which is very frustrating." This underscores the critical role of high-quality customer service in maintaining customer relationships.

The technology dimension encompasses three sub-themes: user experience, improvement, and challenges. Churned customers reported technical issues within the platform, such as lagging and slow loading times, which adversely affected their usage experience. This aligns with Davis's (1989) Technology Acceptance Model, which emphasizes the impact of technical performance on user acceptance.

The overall satisfaction dimension addresses aspects such as user experience, challenges, and sense of belonging. Churned customers generally expressed disappointment with the overall service experience and a lack of affiliation and identification with the brand. This finding is consistent with Oliver's (1999) theory of customer loyalty, emphasizing the importance of satisfaction in customer retention.

The interactivity dimension primarily focuses on participation and sense of belonging. Churned customers noted the platform's lack of effective interactive features, which failed to meet their social needs. This finding resonates with the service encounter theory proposed by Bitner et al. (1994), highlighting the significance of interaction in the service experience.
The word cloud further supports and enriches the thematic analysis results. High-frequency terms such as "technology," "service," "content," and "pricing" visually reflect the aspects that churned customers are most concerned about. The prominence of terms like "dissatisfaction," "issues," and "improvement" indicates the primary reasons for customer churn and potential areas for enhancement. The word cloud generated by NVivo visually showcases the keywords that frequently appeared during the interviews, further supporting and enriching the thematic analysis results.

Through the analysis of the churned customer group, researcher can derive the following key findings:

1. Product quality and content updates are critical factors for customer retention. Companies need to continuously innovate and provide high-quality, diverse content to meet user demands.
2. Pricing strategies need to be more flexible to adapt to market competition and changes in customer perceptions of value. This may involve the development of more personalized pricing models or innovations in membership systems.
3. The quality of customer service directly impacts customer satisfaction and loyalty (Afshar et al., 2019). Improving service response times and problem-solving efficiency is essential for reducing customer churn.
4. While technical performance and user experience are foundational, they are also sources of dissatisfaction for many churned customers. Continuous technical optimization and upgrades are necessary.

5.Enhancing user interaction and community building may be effective methods for increasing customer engagement. This approach can not only boost users' sense of involvement but also create differentiated competitive advantages.

These findings not only validate existing theories of customer relationship management and service quality but also provide new insights for customer retention strategies in the online video service industry. The results emphasize that in a highly competitive digital environment, companies must enhance service quality across multiple dimensions, including content, technology, customer service, and user experience, to reduce customer churn.

Recommendation

This study emphasizes the balanced development of technological innovation and service optimization. It is recommended to adopt a multidimensional customer satisfaction assessment system and to implement precision marketing strategies based on behavioural data. Differentiated retention strategies should be developed for customers with varying risk levels, with a focus on users at high risk of churn. Personalized retention solutions should be offered to achieve precise customer maintenance. These measures not only contribute to enhancing user satisfaction but also effectively reduce customer churn rates, providing support for the sustainable development of enterprises.

At the technical level, the study data indicate that technological performance is the primary factor influencing customer churn. Therefore, it is recommended that companies establish a real-time performance monitoring system, which includes an end-to-end performance tracking mechanism and a rapid response system.

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