Online Brand Communities as A Services Marketing Channel: An Exploratory Study of Apple Support Community Using a Machine Learning Approach

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Online brand communities are a vital services marketing channel and relationship marketing tool. Community members share a common interest and actively engage in community activities, such as content engagement, product, experiences and ideas sharing. These online brand communities offer a range of benefits, including enhanced customer service, incentives for active members, and strengthened brand loyalty. We particularly focus on customer service aspect of online brand communities and investigate how membership types and product categories affect the resolution rate of consumer problems. Using a machine learning approach, we explore dynamic interactions among members within the Apple Support Community over a time span of one year from 2023 to 2024. We investigate the contribution from varying membership types, examine variation in consumer experiences across different product categories and discuss the implications for marketers of consumer service strategies.

Keywords: online brand community, BCG Matrix, resolution rate, machine learning, services marketing, consumer roles

INTRODUCTION

According to marketing guru and bestselling author Mark Schaefer (Forbes, 2023), brand community is the next and last great marketing strategy. When customers join a relevant, supportive, and engaging brand community and interact with other like-minded community members, marketers no longer need to lure them into the company's orbit with ads and SEO; this sense of belonging represents the ultimate marketing achievement. These loyal consumers enjoy and love the brand so much and are willing to evangelize the brand. For example, the Apple Support Community provides a platform where customers voluntarily offer answers and solutions to other customers in need of help and support, in addition to Apple's regular customer support options. However, the research on customer service in online brand communities has been scant, and this study attempts to contribute to the literature by investigating user-to-user customer service experience provided by online brand communities. The main objective is to examine how membership types and product portfolio characteristics affect the likelihood of resolution of customer service tickets.

LITERATURE REVIEW

Online Brand Communities

A brand community is a specialized, non-geographically bound community, based on a structured set of social relationships among admirers of a brand (Muniz and O'Guinn 2001). Members of a brand community share common values and rituals, and participate in group activities to achieve collective goals with a shared enthusiasm and commitment (Cova and Pace, 2006; Stokburger-Sauer, 2010). An online brand community is the presence of a brand community in cyberspace where interactions between members emerge on the internet, and are rarely face-to-face (Sicilia and Palazon, 2008; Jang et al. 2008), but the social relationships in an online brand community are still accompanied by a shared consciousness, rituals and traditions, and a sense of moral responsibility for the brand (Madupu and Cooley 2010; Muniz and O'Guinn 2001).

Online Brand Communities are an essential service marketing channel and a relationship marketing tool (Chi et al., 2022). Information and communication technologies provide a platform for customers to facilitate their service interactions and develop connection with the brand (Rosenbaum and Russell-Bennett, 2021). Successful online brand communities create value and provide many services, for example, the Apple Support Community encourages community members to engage with each other to troubleshoot problems, Lego allows ideas to become official LEGO products if they receive enough support from the community, and Airbnb encourages users to share their travel experiences and reviews, and provides a platform for resource sharing, and user-generated content, to name a few.

Consumer Roles in Online Brand Communities

In online brand communities, consumers interact with other consumers and often with company representatives through a value co-creation process that's beneficial for both the brand and its consumers (Bagozzi and Dholakia, 2006). Consumers are gradually influencing and altering the content in the online environment, shaping the brand community, and consequently creating additional value for the brand (Schau et al., 2009).

It is noteworthy that online brand communities comprise heterogeneous members with varying levels of participation and engagement. Some members are learners with a beginner's level of experience and a fleeting interest, whereas others are experienced enthusiasts of the brand and expert users (Fournier and Lee, 2009; De Valck, 2005). Each member has their own rights, responsibilities, position, and recognition, and they take on different roles in the online brand community to collaborate with other members (Fournier and Lee, 2009). There are different membership types in online brand communities in the co-creation process of value and content, including the role of a producer, a distributor, a marketer and a user of a product (Pitt et al., 2006). Similarly, Pongsakornrungsilp and Schroeder (2011) have identified two types of membership roles: provider and beneficiary. Therefore, we seek to investigate the dynamic roles played by members in the troubleshooting process in Apple Support Community and examine how membership types affect the resolution rate of customer problems.

Products Portfolio in Online Brand Communities: BCG Matrix

In Apple Support Community, member engagement and activities are centered around product categories, such as iPhone, MacBook, Apple watch, etc. These product categories are undergoing varying stages of the product life cycle and have distinctive characteristics inherent in each consumer base. We examine how the resolution rate of consumer problems differs across Apple's product portfolio and caution marketers to employ segment-specific strategies to allocate resources and provide quality consumer service.

The Boston Consulting Group (BCG) Matrix is a strategic planning tool that evaluates divisions in terms of their relative market share positions and industry growth levels in a two-dimensional framework.

The BCG Matrix assists organizations in determining the allocation of resources, product development and management, strategic management and company portfolio analysis (Armstrong & Brodie, 1994; Stern and Deimler, 2012).

The BCG Matrix categorizes business units and product categories into four quadrants, suggesting that organizations maintain a healthy balance within the range, represented by question marks, stars, cash cows, and dogs.

Question Marks

Question mark represents the products in high growth markets and with low market share, and they compete in fast-growing industries. They are also called Question Marks, because currently they do not generate much profitability in their industry. Therefore, the organization must decide whether to build up them with continuous investment and a rigorous strategy or to sell them.

Stars

Star shows the organization has a potential sales leader, which is characterized by the highest positions in both the growth rate and market share. They are the leaders in the business and are considered the best opportunities for the company's growth and benefits (Thompson & Strickland, 1995). They still need continued support for development and promotion.

Cash Cows

Cash Cows indicates that the products have a low growth rate, and a large market share. They generate significant amount of cash, have a very high profit margin and require very limited investment.

Dogs

Dogs displays that both growth and market share are in low position. Due to poor performance, the business units of Dogs are often divested, liquidated, or trimmed down through retrenchment (Mohajan, 2015).

METHODOLOGY

Data Preparation and Overview

Between August 2023 and August 2024, we conducted an extensive data collection effort focused on user interactions (questions and replies) within the Apple Community website. Using a custom-built web scraping tool, we gathered data across the website's 16 main question categories, which were further divided into a total of 52 subcategories. Interestingly, our final dataset included more categories than currently listed on the site, with 26 main categories and 59 subcategories. This discrepancy suggests that category structures may have changed over time, likely expanding or reorganizing in response to evolving community needs or interests.

The comprehensive dataset comprises 464,599 observations, following rigorous data preprocessing that includes the identification and treatment of outliers and missing values. Of these, 119,147 were questions posted by 110,792 unique users, while 345,452 were replies provided by 111,433 unique users. A small but noteworthy portion of replies (5.23% or 18,082 responses) were designated as “Best replies,” while the majority (94.77%) did not achieve this designation at the time of data collection. This insight motivates one of the central research questions: to examine the efficacy of the online community in resolving user queries.

The dataset incorporates features such as product categories, user engagement levels, question and reply text counts, upvotes, downvotes, response times, and others. To further enhance our dataset for analysis, we also engineered new features that provide deeper insights. For instance, we calculated the standard deviation of unique respondents’ points, capturing variability beyond simple metrics like mean or sum. Additionally, we analyzed the sentiment expressed in askers’ replies to respondents using advanced text-mining approaches. These new features enhance our understanding of user behavior and the nature of interactions around each question, which would be valuable for studies on online community dynamics.

PRELIMINARY RESULTS AND DISCUSSION

Advanced Analytical Approach to Resolution Rates

After conducting extensive descriptive analytics, we focused our analysis on understanding the resolution rate of questions. Rather than focusing solely on the 5.23% of questions marked with a "best reply," we aimed to leverage the entire dataset to assess question resolution more broadly. Utilizing both original and newly engineered variables from the community dataset, we applied several machine learning techniques to develop data-driven criteria for classifying questions into “resolved” or “unresolved” groups. Given that the only available label within the data is “resolved,” we followed common practices in online Q&A research, where questions lacking selected replies are often categorized as unresolved. However, recent literature highlights that the absence of a best reply does not necessarily imply an unresolved or unsatisfactory question; quality assessments of answers can vary significantly across contexts (Kim and Oh, 2009; Suryanto et al., 2009).

To address this complexity, we employed data-driven approaches to better define "resolved" questions based on their distinctive characteristics. We applied one-class classification algorithms, including Support Vector Machine (SVM) and Autoencoder (a neural network-based model), to establish a nuanced boundary for resolved questions. This allowed us to determine reasonable resolution rates for each product category within the BCG matrix framework.

Next, we implemented advanced artificial intelligence (AI) techniques to construct binary discriminant classifiers for each BCG matrix quadrant. Through these methods, we investigated the contribution of various factors to class boundaries. SHAP (SHapley Additive exPlanations) was used to interpret model predictions, assigning each feature a SHAP value to quantify its influence on outcomes (Lundberg and Lee, 2017). Drawing on cooperative game theory’s Shapley values, SHAP offers an additive, consistent, and visually interpretable approach to identifying the impact of each feature on the model's predictions. This enhanced interpretability and transparency increased trust in the model, enabling us to better understand the drivers behind question resolution rates.

As anticipated, we observed distinct patterns across each BCG matrix category, with unique feature contributions defining the resolution rates in different areas. These findings highlight the various factors that contribute to resolution likelihood, offering insights that can inform targeted marketing and engagement strategies within the Apple Community. The SHAP outcomes validated several theoretical hypotheses, highlighting distinctive characteristics across BCG quadrants and offering a foundation for strategic applications in community engagement and resource allocation.

IMPLICATIONS FOR THEORY AND PRACTICE

Brand communities rally the most loyal and experienced users in one place, where members share best practices and troubleshoot issues with other community members. These knowledge-sharing experience and user-generated content create tremendous value for organizations and provide effective consumer support. Using a machine learning approach, this study examines how online brand communities, and their members help marketers support consumer services. Based on a one-year observation of Apple Support Community activities, this paper emphasizes the importance of membership types in their contribution to the resolution of customer problems and demonstrates the product portfolio as a boundary condition for these effects. Our findings offer a deep insight into heterogeneity of online brand community members and highlight the importance of product characteristics in affecting customer experience.

Marketers should be aware that it is optimistic to expect all community members to contribute equally to the online environment. Therefore, as marketers attempt to build and maintain a strong brand community, it is wise to identify provide segment-specific strategies based on different member types and avoid irrelevant marketing activities. Our findings also offer a deeper understanding of customer service experiences across the four BCG Matrix product quadrants. We caution marketers to have a keenly sensitivity to product life cycle and strategically allocate resources accordingly.

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