

Sales Resource Optimization Based on Customer Lifetime Value (CLV): A Data-Driven Dynamic Decision Model

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Abstract: This study proposes a framework for a dynamic decision-making model based on Customer Lifetime Value (CLV) to optimize sales resources. This model prioritizes profitability as a benchmark for customer performance, serving as a guide for effective resource allocation and improvement. The paper presents a data-driven approach that combines real-time data and dynamic analysis of customer behavior for resource allocation and adjustment. This method analyzes enterprise data and customer behavior to inform decisions that maximize resource utilization and enhance sales performance. The core idea is to prioritize high-value customers and allocate more resources accordingly. Furthermore, by categorizing customers into different CLV groups, more informed and targeted decisions are made for each customer group. Ultimately, this improves customer retention, thereby enhancing the enterprise's long-term attractiveness and strategic model.

Keywords: Customer Lifetime Value (CLV), Dynamic Resource Allocation, Data-Driven Decisions, Sales Optimization.

Disciplines: Statistical Analysis.

Subjects: Data Mining.

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1 INTRODUCTION

Customer Lifetime Value (CLV) is the total net profit a business expects to earn from a customer over the life of their relationship. It represents the monetary value of a customer to the company and is an important indicator of a customer's long-term health[1]. CLV helps businesses determine how much they should spend on acquiring new customers and retaining existing ones. Importantly, CLV is only an estimate and can vary significantly depending on the industry and business model.

The most commonly used formula for calculating CLV is:

$$\text{CLV} = \text{Average Order Value (AOV)} \times \text{Purchase Frequency} \times \text{Customer Lifetime.}$$

The average purchase frequency is calculated by dividing total sales by the number of unique consumers who purchased during the same period. For example, if a business has 500 unique customers and 1,000 purchases, the average purchase frequency would be two. More complex CLV calculations may also consider variables such as churn rate and gross profit per customer.

Customer Lifetime Value (CLV) (also known as CLTV or LTV) helps organizations measure customer loyalty and understand the average incidence of customer churn. By understanding customer lifetime value (CLV), organizations

can better comprehend the needs of their existing customers and invest in fostering loyalty among these customers[2]. Tracking CLV helps organizations make more informed decisions based on actual value. The data collected is based on factors such as how often customers typically purchase from a business and the total amount they spend over the lifetime of the relationship. Understanding this data enables organizations to develop more intelligent strategies that focus on growing customer relationships over time. Understanding CLV can also enhance the quality of products and services offered, inform overall decision-making, and extend the average lifespan of customers. An organization's CLV should be the foundation of its overall business strategy, whether it's continuing to invest in customer retention or focusing on attracting new ones. By mastering customer data and calculating CLV, organizations can stabilize cash flow and help achieve more growth, lower churn, and overall profitability. Understanding the metric isn't enough; realizing value from the data requires action.

The study goal of this article is to optimize sales resource allocation through a data-driven dynamic decision-making model, specifically, resource allocation based on customer lifetime value (CLV). With intensified market competition and diverse customer behaviors, traditional sales strategies often struggle to keep pace with the rapidly changing market environment. A dynamic decision-making model can adjust sales resource allocation based on real-time data, allowing for optimal resource utilization and maximizing sales performance under constantly changing

conditions. By comprehensively considering multiple factors throughout the customer lifecycle, including churn rate and gross profit, this article aims to provide companies with a more precise and flexible framework for allocating sales resources, supporting more effective customer relationship management, and informed marketing decision-making.

2 RELATED WORK

2.1 APPLICATION OF CLV IN SALES AND MARKETING

In sales, customer lifetime value (CLV) helps you understand and assess the loyalty of your current customers. If customers continue to buy from you, it's generally a good sign that your business is doing well. [3-4] Furthermore, the greater the customer lifetime value (CLV), the lower your customer acquisition costs. For example, if a Honda owner is happy with their car or van and purchases several more over the years, their CLV could be as high as \$100,000 (approximately 710,000 RMB). A regular coffee drinker, depending on how many cups of coffee they drink daily and where they buy them, could have an even higher CLV. Conversely, someone who has only bought two houses in their lifetime might be worth only \$15,000 (approximately 106,000 RMB) to a real estate agent because, while the purchase value is significant, the commission paid to the agent is only a small fraction of the total. More broadly, customer lifetime value (CLV) assesses the profit associated with a specific customer relationship and serves as a guide for determining how many resources are worth investing in maintaining that relationship. In other words, if you estimate a customer's LTV to be approximately \$500 (3,560 RMB), spend more than that to maintain the relationship. CLV will help develop an overall business strategy to retain existing customers rather than investing resources in acquiring new ones. Of course, both new and existing customers play an important role in overall business development.

In sales and marketing, customer lifetime value (CLV) has become a core metric for measuring customer value, optimizing resource allocation, and making informed decisions. By accurately calculating CLV for different customer segments, companies can identify which customers generate the most revenue and which customer relationships drive the most sales. This insight can help companies determine how many resources to allocate to acquiring new customers (CAC) and retaining existing ones, ensuring the optimal use of marketing budgets[5-6]. For example, based on CLV, companies can design personalized marketing strategies for high-value customer segments, such as customized product recommendations, exclusive offers, or loyalty rewards, aiming to increase customer stickiness and lifetime contributions. Furthermore, CLV can be used to optimize customer support services by identifying high-value customer segments and providing more targeted services, further improving customer satisfaction and retention.

Furthermore, CLV's applications extend beyond marketing and customer relationship management; it broadly influences a company's overall sales decisions and strategic direction. By understanding the purchase frequency and spending amounts of different customer segments, companies can more accurately forecast future revenue and plan production and inventory management rationally. This enables companies to optimize resource utilization while ensuring that products and services can respond to fluctuations in market demand. For example, companies can use CLV data to adjust pricing strategies or launch up-selling campaigns to increase the average transaction value of their customers. Furthermore, by analyzing CLV trends, companies can identify potential churn risks and implement timely customer retention strategies, such as offering discounts, improving products, or enhancing service quality, to prevent customer churn. Therefore, CLV is not just a static financial metric, but a dynamic business decision-making tool that enables companies to make more informed and forward-looking strategic decisions in a highly competitive market.

2.2 SALES RESOURCE ALLOCATION

Sales task allocation is a core component of sales management. It refers to the process of assigning sales tasks to team members based on customer needs, sales team capabilities, and business objectives. Its core value lies in improving resource utilization, shortening the closing cycle, and ensuring efficient team collaboration. Funshare CRM utilizes intelligent customer grading, dynamic assignment rules, and data analysis capabilities to enable companies to achieve precise and automated task allocation, thereby optimizing the overall sales process. In most companies, departments such as sales, marketing, customer service, and supply chain often operate independently, with data scattered across multiple systems, including CRM, ERP, social media, official websites, and offline channels[7]. Data silos hinder sales teams from gaining a comprehensive view of customers, significantly impacting business growth and decision-making efficiency. According to IDC's "China Enterprise Digital Transformation White Paper (2023)," data integration capabilities directly determine the sales team's responsiveness to market opportunities and conversion rate.

A CDP (Customer Data Platform) connects various data sources across the sales process through efficient data integration and governance, enabling unified aggregation and dynamic updating of customer information[8]. Platforms like Fanruan's FineDataLink excel in this area: they not only automatically collect data from CRM, ERP, and third-party platforms, but also support customizable rule-based cleaning and intelligent tagging, ensuring traceability, auditability, and high-quality data accumulation. Sales task allocation is a systematic management process that breaks down a company's sales goals into specific, actionable tasks and allocates them appropriately to sales teams or individuals. It's more than simply assigning tasks; it involves a complete

closed-loop process of resource optimization, capability matching, and dynamic adjustment.

Essential Characteristics of Sales Task Allocation:

Goal-Oriented: Directly aligned with company revenue targets, task decomposition transforms strategy into quantifiable actions.

Resource Coordination: Balancing customer value, sales cycle, and team capabilities.

Dynamic Adaptability: Allocation strategies can be adjusted in real-time based on market changes, personnel changes, and other relevant factors.

2.3 METHODS FOR SALES TASK ALLOCATION

1. Task Allocation Based on Customer Tier

Customer tiering is a core logic for allocating sales tasks. Using the RFM model (recent purchase date, purchase frequency, and spending amount) or customer lifecycle stages (potential, active, and dormant), tiers are typically assigned to senior sales staff, while mid- and low-tier accounts are assigned to new sales staff or automated tools. Funshare CRM's customer tagging system supports dynamic tiering[9]. When customer behavior data changes, the system automatically triggers task reallocation, ensuring resource allocation aligns with customer value. For example, one consumer goods company automatically assigned customers with monthly purchases exceeding 500,000 yuan to the key account team, reducing response time by 60%.

2. Dynamic Allocation Based on Sales Capability

A salesperson's performance history, areas of expertise, and real-time workload must be factored into the allocation algorithm. A dual-dimensional assessment system, "Skills Matrix + Workload Dashboard," is used: the Skills Matrix quantifies salespeople's scores in areas such as industry knowledge and negotiation skills, while the Workload Dashboard monitors their current task saturation[10]. FunShare's intelligent dispatching engine prioritizes assigning healthcare clients to salespeople with a pharmaceutical background, while ensuring that individual workloads do not exceed thresholds. In one case study, this dispatching approach increased salesperson productivity by 35% and reduced overload alerts by 72%. The dynamic adjustment mechanism also automatically balances team workloads during peak seasons, preventing idle resources or excessive resource congestion.

2.4 DYNAMIC DECISION MODELS IN RESOURCE ALLOCATION

Dynamic decision models in resource allocation focus on optimizing the distribution of limited resources over time, adapting to changes in demand and supply. These models are crucial in environments where resources are discrete and must be allocated efficiently to maximize performance or

minimize costs. For example, in manufacturing, the allocation of machines to different work centers or specific tasks must be dynamically adjusted in response to real-time production needs. Similarly, in operations management, resources such as cranes or operators must be allocated at various points to ensure the timely completion of tasks, such as unloading ships. These resource allocation decisions, typically formulated as integer programs, require sophisticated algorithms, especially for large-scale problems, due to the combinatorial nature of possible resource distributions. As such, heuristic or approximation algorithms are often employed to find feasible and optimal solutions within a reasonable computational time.

In fields such as healthcare, dynamic resource allocation models play a pivotal role in managing interventions during crisis situations, where the goal is to optimize the use of limited medical resources. During outbreaks of infectious diseases, for example, the allocation of medical staff, equipment, and medications must be continuously adjusted based on evolving patient numbers and available resources. These models typically aim to minimize harm and maximize the effectiveness of interventions, guiding policymakers on how to distribute resources across various regions or treatment centers. Dynamic models are particularly beneficial in scenarios where resource availability is uncertain or fluctuates rapidly, requiring constant reallocation based on real-time data and projections.

Although dynamic resource allocation models are commonly applied in healthcare and manufacturing, they are underutilized in disaster management and response. In such situations, where the stakes are high and the available resources are often scarce, these models can be used to optimize the allocation of rescue teams, medical supplies, and emergency vehicles. The challenge in disaster response is not only the real-time allocation of resources but also the need to plan for unpredictable circumstances and rapidly changing conditions. For instance, in the aftermath of a natural disaster, such as an earthquake or wildfire, the allocation of rescue resources must be continuously adapted as new information becomes available, including the number of casualties or the progression of the disaster. By leveraging dynamic decision models, disaster management authorities can make informed, timely decisions to mitigate damage, save lives, and reduce overall fatalities, ensuring that resources are allocated where they are needed most at each point in time.

3 MODEL FOR SALES RESOURCE ALLOCATION BASED ON CLV

3.1 DYNAMIC SALES RESOURCE ALLOCATION MODEL

Optimizing resource allocation to improve resource utilization efficiency not only reduces costs but also directly impacts a company's market competitiveness and profitability.

Many companies mistakenly believe that resource optimization is simply about reducing expenses or tightening budgets. However, true resource optimization is achieved through precise operational analysis. This study explores how to use operational analysis to optimize resource allocation and maximize resource utilization. Resource allocation cannot be static; it must be dynamically adjusted based on market fluctuations. Operational analysis provides real-time data support, making resource adjustments more flexible. For example, during peak tourist season, a hotel analyzed market demand data to rationally adjust staff shifts and room allocations, improving customer satisfaction and profitability. During the off-season, the hotel optimized marketing strategies and cost controls to ensure efficient resource utilization.

The key to dynamic resource allocation lies in:

- Market demand analysis: adjusting resource allocation based on market fluctuations
- Cost-benefit analysis: optimizing resource utilization to reduce operating costs
- Competitor analysis: adjusting resource allocation by analyzing competitor strategies

This model uses CLV as the core decision-making input and treats sales resources (such as sales staff time, promotional budget, and customer service support) as a configurable and dynamically adjustable "resource pool." Drawing on the concept of Model Predictive Control (MPC) from Ciocan & Farias (2012), this approach optimizes resource allocation at each time step based on the latest observations and forecasts. In a sales scenario, the model first calculates the CLV estimate for each customer or customer group. These estimates then provide resource allocation priorities: higher CLV customers receive more resources, while lower CLV customers receive less.

The dynamic element is reflected in the fact that as customer behavior (such as recent purchases, purchase frequency, potential churn, and profit contribution) and market conditions (such as competitive conditions and macro-promotional policies) change, the model reassesses customer CLV and resource allocation effectiveness within a rolling time window (e.g., monthly or quarterly), adjusting resource allocation strategies accordingly. This is consistent with Ciocan & Farias' dynamic resource allocation model, which emphasizes a closed-loop mechanism of "based on the latest state - prediction - optimization" when facing unknown or fluctuating demand.

3.2 VARIABLES CONSIDERED IN THE MODEL

The core variables of the model include the following:

- ① Average Order Value (AOV)—the average amount per order;
- ② Purchase Frequency—the number of purchases a customer makes per unit time; and
- ③ Customer Lifetime—the expected duration of the customer-company relationship (or expected contribution cycle). These variables together

determine the net contribution of a single customer to the company over its lifetime[11]. Furthermore, the model must consider factors such as gross profit margin and customer churn rate to further expand CLV estimation from "sales" to "net profit." Furthermore, the model should incorporate auxiliary variables such as customer segmentation (e.g., high-value customers, potential customers, and low-value customers), sales cycle length (e.g., the time from first contact to repeat purchase), and market volatility factors (e.g., promotional response, competitive breakthroughs, and new product cycles). By incorporating these variables into the model, the dynamic process of "customer value-resource matching" can be more accurately reflected, thereby enhancing the flexibility and practicality of resource scheduling mechanisms.

3.3 MATHEMATICAL FORMULATION OF THE MODEL

In this study, we define the sales resource allocation problem as a **dynamic optimization model** where limited sales resources are distributed among customers based on their *Customer Lifetime Value (CLV)* and real-time behavioral data. Let $i \in \{1, 2, \dots, N\}$ denote the set of customers, and $t \in \{1, 2, \dots, T\}$ denote discrete decision periods (e.g., months or quarters). The decision variable $R_{i,t}$ represents the amount of sales resource allocated to customer i at time t , such as sales representative hours, marketing budget, or personalized service effort.

Each customer has a predicted lifetime value $CLV_{i,t}$ that changes dynamically according to updated purchase behavior, churn probability, and revenue contribution. Thus, $CLV_{i,t}$ serves as the core state variable driving the allocation decision. The company's objective is to maximize the expected total profit over the planning horizon while considering the total available resources $R_{total,t}$, and the cost c associated with resource deployment:

$$\max_{t=1} \sum_{i=1}^N [CLV_{i,t}(R_{i,t}) - c \cdot R_{i,t}]$$

subject to

$$\sum_{i=1}^N R_{i,t} \leq R_{total,t}, R_{i,t} \geq 0, \forall i, t$$

Here, $CLV_{i,t}(R_{i,t})$ is modeled as a **response function** that increases with allocated resources but exhibits diminishing returns, often represented by a concave function such as:

$$CLV_{i,t}(R_{i,t}) = CLV_{i,t-1} \gamma_i (1 + \delta_i R_{i,t})$$

where γ_i and δ_i are elasticity coefficients reflecting the responsiveness of customer i 's lifetime value to resource inputs. This functional form captures the empirical observation that while additional investment in high-value customers yields positive returns, the marginal gain decreases over time. To ensure operational feasibility, the model can

include additional business constraints such as sales team capacity, market coverage targets, and minimum engagement thresholds. The decision policy derived from this model is not static—it continuously forecasts future CLV trajectories and recalculates optimal allocations at each step, balancing short-term profit maximization and long-term relationship growth.

In summary, this mathematical formulation integrates the predictive and adaptive nature of dynamic decision models with customer-centric value optimization, enabling data-driven sales resource management that evolves with market and customer behavior.

4 MODEL APPLICATION AND CASE STUDY

4.1 RETAIL INDUSTRY SALES OPTIMIZATION

Data-Driven Decisions: How Reallocating Resources to High-Value Customers Increased Overall Sales

In a retail setting, leveraging Customer Lifetime Value (CLV) can significantly enhance profitability by guiding resource allocation decisions. According to Kumar et al. (2006), maximizing CLV is most effective when customers engage in cross-purchasing, exhibit multi-channel shopping behaviors, maintain long-term relationships, purchase specific product categories, and demonstrate frequent buying patterns[12]. By computing individual CLV scores, retailers can identify high-value customers and tailor their strategies accordingly.

Sales Resource Optimization Based on Customer Lifetime Value (CLV)

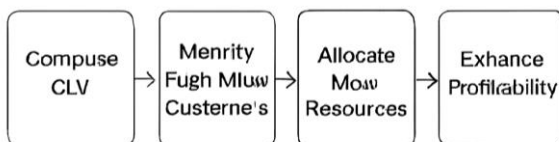


FIGURE 1. SALES RESOURCE OPTIMIZATION BASED ON CUSTOMER LIFETIME VALUE (CLV)

As shown in Figure 1, a retailer might discover that customers who frequently purchase from multiple product categories and engage across various channels (e.g., online and in-store) contribute more significantly to long-term profitability. This insight allows the retailer to allocate more resources, such as personalized marketing efforts or exclusive promotions, to these high-value segments. Implementing such a CLV-based approach can lead to increased customer retention and higher sales volumes. By focusing efforts on customers with the highest lifetime value, retailers can optimize their marketing expenditures and enhance overall profitability[13]. This strategy not only improves immediate sales outcomes but also fosters long-term customer loyalty and sustained business growth.

4.2 CLTV: THE KEY TO SAAS BUSINESS

GROWTH

For SaaS businesses, the initial sale is just the beginning of the customer journey. The real value lies in building long-term relationships that generate recurring revenue. That's where Customer Lifetime Value (CLTV) takes center stage. CLTV is the key to understanding the total revenue potential of each customer, empowering you to make data-driven decisions about marketing, sales, and customer success. It's not just about acquiring new customers; it's about nurturing those relationships to maximize their lifetime value.

Key Takeaways:

- CLTV provides a holistic view of customer profitability: Understanding this metric informs strategic decisions across your business, from marketing and sales to product development and customer success. Knowing your CLTV helps you allocate resources effectively and maximize your return on investment.
- Regularly calculating it empowers smarter decisions: Tracking CLTV helps you understand customer behavior, optimize pricing, and project future revenue. This data-driven approach enables informed decisions about marketing spend, product development, and customer segmentation.
- A customer-centric approach is key to improvement: Prioritize enhancing customer experience, implementing loyalty programs, and personalizing marketing efforts. Strong customer relationships and loyalty directly contribute to increased CLTV and sustainable business growth.

Understanding your customer lifetime value (CLTV, or sometimes CLV) is crucial for the financial health of your SaaS business. It's a metric that tells you the total profit you can expect from a single customer throughout your entire relationship. Think of it as a prediction of all the revenue one customer will generate for your business. This isn't just about the initial purchase; it includes every subscription renewal, upsell, or additional service they might buy down the line[14]. Knowing this number helps you make smart decisions about sales, marketing, and customer retention. For example, CLTV informs how much you can reasonably spend to acquire a new customer and still remain profitable. It provides that essential long-term perspective on customer profitability, moving beyond the immediate transaction to the overall value they bring to your business.

CLTV offers a valuable lens through which to view your customer base. It shifts the focus from individual transactions to the ongoing relationship, providing a more holistic understanding of a customer's worth. This metric is particularly important for subscription-based businesses, as it helps predict future revenue streams and make data-driven decisions about growth strategies. By understanding this metric, you can more effectively allocate resources to acquire

new customers, retain existing ones, and ultimately maximize your overall revenue. This forward-looking approach allows you to invest strategically in initiatives that will yield the highest return over the long term. Want to learn more about optimizing your pricing strategy? Check out our resources on value-based pricing and tiered pricing models.

5 CONCLUSION

In conclusion, this study introduces a novel framework for optimizing sales resource allocation, grounded in the dynamic application of Customer Lifetime Value (CLV). The model's flexibility allows businesses to adapt in real-time to changes in customer behavior, market conditions, and competitive strategies. By focusing on high-value customers and dynamically adjusting resource allocation based on updated CLV estimates, companies can ensure that sales resources are used most effectively, leading to improved profitability and long-term growth. Furthermore, the application of this model can drive more informed marketing decisions, customer relationship management, and ultimately contribute to overall business success.

The model also highlights the critical role of customer-centric strategies in modern sales management. By leveraging CLV as a guiding metric, organizations can develop targeted marketing strategies, personalized customer experiences, and improved retention efforts, all of which are crucial in a competitive market. This approach moves beyond traditional resource allocation models by incorporating real-time adjustments and predictive insights, ensuring that sales teams not only meet immediate goals but also invest in sustaining customer relationships and long-term revenue growth.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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