Understanding and Addressing Contractor Churn in the Thai Building Material Industry

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ABSTRACT

The Thai building materials market is vital for the country's growth, but suppliers often struggle with customer churn due to fluctuating prices, evolving standards, and changing customer preferences. In our study, we employed various machine learning models and determined that the XGBoost model demonstrated the highest accuracy in identifying potential contractor churns. Additionally, the model allows for the extraction of critical factors contributing to churn, enabling more customized and effective business interventions. Our results uncovered that while large orders can lead to higher churn, a concern since losing such high-value contracts can have a disproportionately large impact on revenue, regular purchases and active participation in loyalty programs significantly reduce it. To act on these insights, we recommend suppliers focus on building long-term relationships through tailored loyalty programs, exclusive offers, and localized engagement strategies. These practical suggestions, derived from our research, can boost profitability in this competitive market. Future work can adapt our methods to different industries, enhancing our understanding of churn and customer loyalty in diverse markets.

Keywords: Customer Churn, Building Material Industry, Causal Analysis, Prediction Modeling

1. INTRODUCTION

The building material market in Thailand is crucial for the country's development. Recently, it has grown a lot because cities are expanding and there's a big need for good building materials. But this growth brings challenges. Suppliers in this competitive market try to stand out by offering high-quality products and building strong relationships with clients. One major issue they face is 'customer churn,' where contractors often switch suppliers for better deals or services. Losing even one contractor can mean losing a lot of business, as they are involved in big, ongoing projects. So, for suppliers, dealing with churn is not just about keeping good relationships; it's also important for their financial success.

Understanding churn is tricky. Suppliers face many issues trying to keep their contractor customers. Changing prices, new construction standards, the need for novel materials, and shifting contractor tastes make keeping customers hard. While past research mostly used models to predict churn (Ascarza et al., 2018; Du, Lee, & Ghaffarizadeh, 2019), the reasons behind it remain unclear. Predictive models, while helpful, don't always explain why churn happens, giving suppliers a prediction but not clear next steps.

Our research dives into why contractors churn in the Thai building material market. We want to uncover what drives contractor loyalty and provide a foundation for effective ways to keep them. We have three main goals:

1. Build a model to predict when contractors might leave suppliers.
2. Discover the main reasons contractors churn in this market.
3. Offer practical suggestions and methods for suppliers to reduce contractor churn.

By merging churn prediction with a deep understanding of its underlying reasons, we aim to offer a comprehensive view of the factors causing churn. Our goal is to empower suppliers with the tools they need to retain their customers, thereby increasing profits and helping them thrive in the competitive Thai building material market.

Our study offers substantial benefits to the Thai building material market. By combining churn prediction with a deep understanding of its causes, we equip suppliers with insights to improve contractor loyalty and customer retention. This approach is often more cost-effective than acquiring new clients and leads to increased profitability. Additionally, it helps suppliers gain a competitive edge and adapt to market trends, supporting their long-term success in this competitive industry.

The remainder of this paper is organized as follows: Section 2 reviews related literature, Section 3 outlines the methodology employed in this study, Section 4 presents the results, Section 5 delves into discussions and analysis, and finally, Section 6 provides our conclusions.

2. LITERATURE REVIEW

2.1 Churn predictive models

Many studies have created models to forecast customer churn, helping businesses foresee and address potential customer departures. For example, Wangperawong et al. (2016) and Cenggoro et al. (2021) explored deep learning methods in the telecom sector. Their work showed strong results in predicting churn and stressed the importance of understanding customer actions. Mirkovic et al. (2022) demonstrated how to predict churn in B2B situations using past invoice data, highlighting the value of using past data to improve predictions. But the building material sector has its own set of hurdles, so it's crucial to modify these models for its unique needs. Our research is influenced by these earlier studies, aiming to create a churn prediction model that fits the specific challenges of the building material sector.

2.2 Causal analysis for churn

Predicting churn is essential, but grasping its root causes is equally important for holistic business planning. Prior studies, like those by Du, Lee, & Ghaffarizadeh (2019) and Shah et al. (2019), probed into the reasons for customer churn, using advanced methods to pinpoint its core drivers. In our research, we drew inspiration from Rudd, Huo, & Xu (2022), who used causal analysis in banking with significant precision. Their methodology offers a solid base as we explore the specific causal elements in the building material sector.

3. METHODOLOGY

Our methodology adopts a structured, data-centric approach to discern contractor churn in the building material supplier realm. We hold that data-driven insights empower businesses to make decisions that significantly boost their profitability and longevity. Figure 1 graphically illustrates our method.

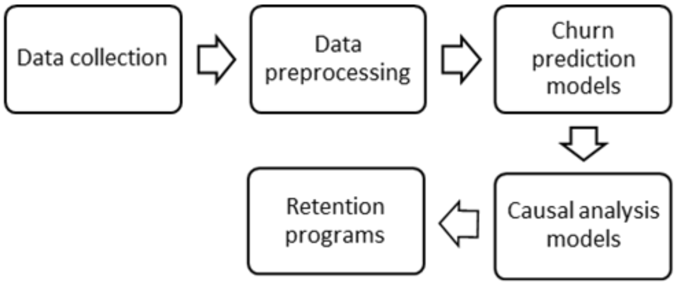

Fig. 1: The Proposed Approach

We initiated by gathering data from contractors associated with a leading Thai building material supplier, underscoring the importance of robust data in strategic decision-making. In the preprocessing stage, we preprocessed this data to closely mirror the industry's landscape. Our specialized predictive model pinpointed key factors driving churn, offering direction for business tactics. Conclusively, our causal analysis delved into churn's underlying causes, equipping businesses to address fundamental challenges and devise potent retention measures.

3.1. Data Collection

For our study, we collected data from a prominent building materials supplier in Thailand over a five-year period, from 2018 to 2022. This supplier is a well-known provider of construction materials in the country, catering to a diverse range of contractors involved in various building projects. To ensure our analysis is closely aligned with the supplier's operations, we conducted a segmentation of the contractors based on the company's internal criteria. This segmentation allowed us to categorize contractors in a manner that is consistent with the supplier's business practices, facilitating a more accurate and relevant interpretation of the data.

3.2. Data Preprocessing

During this stage, we preprocessed the accumulated data, emphasizing its authenticity and applicability. We tackled challenges like missing data and extraneous data points. Furthermore, we addressed the prevalent issue of dataset imbalance, using widely recognized methods. Our objective was to sculpt a balanced dataset, setting the stage for precise and actionable findings pertinent to the building materials domain.

3.3 Analytic Models

3.3.1 Churn Predictive Models

We explored various predictive methodologies, commonly used in different sectors, to understand customer behaviors. Our goal was to identify key factors contributing to churn. With insights into these factors, businesses might be better positioned to devise strategies addressing contractor turnover.

We utilized the F1-score, a harmonic mean of precision and recall, to assess the performance and relevance of our model. The F1-score is a valuable metric in evaluating the accuracy of a model, especially in cases where there is an uneven class distribution or when false positives and false negatives carry different costs. In the context of our study, it helped us quantify the balance between precision (the number of true positive results divided by the number of all positive results) and recall (the number of true positive results divided by the number of positives that should have been retrieved). By achieving a high F1-score, we ensured that our model is reliable and effective in capturing the necessary insights from the data.

3.3.2 Causal Analysis Models

Understanding the reasons behind customer churn in the building material industry is crucial for devising effective retention strategies. Our aim was to gain insights into the primary causes of customer departures. In our causal analysis, we looked at straightforward metrics like purchase frequency and categorized them into groups like 'low frequency' and 'high frequency'. Our categorization was based on two approaches: one that combined data analysis with practical business insights (median-based approach), and another that focused on significant data patterns (machine learning-based approach).

We've illustrated our insights from the churn prediction model in a causal graph (Figure 2), highlighting the relationships between customer behaviors and their propensity to churn. At the heart of the graph is "churn," our dependent variable, surrounded by other primary factors under examination. The connecting lines between these nodes signify influence. For instance, the link between "churn" and "high_tenure" indicates that the "high_tenure" factor has a bearing on churn. From this causal graph, we conducted a causal analysis to evaluate the strength of these connections. Our intent is not just to identify potential churners but to understand their reasons for leaving. Through this, we hope to provide businesses in the building material industry with insights that could help nurture long-term customer relationships and encourage steady growth.

In our causal analysis, we also employed the propensity score weighting method to balance the characteristics between different groups in our study, such as those with high and low purchase frequencies. This method calculates the probability of being in a particular group (e.g., high or low purchase frequency) based on observed characteristics. This approach allowed us to more accurately estimate the true causal effects of various factors, such as the order frequency on churn. The use of propensity score weighting in our analysis enhances the reliability of our findings, providing a more precise understanding of the causal relationships illustrated in our causal graph.

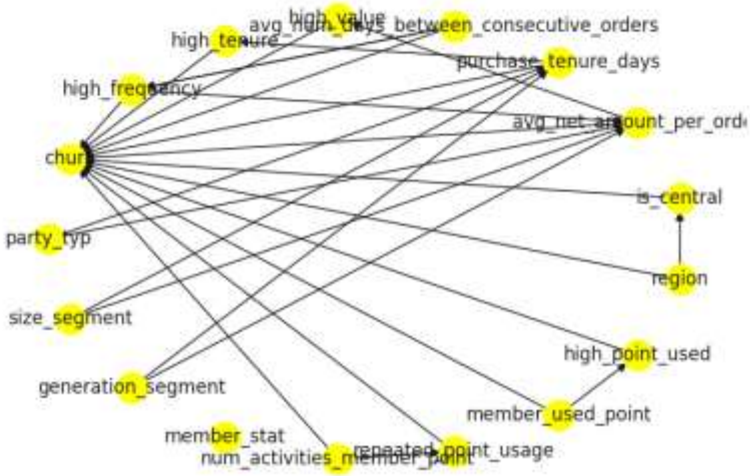

Fig. 2: The Causal Graph

3.4 Research Tools

In our study, we employed a range of tools for data handling and analysis. For data collection and preprocessing, we used a company's data repository, maintained for accuracy by its IT department. Our predictive modeling was conducted using custom Python programs, utilizing libraries like Scipy and Scikit-learn, allowing for tailored and sophisticated analysis. For causal analysis, we utilized the DoWhy library in Python, enabling us to investigate and understand the causal relationships in contractor churn.

To ensure the validity of our research instruments, we took two steps:

- Content Validity: We collaborated with Customer Relationship Management (CRM) teams to ensure our data variables accurately represented contractor behaviors. Their insights helped us align our data analysis with real-world scenarios in the building material market.
- Criterion-related Validity: We validated our predictive models by partitioning our data into training and testing sets. The testing set was used to assess the accuracy of our churn predictions, ensuring that our models are both reliable and effective for practical application.

4. RESULTS

4.1 Churn predictive models

In the predictive modeling stage, an array of machine learning algorithms was evaluated for their ability to predict customer churn. The performance metrics of each model, specifically the F1 score, were calculated and are presented in Table 1 for comparison. The F1 score is a measure of a model's accuracy, calculated as the harmonic mean of precision and recall. It ranges from 0 to 1, with 1 being perfect precision and recall, and 0 indicating neither precision nor recall. In essence, it provides a balance between the model's ability to correctly identify true positives and its tendency to not label true negatives as false positives.

The XGBoost algorithm proved to be the most effective among those tested, achieving an impressive F1-score of 0.9534, highlighting its reliability in predicting customer churn across different scenarios and parameters.

Table 1: Comparison of F1-scores of different models.

Model	F1-score
XGBoost	0.9534
Random Forest	0.9521
Extra Trees	0.9483
Gradient Boosting	0.9474
Logistic Regression	0.9456
Decision Tree	0.9339
AdaBoost	0.9336
Stack Ensemble	0.8767

4.2 Causal analysis models

In our analysis to uncover the drivers behind customer churn, we examined key business metrics to discern their influence on churn, as presented in Tables 2 and 3. In the causal analysis stage, we applied the propensity score weighting method to the binary features identified in the causal graph. The propensity score represents the probability of treatment assignment based on observed data. By using this method, we can balance the observed characteristics between treated and untreated groups, allowing for a more accurate estimation of the causal effect. These propensity scores, which aid in interpreting the potential causal impacts of the features on churn, are presented in Tables 2 and 3.

Table 2, informed by data insights and industry knowledge, categorizes contractors into 'Large' and

'Small', detailing how each segment responds to specific factors. For instance, large contractors spending over THB 10,000 see a 13% rise in churn, while those engaged over a year are 45% more loyal. For small contractors, high order values slightly increase churn, yet a relationship beyond 1.75 years results in a 51% churn reduction. The central region's influence on churn, despite its operational significance, did not warrant a detailed regional breakdown.

Table 3, utilizing advanced analytics, highlights churn tendencies. Large contractors spending above THB 11,500 face a 14% churn increase. Loyalty aspects, like a relationship over 4 years and active loyalty program engagement, significantly reduce churn. Conversely, small contractors with higher average order values see increased churn. Extended relationships and frequent shopping patterns notably decrease churn likelihood. These findings underscore pivotal strategies to enhance contractor loyalty and mitigate churn.

Our findings from the propensity score weighting causal analysis reveal a consistent direction of influence for key variables in predicting churn, irrespective of the method—median-based or machine learning-based—used for threshold determination. This consistency underscores the reliability of our analysis and the pivotal strategies to enhance contractor loyalty and mitigate churn.

Table 2: Propensity score for the median-based approach

Feature Type	Description	Large Contractors		Small Contractors	
		Threshold	PSW	Threshold	PSW
High Value	Average net amount per order	> THB 10,000	0.13	> THB 6,500	0.03
High Tenure	Days of engagement	> 365 days (~1 year)	-0.45	> 635 days (~1.75 years)	-0.51
High Frequency	Days between orders	<= 30 days	-0.1	<= 15 days	-0.02
High point used	Total points used	> 10,000 points	-0.41	> 7,500 points	-0.36
Repeated point usage	Points are used	> 1 time	-0.31	> 1 time	-0.19
Is central	Region	is 'central'	-0.05	is 'central'	0.02

Table 3: Propensity score for the machine learning-derived approach

Feature Type	Description	Large Contractors		Small Contractors	
		Threshold	PSW	Threshold	PSW
High Value	Average net amount per order	> THB 11,500	0.14	> THB 31,000	0.14
High Tenure	Days of engagement	> 1,477 days (~4 years)	-0.83	> 1,582 days (~4.3 years)	-0.8
High Frequency	Days between orders	<= 1 day	-0.15	<= 1 day	-0.3
High point used	Total points used	> 79,770 points	-0.52	> 5,840 points	-0.31

Feature Type	Description	Large Contractors		Small Contractors	
		Threshold	PSW	Threshold	PSW
Repeated point usage	Points are used	> 1 time	-0.31	> 1 time	-0.19
Is central	Region	is ‘central’	-0.06	is ‘central’	0.02

Note: PSW = Mean estimate from propensity score weighting model

5. DISCUSSIONS

5.1 Business Implications

Our research delves deeply into the operational nuances of the building materials sector, providing actionable insights for businesses to navigate challenges and opportunities. One notable observation is the correlation between decreased purchase frequency and potential challenges that a business might face. This decline could stem from a myriad of reasons, from operational bottlenecks to changing consumer preferences, disruptions in the supply chain, or an increasingly competitive market landscape.

When analyzing the influence of order value on churn, it becomes evident that businesses need to be adaptive in their pricing strategies. Rigid pricing might deter contractors from making more substantial purchases. Thus, introducing tiered pricing models, loyalty-driven discounts, or incentives for bulk purchases might alleviate this. Integrating these insights and adapting them to daily operations can serve as a crucial foundation to enhance contractor loyalty, reduce churn, and establish a robust rapport with contractors.

Aligning with the findings of Wangperawong et al. (2016) and Cenggoro et al. (2021), our study also underscores the importance of understanding customer actions and adapting strategies accordingly. However, unlike the telecom sector they studied, we observed unique trends in the building materials sector, such as the critical impact of purchase frequency on churn.

5.2 Strategic Retention Initiatives

The nuances of the Thai building materials industry, as brought out by our findings, necessitate specialized retention strategies. It's concerning to note that high order values are seemingly driving churn across both contractor segments. This challenges businesses to reconsider their pricing dynamics. By introducing flexible pricing structures, offering bulk-buying incentives, and other loyalty-driven benefits, contractors might be more inclined towards making substantial purchases.

The value of long-standing relationships with contractors cannot be overstated. Such relationships naturally lower the churn rate, so there's a compelling reason for businesses to invest in strengthening these ties. This can be achieved through loyalty-based discounts, granting contractors exclusive previews to new product launches, or offering them early-bird specials.

Encouraging regular purchasing behaviors is crucial. Businesses could consider innovative loyalty schemes or bonus point systems to incentivize frequent orders. Depending on the purchasing patterns of contractors, specialized deals, discounts, or other exclusive benefits could be extended.

While the central region's influence on churn is subtle, it does present a unique opportunity. Tailored marketing strategies, region-centric promotional events, or exclusive regional offers can effectively address these slight churn variations and bolster regional loyalty.

5.3 Recommendations

Effectively countering contractor churn requires a comprehensive understanding of the customer base and the industry landscape. One strategy to enhance contractor loyalty and reduce churn is to revamp existing loyalty programs. By offering rewards that are proportional to order frequency or value, contractors might be motivated to increase their spending.

Personalization is another vital strategy. By tailoring marketing campaigns based on contractors' past purchasing behaviors and preferences, businesses can forge a stronger, more personal bond with their customers. Regular engagement initiatives, such as feedback solicitation or hosting exclusive contractor-centric events, can solidify these relationships further.

Broadly, businesses can take a leaf out of global suppliers' books. Many have successfully minimized churn rates by proactively addressing customer feedback and concerns. By localizing such strategies to fit the Thai building materials industry's unique characteristics, businesses can not only reduce churn rates but also pave the way for sustainable growth and expansion.

Our research corroborates the approach by Du, Lee, & Ghaffarizadeh (2019) and Shah et al. (2019) in understanding the reasons for customer churn. However, in contrast to their general findings, our study reveals that personalized loyalty programs and contractor engagement are more critical in the Thai building materials sector.

5.4 Limitations

Despite our efforts to provide a comprehensive analysis, this study has its limitations. The data is sourced from a single building material supplier in Thailand, which might not capture the full spectrum of the industry's dynamics. Moreover, cultural and regional nuances specific to Thailand might not be universally applicable. External factors, such as economic shifts or industry regulations, which could influence churn, were not extensively explored. Future studies might benefit from a broader data set and a more global perspective to address these limitations.

6. CONCLUSIONS

In our study of customer churn in the Thai building materials sector, we delved deep into the metrics and reasons behind customer departures. Through rigorous testing, the XGBoost predictive model stood out, enabling us to forecast potential churn effectively. This model highlighted vital drivers, such as order value, how long customers have been with the business, how often they purchase, and their use of loyalty programs. For businesses, this means that those making larger orders might appreciate better pricing, like bulk discounts. The data also shows that staying engaged with customers through regular purchases and loyalty schemes can significantly reduce their chances of leaving.

Our causal analysis reinforced these findings and provided additional layers of understanding. We found that the size of the contractor played a role in their churn behaviors. Larger contractors, especially those with higher spending, were at a churn risk, emphasizing the need for special attention and strategies for this group. Conversely, both large and small contractors exhibited reduced churn tendencies when they had longer ties with the business.

To capitalize on these insights, businesses should prioritize fostering long-term relationships, perhaps through tailor-made loyalty schemes, exclusive offers, or even region-focused promotions. Though the regional influence on churn was subtle, it suggests an opportunity for more localized engagement strategies.

Looking ahead, the techniques and findings from our study can be adapted for various industries beyond the Thai building materials sector. This research offers a solid foundation in understanding customer churn and loyalty, a continuously evolving area of study. We are hopeful that our work will guide businesses towards more strategic decision-making and inspire further research. To enhance future studies, we recommend a mixed-methods approach, combining qualitative methods such as interviews and focus groups with our quantitative analysis. This integration will provide a more comprehensive understanding of churn, revealing deeper insights and supporting the creation of more effective customer retention strategies in diverse business environments.

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