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Predicting Enterprise Marketing Decision Making with Intelligent Data-Driven Approaches

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Abstract: In order to improve the marketing effect of new media, traditional enterprises should increase the proportion of new media advertising and pay attention to the flow of audience's attention. On the basis of integrating data and information, advertising should conform to the changing trend of the media environment and increase the proportion of new media, so as to understand the audience's consumption habits of media use and formulate a reasonable media mix plan. Promote the integration of traditional media and new media to obtain higher publicity results at the lowest cost. This article delves into the key role of data-driven user profiling in marketing decisions. By analyzing user behavior, preferences, and needs, marketing teams are able to more accurately determine target markets, product positioning, and differentiation strategies. In addition, data-driven user profiles can guide the development of marketing and communication strategies, and enable enterprises to implement personalized marketing and customer relationship management. This personalized marketing and service experience helps to improve user loyalty and satisfaction, which in turn enhances the market competitiveness of enterprises. Overall, data-driven profiling plays an integral role in helping businesses achieve their continued growth and profitability goals.

Keywords: New Media Advertising, Audience Attention, Data-driven User Profiling, Marketing Decisions.

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1 Introduction

In today's competitive market environment, one of the keys to business success is to effectively predict product sales. Sales forecast refers to the estimation of the sales volume and price of the product in a specific time in the future. Such estimation should be based on the current market situation and previous sales experience, while weighing various factors that can affect sales, and synthesizing the sales target that can be achieved objectively.

In implementing a sales forecast, there are a number of steps that need to be taken. First, it is crucial to identify the target of the forecast. [1,2] Product sales is a system of multiple variables interacting, around the center of product sales, the relevant variables are mainly product price, supply and demand, market share and so on. To forecast this complex system, according to the length of the forecast period, the required data and analysis methods are different, so the determination of the forecast target is the first problem in sales forecasting. Second, gathering and analyzing data is a key step in achieving accurate predictions. After having the exact goal, the data collection and analysis should be carried out based on this goal. Since the accuracy and detail of the data will have a great impact on the prediction results, the collected information should meet the requirements of pertinence, authenticity, integrity and comparability.

The significance of sales forecasting is self-evident. [3] Through sales forecasting, enterprises can better plan production, avoid inventory redundancy, and improve the efficiency of capital utilization. In addition, through sales forecasting, production can be arranged more reasonably, timely replenishment, so as to meet market demand and enhance market competitiveness. The most important thing is that through sales forecasting, sales staff can set goals, improve the enthusiasm of work, stimulate their sales potential, and promote the steady growth of enterprise sales performance.

In conclution, the sales forecasting method based on intelligent data is of great significance to the development of enterprises. This article will explore how an intelligent data-driven approach can be used to improve the accuracy and efficiency of sales forecasting to help businesses better meet market challenges and achieve sustained growth.

2 Related Work

2.1 Traditional Sales Decisions

In the business competition, the purpose of marketing is still subordinate to the overall goal of the enterprise, and the success of the enterprise depends on the success of the comprehensive elements, that is, the success of the enterprise management. In order to gain advantages in the competition, enterprises must follow reasonable business logic, and have enough business talents, resources, organizations and capabilities. Some people may mistakenly believe that a single marketing idea can save the business, this idea is one-sided and absolute, and does not respect the operation of the business world. [4,5] For example, some people have learned a little Sun Tzu's Art of war, and every day they think about overtaking curves through various tricks, and want to gain something without effort. However, business success does not depend on accidental success ideas, but is built on sound business logic and has overwhelming advantages.

In business competition, only enterprises with certain advantages can be successful. However, many entrepreneurs ignore this point and believe too much that just "marketing well" can bring the business back to life. This idea is ironic because many people do not want to believe in simple principles, but are happy to believe that there is a simple way to make a business successful. So how can companies gain a competitive advantage? First, it must follow sound business logic. The business activities of the enterprise should conform to the laws of business and make sense from common sense and common sense. [6] Only when the business logic of the enterprise is correct, the enterprise can gain advantages and stand out in the competition.

The essence of marketing strategy is to deliver value. Therefore, when formulating marketing strategy, we must stand on the strategic height and think about how to better help the creation and dissemination of value. The core of marketing strategy is to solve three problems: who is the customer, what is the problem, where is the target market, and how to position yourself and solve the problem. The development of marketing strategy is a systematic activity that needs to be prepared in advance. This includes understanding the background of the industry, understanding market trends, and analyzing the competitive environment and success factors. Only through in-depth preparation in advance, enterprises can develop marketing strategies that conform to business logic and gain advantages in competition.

2.2 Data-Driven Decision

The core of data-driven decision-making lies in mining the patterns and trends hidden behind the massive amount of information. [7] In nursing, this means the systematic collection, integration, and analysis of diverse data sources, such as basic patient information, medical history, indicators of care practices, and feedback on patient satisfaction. Through these data, we can reveal the problem points, bottlenecks and optimization space in the nursing process. For example, in ward management, real-time monitoring and analysis of key data such as bed turnover rate and nurse work efficiency can help managers quickly locate factors affecting work efficiency, adjust human resource allocation, reduce waiting time, and improve patient turnover speed. In addition, by analyzing patients' physiological indicators, disease development and rehabilitation process, medical staff can more accurately predict changes in the condition, formulate intervention measures in advance, and achieve precise care. In addition, with artificial intelligence and machine learning technologies, data-driven decision-making can be applied in the field of preventive care. [8] By learning a large amount of clinical data and model training, the system can automatically identify high-risk groups, provide scientific basis for nursing intervention, and reduce the probability of adverse events.

A data-driven approach also plays a key role in corporate marketing decisions. By collecting, integrating, and analyzing information such as market data, consumer behavior, and competitor intelligence, companies can better understand market needs and trends, as well as customer preferences and behavior patterns. For example, a retail business might use data analytics to determine the best product pricing strategy. [9] By analyzing historical sales data, market competitive landscape, and consumer feedback, companies can identify price-sensitive product categories and develop pricing strategies to remain competitive in the market.

In addition, companies can use data analytics to optimize marketing channels and promotions. By analyzing the effectiveness of different channels, the purchase path of consumers, and the return on advertising delivery, companies can adjust their resource allocation and invest more in efficient channels and campaigns to improve marketing effectiveness and ROI. In short, data-driven marketing decisions can help companies gain more accurate insights into the market, develop more effective marketing strategies, enhance market competitiveness, and achieve business growth and profitability goals.

2.3 Enterprise Data Drives Marketing Decisions

Data has become the fifth factor of production after land, labor, capital, and technology. This statement emphasizes the value of data to economic development, and in the field of marketing, and even in the field of communication, data has become a core driver. Marketing in the traditional era relies on marketing decision-makers' understanding of their own business and marketing system, and many decisions are based on their subjective feelings and judgments. It is precisely because of the generation of data that marketing becomes a science, thus becoming quantifiable and more rational [10-11].

In particular, it is manifested as:

1. Marketing ROI

The collection of data on the enterprise side will consolidate the user (including customers and potential customers) database of the enterprise, and import the data of the enterprise side into the media platform for matching when the enterprise is advertising, so as to improve the precision of advertising crowd, so as to improve the return on investment of marketing [12]. For example, a sports brand has built its own database and imported the data of corporate CRM system, website retention, media delivery retention and wechat retention into the self-built data platform (such as data center), which has been deposited as the data assets of the enterprise. With the continuous progress of marketing activities, the attributes of user data and user behaviors have changed. The data itself is constantly iterated and improved to enrich the 360 portrait of the user.

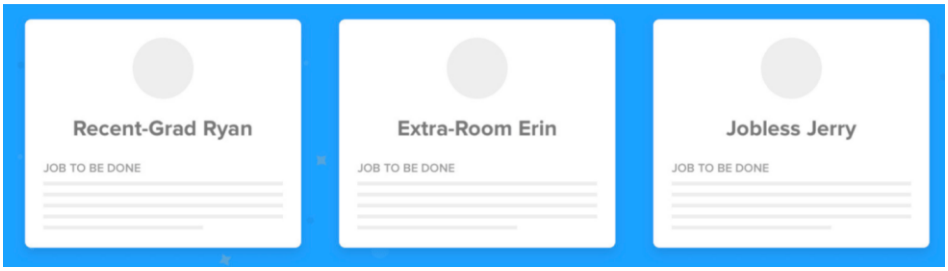


Figure 1. Assumptions for key user profiles

For example, in the product advertising recommendation of the e-commerce platform, the effect is very obvious after the use of this kind of data import matching method, according to statistics, the targeted recommendation of goods can usually bring about 10% of the purchase increase, which is a real direct sales.

2. Agility value

The effect of marketing activities can be tracked, monitored and measured [13]. This is reflected in three aspects: On the one hand, what kind of marketing results has been brought by a marketing campaign, compared with the last time or competitive products, whether it is better? Which channel has the lowest customer acquisition cost? Is the flow quality relatively high? Analyze these common marketing questions and the data will tell you the answer.

On the other hand, marketing and sales often argue about who the core contributors to customer leads are, so what exactly is the source of an end customer's sale? What is the contribution weight of the Marketing Department? At the operational level, various monitoring systems and means, such as [14] UTM tracking distribution code, web dissector of China and China, ads dissector and other monitoring tools, can be used to track, to understand where customers initially contact the source of the brand, what the subsequent user path is like, and how much role the market department plays.

These data monitoring and lead attribution systems and techniques give the [15-18] Marketing Department objective evidence to help quantify value. This is very meaningful in the case that the Marketing Department does not directly face customers, does not directly convert customers, and sales contribution is easy to be underestimated. The value of data is immeasurable in terms of resources or future cooperation with the sales department.

Third, data helps marketers gain real-time customer insights, which is not possible in the traditional marketing era, on the one hand, the data needs to be objective and comprehensive, and on the other hand, it needs to be agile enough to help marketing decision-makers make quick and correct decisions to take action. In the actual business scenario, when the customer needs, if you do not quickly and accurately insight into his needs, you may find that he has switched to the arms of competitors, so it must be fast, and the monitoring of individual customer behavior data, real-time tracking provides the possibility of rapid insight into customer needs, so as to take targeted marketing actions.

3 Methodology

3.1 Validation and Refinement

Hypothesis 1: As a new urban worker, I want to find suitable housing so that I can work nearby.

This user portrait represents young professionals or recent graduates looking to find affordable and easily accessible housing. This assumption can solve the challenges of finding an apartment, including high rent and poor transportation.

Hypothesis 2: As a city dweller, I want to find a nearby convenience store or supermarket to buy daily necessities.

This user portrait represents busy city dwellers who want to be able to find a convenience store or supermarket nearby to buy daily necessities. [19-21] This assumption can solve the problem of spending time and energy while shopping, and provide a more convenient shopping experience.

Hypothesis 3: As a family that has just moved, I need

to find moving services and furniture stores.

This user portrait represents a family that needs to move or redecorate, and they need to find a moving service and a store to buy furniture. This assumption can solve the problem of not finding the right service and product encountered in the process of moving or decorating, providing a more convenient solution.

Through user interviews with target users, we can test these assumptions and further refine the user profile to understand their real needs and pain points. Based on data such as user feedback emails, NPS scores and user interview notes, we can gain insight into user habits, preferences and expectations to continuously optimize products and services and enhance user experience.

3.2 Verification design

In interviews, a variety of methods need to be used, including traditional leaderless user interviews and agile question interviews. Through these interviews, we aim at three things:

First, we want to understand the user's specific scenario when solving the problem. By asking random behavior-based questions, such as asking recent college graduates about their last furniture purchase, we can get a sense of whether they've recently encountered problems related to our products and how they've resolved them.

Second, we need to confirm that the interviewee agrees with us documenting the urgent and painful problems they are trying to solve. [22] By telling our own experiences, such as difficulties in buying furniture after graduation, we can see if the interviewee can empathize with and identify with the problems we face. If the interviewees do not show emotional ups and downs that exceed normal standards, it may mean that the question is not the most distressing question for them, thus affecting their likelihood of becoming an active user.

Finally, we need to distinguish whether the interviewed user has the potential to become an active user. By recording the views that interviewees most agree with, we can assess whether they have the potential to become active users of our products.

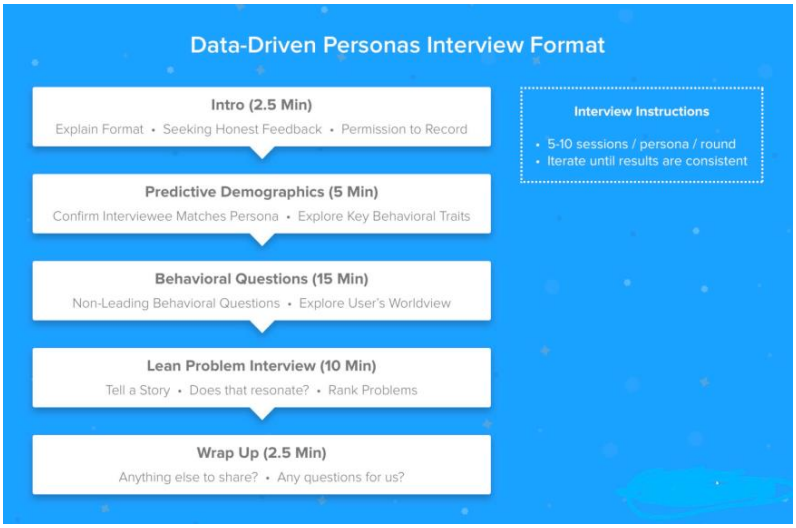


Figure 2. Confirm or reject the user profile hypothesis through a series of short user interviews

On the other hand, if they are excited about your story and show some empathy, or tell your story about their similar experience. [23-24]This shows that you have found a problem that they really care about and need to solve. Finally, remember to ask demographic questions that you haven't covered before, especially those key attributes that you think might influence some users to become active users. For example, you may think that recent college graduates have a decent income and can afford to buy new furniture, so they are unlikely to become your customers. In this case, remember to ask about their income.

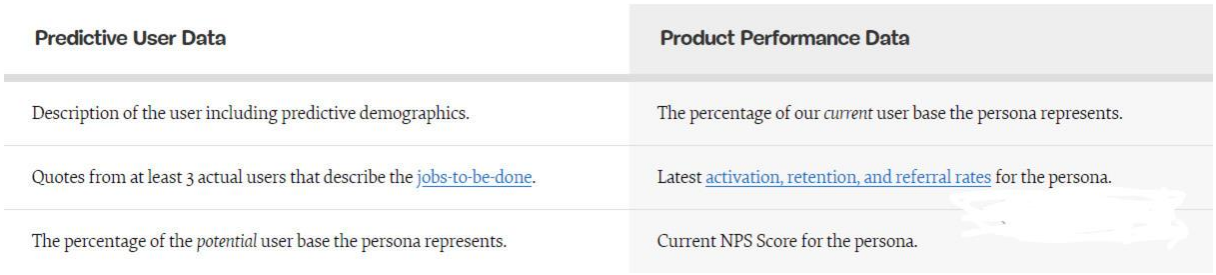
You're looking for predictable patterns, meaning that if four out of five interviewees have encountered the problem you're trying to solve, then you can create a key user profile based on those.

Also, if you get a different answer, you may need to redefine your hypothesis and repeat the process above, using what you learned in the interview to refine the new hypothesis. If you can't find the target audience for the problem, then you won't be able to get those people to use your product, so don't skip this step just to save time.

3.3 Marketing decisions to create user profiles

The penultimate step in the process, creating a real user portrait, is the most interesting. Unlike traditional static user portraits, [25]data-driven user portraits will be dynamic files that can be updated in real time. The purpose of this step is to combine the data learned in the above process (who the user is and what they need) with the data that will allow you to iterate on your product to meet the needs of the user.

In the enterprise, every user profile has two aspects:



Predictive User Data	Product Performance Data
Description of the user including predictive demographics.	The percentage of our *current* user base the persona represents.
Quotes from at least 3 actual users that describe the jobs-to-be-done.	Latest activation, retention, and referral rates for the persona.
The percentage of the *potential* user base the persona represents.	Current NPS Score for the persona.

Figure 3. User profile classification in the enterprise

If you want to learn more about the data required for a profile, check out Coryndon Luxmoore's discussion of how the team created a data-driven profile on Buildium. Getting this information will take a long time for the team, but you can start with what you already have and update it as you go. User portraits shouldn't be lying in a drawer asleep, and every time you release a new feature or optimize an existing one, you should evaluate the changes and update your user portraits.

3.4 Discustion

Data-driven user profiling plays a key role in marketing decisions. By understanding user behavior, preferences and needs, marketing teams can more accurately develop marketing strategies to meet user expectations and improve market competitiveness. Here are a few aspects of data-driven profiling in marketing decisions:

Target market determination: Through user profiling, marketing teams can better understand their target market, including user characteristics, preferences, and behaviors. This helps identify the most attractive market segments and provides guidance for targeted marketing campaigns.

Product positioning and differentiation: Through the analysis of user profiles, marketing teams can determine product positioning and differentiation strategies. [26]Understanding users' needs and preferences can help them determine a product's unique selling point in the market and differentiate it from competitors.

Marketing and communication strategies: Data-driven profiles can also guide marketing and communication strategies. By understanding the channel preferences and consumption behaviors of users, marketing teams can choose the most effective promotion channels and communication methods to maximize the appeal of target user groups.

Personalized Marketing and Customer Relationship Management: User portraits can help marketing teams implement personalized marketing and customer relationship management strategies. Through a detailed understanding of users, they can be provided with personalized product recommendations, customized marketing messages and personalized service experiences, thereby enhancing user loyalty and satisfaction.

In summary, data-driven user profiling plays a crucial role in marketing decisions, helping marketing teams better understand users, position products, develop promotional strategies, and implement personalized marketing and customer relationship management.

4 Conclusion

There are many advantages to data-driven marketing decisions, among which:

More accurate target market determination: Through data-driven user profiling, marketing teams are able to more accurately understand the target market, including user characteristics, preferences and behaviors, to identify the most attractive market segments and provide guidance for targeted marketing campaigns.

Product positioning and differentiation: [27-30] Through the analysis of user profiles, marketing teams can determine product positioning and differentiation strategies. Understanding users' needs and preferences can help them determine a product's unique selling point in the market and differentiate it from competitors.

Marketing and communication strategies: Data-driven user profiles can also guide marketing and communication strategies. By understanding users' channel preferences and spending behaviors, marketing teams can choose the most effective promotion channels and communication methods to maximize the appeal to their target user groups.

Personalized Marketing and Customer Relationship Management: User portraits can help marketing teams implement personalized marketing and customer relationship management strategies. With a deep understanding of their users, they can provide personalized product recommendations, customized marketing messages, and personalized service experiences that increase user loyalty and satisfaction.

Therefore, with the continuous development of data science and artificial intelligence technology, the role of data-driven marketing decisions in enterprises will be further enhanced. In the future, we can expect the following developments:

Smarter data analytics tools: As technology advances, data analytics tools will become smarter, able to analyze massive amounts of data more quickly and accurately, and provide deeper insights to support marketing decisions.

More personalized marketing strategies: With data-driven user profiles, businesses will be able to implement more personalized marketing strategies and provide customized products and services to different users, thereby increasing user satisfaction and loyalty.

Cross-platform integrated marketing: In the future, enterprises will pay more attention to cross-platform integrated marketing, through the integration of data and information from different channels, to achieve seamless marketing activities, improve marketing effectiveness and ROI.

Real-time decision support: With the advancement of data analysis technology, enterprises will be able to achieve more real-time marketing decision support, timely adjustment of marketing strategies, seize market opportunities, and respond to market challenges.

In general, the advantages and prospects of data-driven marketing decisions for enterprises are multifaceted, and by making full use of data science and artificial intelligence technology, enterprises can achieve more accurate, personalized and intelligent marketing, thereby enhancing market competitiveness and achieving business growth and profitability goals.

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