International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 21, Issue 8 (August 2025), PP 157-161

Maximizing Revenue in Subscription Economies with AI-Driven Dynamic Pricing Models

Gopi Chand Edara
University of Cumberlands
AI in Business Development

Sonu Pradheen Kotapati
University of Cincinnati
AI in Business Development

Bhavana Kucharlapati
University: Texas Tech University

Venkata Revanth Kollipara
University: Texas Tech University

Abstract
In this research, we study how AI-driven dynamic pricing can benefit subscription economy businesses by ensuring they earn the greatest amount of recurring revenue. The main aim of this study is to determine how artificial intelligence can help set flexible subscription prices in response to changes in market demand, what customers do and the impact of different seasons.
The study applies a blended research method with analysis of industries, case studies including the Paterson campaign and by utilizing commercial AI tools such as Pricefx to check pricing relevance in different markets. Support for the model comes from data from McKinsey research and actual business results.
These results reveal that using AI in pricing helps businesses see added revenue, better manage customer classes and increase users both when demand is high and low. The findings of the research include identifying important ethical points and emphasizing the need for transparent and private methods.
The purpose of this study is to offer a scalable, facts-based system for pricing in subscription businesses, giving careful attention to practical points and the future. As the principal researcher, I customized the model for market research, sorted through the findings and made recommendations to maintain the company's success and customer relations. The findings indicate that using AI dynamic pricing now plays a key role in the changing subscription economy.

Date of Submission: 11-08-2025 Date of acceptance: 24-08-2025

I. Introduction

Because of SaaS, streaming services, fitness companies and online academies, value is now delivered in a fundamentally new way and is often charged through subscriptions. Unlike traditional ways of selling, recurring revenue models in subscriptions make choosing the right prices very important for financial health and future growth. Still, a single price point for everyone rarely responds to changes in demand, hot or cold periods or market swings and as a result, many opportunities to increase profits are ignored.

By using artificial intelligence, dynamic pricing is able to bring major improvements to markets today. These systems change the pricing in real time using information about users, the amount of demand and what competitors are doing. This method helps businesses make the most money when things are busy and keeps user numbers steady during lulls. While dynamic pricing is growing in retail and travel, it's not often used in subscription services, as putting trust in and being open about pricing is very important for those companies.

The research seeks to answer how to use AI for dynamic pricing in subscription services without hurting trust or fairness. We offer a practice and ethical approach that works with AI tools such as Pricefx and Dynamic Pricing AI, to manage live price optimization. Data from history, consumer habits and seasonal changes are used, along with testing the campaign in Paterson to achieve an 18% rise in income by smartly setting prices.

The world's framework for health planning is thanks to this work. Digital growth in emerging countries means that to succeed, companies must have flexible and responsive pricing programs. What we found supports businesses as they use AI thoughtfully and secure recurring revenue in today's competitive market.

II. Overview of Literature / Background

There has been a lot of attention from both academics and industry regarding dynamic pricing in today's digital economies. Original work by Chen et al. (2016) and Elmaghraby & Keskinocak (2003) demonstrated that variations in price can bring higher profits to retail and airline businesses. Lately, Bergemann and Bonatti (2019) have shown that AI and machine learning can be used to automate personalized pricing for items purchased on the web.

While dynamic pricing is commonly used for e-commerce and hospitality (Zhang & Gershwin, 2007), using it in subscription services is not well explored. Adding unclear or inconsistent pricing into the mix often disrupts the important issues: customer retention, regular income streams and trust.

Most studies look at how cost is set for a single sale, while leaving out how people behave when they pay regularly. For instance, Gupta et al. (2020) discovered that changes in subscription prices that seem unfair can greatly increase the chance of consumers leaving. Because of this difference, it becomes clear we need transparent and flexible pricing practises.

We solve these problems by proposing a complete, AI-based framework for subscription services pricing. Our strategy differs from previous methods by taking into account changes over the seasons, the makeup of customers and non-private data to improve pricing and still build trust.

The authors also refer to the Paterson subscription campaign and use AI solutions such as Pricefx and Dynamic Pricing AI, connecting what is learned in theory to what is used in practise. As a result, we have proved in our research that using AI prices in subscriptions can help companies increase revenue by 18% without harming user satisfaction or compliance rules.

III. Methodology

The researchers analysed records, used AI frameworks and checked with true examples to learn about the success of dynamic pricing in subscription businesses. The tools and methods were made to help ensure the results can be checked and useful for both small and medium digital service providers.

Data gathering is step 4.

We looked at both facts gathered by ourselves and information already in the market.

Collected from a mid-sized SaaS platform over 12 months: user joining rates, customer leaving rates, how their interest in the service changes by season and responses to price changes.

Market Demand Signals come from analysing web scraping and Google Trends to observe when interest in subscription services increases or decreases over seasons (for example, a rise in fitness app usage during January).

As a case study, data from Q1 and Q2 of the 2023 Paterson campaign were applied to confirm the efficiency of the invented pricing strategies.

Creating and putting into use the AI model is the fourth step.

We used the following techniques to construct our multi-factor dynamic pricing model:

Using both ARIMA and LSTM models, I was able to forecast moments of higher and lower demand each week.

To see how price sensitivity varied, I trained models using historical user behaviours.

Users were clustered by k-means using location data, how much they used the service and when they opened their account, to help with pricing precision without accessing private details.

PlainModel Data: Price optimization was deployed using the Pricefx API and custom Python routines, helping match live transactions with users' requirements.

4.4 Testing and Validation

We organised two groups for this study using a quasi-experimental design.

The basic comparison was done with the pricing model that is already used.

Test Group: AI suggestions for dynamic pricing are updated each week.

For both groups, we kept an eye on their revenue performance, how many clients churned and what their customers thought through ten weeks of the trial.

4.4 Covering the Ethical Framework and Transparency Layer

We included an XAI layer so that customers saw a reason for higher prices, for example, "Since it's a peak time, we had to adjust the price." Notwithstanding, no information about users or their income or internet browsing was processed which satisfied GDPR and maintained customer trust.

Lots of Innovation and Unique Items

Rather than counting on only one purchase or revealing lots of personal details, we use a different model.

The system is designed to work with businesses that charge for subscriptions.

Makes sure to be honest and equal through explainable AI.
It uses differences in behaviour and time of year, instead of personal information.
Shows that AI tools can be used effectively in the real world, based on proven examples from business.

IV. Results

This section presents the outcomes of the AI-driven dynamic pricing implementation, comparing its performance against traditional static pricing models in a subscription-based service environment. Both quantitative metrics (e.g., revenue uplift, churn rate) and qualitative insights (e.g., customer sentiment) were analyzed over a 10-week testing period.

5.1 Revenue Growth and Price Optimization
Table 1 compares the average monthly revenue per user (ARPU) and overall revenue growth between the control (static pricing) and test (dynamic pricing) groups.

Table 1: Revenue Performance Comparison

Metric	Static Pricing Group	Dynamic Pricing Group
ARPU (USD)	$21.30	$24.75
Revenue Growth (%)	—	+18.2%
Conversion Rate (%)	11.4%	13.6%
Customer Churn Rate (%)	8.1%	6.3%

Figure 1 (inserted) displays high level of revenue growth in both groups for 10 consecutive weeks.

The adoption of AI for pricing resulted in a 18.2% higher monthly recurring revenue when compared to the previous method. In addition, higher conversion rates by 2.2 percentage points show that the company's pricing and customer needs are more in step.
5.2 Understanding Your Customers' Loyalty
The management watched customer churn every week to gauge how changing prices affected user loyalty. Thanks to lower prices given during slow seasons, as well as an understandable explanation of pricing, there was a 22% drop in the churn for the test group.
Figure 2 (which will follow): Bar chart showing how churn differed each week in the control and test groups.
How do survey and behavioral segmentation together support our responsiveness to demand?
The models correctly detected when seasonal demand was higher. For instance:
With 35% more people joining the platform in the New Year's resolution period, premium plans were raised by 10%.
Setting different prices in a time of reduced demand resulted in an increase of 19% in people joining us, compared to the previous year in the same period.
Seasonal pricing changes and the corresponding amounts of revenue in Table 2.
5.5 Gathering and Watching for Customer Comments
The results from surveys and support tickets suggest that 85% of customers think the dynamic pricing is either "fair" or "understandable" once they get explanations. When a pricing rationale was added, there were far fewer complaints than at the start of the beta experiment where price changes went unexplained.
Important Quote from Users:
It's useful to understand what caused the price change. I thought it looked more like a deal than a fine for me."

5.5 Unexpected Results
It turned out that brand-new users found dynamic pricing easier to handle than people who used the system regularly. If variable pricing was shown as only available for a short time, new users were 2.7 times more likely to accept it. In other words, how AI-driven pricing information is presented and communicated greatly affects the strategies' success.
List of the main findings.
DP helped contribute to a 18% increase in ARPU and revenue.
Because of deliberate and clear pricing, the number of people leaving the company dropped by 22%.
As a result of improved seasonal demand responsiveness, acquisition improved by up to 35%.
Customers were generally very happy using explainable AI.
Charging new subscribers a higher rate made them more likely to stay than old subscribers.

V. Discussion

The results prove that using AI for dynamic pricing can increase success and strategy in subscription companies. The switch to real-time pricing that uses data helped the company earn 18% more revenue and win customers' trust and loyalty, things that are often not easy with regular dynamic pricing.

Explaining the most relevant findings of the study

The success of these strategies was discovered by observing both higher earnings and satisfied customers. Since the rate of lost customers fell by 22% and average revenue went up, it seems customers prefer variable pricing when the rules are explained and the benefits are clear.

Besides, the opportunity to see how both types of users react points out that new subscribers like special offers, while existing users are more comfortable with similar services. Differing behaviors are key when planning how to divide the market for future pricing campaigns.

Comparison between the Research Project and Previous Work

Unlike earlier research that looked at by-transaction pricing in e-commerce and aviation worlds (such as the work by Elmaghraby & Keskinocak in 2003 and Zhang & Gershwin in 2007), this study extends dynamic pricing to the subscription world that usually uses a single or tiered pricing model.

Gupta et al. (2020) noted that dynamic pricing for repeat services may cause customer trust to decrease, so we turned to explainable AI and privacy-respecting segmentation and found that transparent and less data-intensive methods can offer both value and trust to customers.

This research aims to improve on previous study methods by proving its conclusions in real campaigns such as the Paterson case, where revenue and engagement did go up.

6.4 What Does This Mean and What's Next

The findings matter for both choosing the right business strategies and putting new technologies to use in the subscription economy.

With these findings, business leaders should encourage agile pricing and get together the pricing team with data science and marketing departments to ensure AI fits with messaging designed for customers.

Developers and Data Scientists must be able to rely on tools that make AI models both correct and ethical as a basic feature.

For those who set policies and for those who are users: The study highlights that new rules and standards in dynamic pricing are needed, as AI contributes to making pricing more transparent and fair in online services.

Further studies might develop this work in several ways.

Applying the same pricing model in several places with different incomes to see its effects on equity.

Understanding how sentiment analysis right now impacts pricing decisions.

Considering ways to join loyalty programs to ensure lasting stability in revenue.

Societal and Industrial Effect

The findings of this research lead to improvements in fair AI methods for business, helping to build systems for ethical automated pricing. With the help of explainable and properly used data, dynamic pricing allows both businesses and their customers to be treated more fairly.

Thanks to AI-driven pricing, companies in many sectors such as SaaS and health apps, can absorb changes in the economy, deal with seasonal changes and maintain an advantage over their competitors as they focus on smart growth.

VI. Conclusion

The study provides a complete and usable strategy for applying AI-based dynamic pricing in subscription companies, representing major progress in strategic pricing and ethical AI. Using instant market changes, grouping users by behavior and honest communication, we have shown better earnings (+18% increase in revenue), less churn (22% lower customer loss) and happier users.

We have introduced several important improvements through our studies.

Making dynamic pricing work with recurring revenues, something usually managed with static or tiered pricing designs.

Applying scripts that are easy to follow to price decisions, so that all aspects of pricing are open and seem fair.

Let small and midsize companies leverage AI models made simple using market-ready tools like Pricefx.

The approach in this work makes AI an enabler for businesses to improve and satisfy their customers. FinConnect 2143 is special because it demonstrates that AI can be justified and profitable at once—simply by including transparency, fairness and customer behavior from the start.

We are currently developing a flexible pricing toolkit suitable for early-stage SaaS companies using automated methods for demand forecasting, anticipating customer loss and summarizing pricing choices. There is potential to investigate where dynamic pricing works other than in retail, notably in the world of education, digital services and health and wellness.

Because we are living in a world where data and automation are expanding, our results guide businesses on how to use AI both to grow financially and to act responsibly.

Reference

[1]. **Pillai, K. A. (2023).** AI-Driven Dynamic Pricing Strategies for Subscription Features: Leveraging Artificial Intelligence for Real-Time Pricing Optimization. International Journal of Computer Engineering and Technology, 14(3), 98–103.

[2]. **Liu, J., Zhang, Y., Wang, X., Deng, Y., & Wu, X. (2019).** Dynamic Pricing on E-commerce Platform with Deep Reinforcement Learning: A Field Experiment. arXiv preprint arXiv:1912.02572.

[3]. **Apte, M., Kale, K., Datar, P., & Deshmukh, P. (2024).** Dynamic Retail Pricing via Q-Learning: A Reinforcement Learning Framework for Enhanced Revenue Management. arXiv preprint arXiv:2411.18261.Buczak, A. L., & Guven, E. (2016). A survey of data mining and machine learning methods for cyber security intrusion detection. *IEEE Communications Surveys & Tutorials*, *18*(2), 1153–1176. https://doi.org/10.1109/COMST.2015.2494502

[4]. Sommer, R., & Paxson, V. (2010). Outside the closed world: On using machine learning for network intrusion detection. In *2010 IEEE Symposium on Security and Privacy* (pp. 305–316). IEEE. https://doi.org/10.1109/SP.2010.25

[5]. Sarker, I. H., Kayes, A. S. M., & Watters, P. (2020). Cybersecurity data science: An overview from machine learning perspective. *Journal of Big Data*, *7*, 41. https://doi.org/10.1186/s40537-020-00318-5

[6]. Ahmed, M., Mahmood, A. N., & Hu, J. (2016). A survey of network anomaly detection techniques. *Journal of Network and Computer Applications*, *60*, 19–31. https://doi.org/10.1016/j.jnca.2015.11.016

[7]. Yin, C., Zhu, Y., Fei, J., & He, X. (2017). A deep learning approach for intrusion detection using recurrent neural networks. *IEEE Access*, *5*, 21954–21961. https://doi.org/10.1109/ACCESS.2017.2762418

[8]. Tavallaee, M., Bagheri, E., Lu, W., & Ghorbani, A. A. (2009). A detailed analysis of the KDD CUP 99 data set. In *Proceedings of the IEEE Symposium on Computational Intelligence for Security and Defense Applications* (pp. 1–6). IEEE. https://doi.org/10.1109/CISDA.2009.5356528

[9]. Moustafa, N., & Slay, J. (2016). The UNSW-NB15 dataset for network intrusion detection systems. *Proceedings of the Military Communications and Information Systems Conference (MilCIS)*, 1–6. https://doi.org/10.1109/MilCIS.2015.7348942

[10]. Kim, G., Lee, S., & Kim, S. (2014). A novel hybrid intrusion detection method integrating anomaly detection with misuse detection. *Expert Systems with Applications*, *41*(4), 1690–1700. https://doi.org/10.1016/j.eswa.2013.08.066

[11]. Javaid, A., Niyaz, Q., Sun, W., & Alam, M. (2016). A deep learning approach for network intrusion detection system. In *Proceedings of the 9th EAI International Conference on Bio-inspired Information and Communications Technologies* (pp. 21–26). https://doi.org/10.4108/eai.3-12-2015.2262516

[12]. Wang, W., Zhu, M., Zeng, X., Ye, X., & Sheng, Y. (2017). Malware traffic classification using convolutional neural network for representation learning. In *2017 International Conference on Information Networking (ICOIN)* (pp. 712–717). IEEE. https://doi.org/10.1109/ICOIN.2017.7899588

[13]. Sood, A. K., & Enbody, R. J. (2013). Targeted cyberattacks: A superset of advanced persistent threats. *IEEE Security & Privacy*, *11*(1), 54–61. https://doi.org/10.1109/MSP.2012.90

[14]. Kissel, R. (2013). *Glossary of key information security terms* (NIST IR 7298 Revision 2). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.IR.7298r2

[15]. Goodfellow, I., McDaniel, P., & Papernot, N. (2018). Making machine learning robust against adversarial inputs. *Communications of the ACM*, *61*(7), 56–66. https://doi.org/10.1145/3134599

[16]. Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*.https://arxiv.org/abs/1702.08608

[17]. Olusola, A., Oladele, A., & Abosede, O. (2010). Analysis of KDD '99 intrusion detection dataset for selection of relevance features. *World of Computer Science and Information Technology Journal (WCSIT)*, *2*(3), 1–7.

[18]. Zhang, J., & Paxson, V. (2000). Detecting stepping stones. In *Proceedings of the 9th USENIX Security Symposium* (Vol. 171, p. 184).

[19]. Dhanabal, L., & Shantharajah, S. P. (2015). A study on NSL-KDD dataset for intrusion detection system based on classification algorithms. *International Journal of Advanced Research in Computer and Communication Engineering*, *4*(6), 446–452.

[20]. U.S. Department of Homeland Security. (2016). *Strategic Principles for Securing the Internet of Things (IoT)*. https://www.cisa.gov/publication/strategic-principles-securing-iot

[21]. Mmaduekwe, E., Kessie, J., & Salawudeen, M. D. (2024). Zero trust architecture and AI: A synergistic approach to next-generation cybersecurity frameworks. *International Journal of Science and Research Archive*, *13*(2), 4159-4169.

[22]. Mmaduekwe, E., Mmaduekwe, U., Kessie, J., & Salawudeen, M. D. (2023). Adversarial machine learning in cybersecurity: Mitigating evolving threats in AI-powered defense systems. *World Journal of Advanced Engineering Technology and Sciences*, *10*(2), 309-325.

[23]. Mmaduekwe, U., & Mmaduekwe, E. Cybersecurity and Cryptography: The New Era of Quantum Computing. *Current Journal of Applied Science and Technology*, *43*(5).

[24]. Paul, E. M., Mmaduekwe, U., Kessie, J. D., & Dolapo, M. (2024). Zero trust architecture and AI: A synergistic approach to next-generation cybersecurity frameworks.

[25]. Eleje, L., C. Metu, I., C. Ikwelle, A., G. Mbelede, N., C. Ezeugo, N., N. Ufearo, F., A. Okenwa-Fadele, I., & E. Ezenwosu, N. (2022). Influence of Cyber-security Problems in Digital Assessment on Students' Assessment Outcome: Lecturers' Perspective. Journal of Scientific Research and Reports, 28(10), 11–20. https://doi.org/10.9734/jsrr/2022/v28i1030551

[26]. Okoro, D. C. (2025). An Evaluation of Cybersecurity Frameworks and Privacy Regulations for Companies in the Digital Age: A Legal Approach. Asian Journal of Economics, Business and Accounting, 25(4), 431–440. https://doi.org/10.9734/ajeba/2025/v25i41761

[27]. Conti, M., Dehghantanha, A., Franke, K., & Watson, S. (2018). Internet of Things security and forensics: Challenges and opportunities. *Future Generation Computer Systems*, *78*, 544–546. https://doi.org/10.1016/j.future.2017.07.060

[28]. Chakraborty, S., Alam, M., Elovici, Y., & Rokach, L. (2020). Adversarial attacks and defenses: A survey. *arXiv preprint arXiv:1810.00069*.https://arxiv.org/abs/1810.00069