Method for Effect Evaluation of a Reception System on Sales, Number of Customers, Hourly Productivity and Churn Based on Intervention Analysis

Kohei Arai[1], Ikuya Fujikawa[2], Sayuri Ogawa[3]
Department Information Science, Saga University, Saga City, Japan[1]
SIC Holdings Co., Ltd., 1-7-1 Jyurokucho, Nishi-ku, Fukuoka City, Japan[2, 3]

***Abstract*—We propose a method of AI-based evaluation of sales, number of customers, and churn before and after the introduction of a hair salon based on intervention time series analysis. We also used the software package of CausalImpact for the intervention time series analysis. The problem with this method is that the prediction accuracy is insufficient, and the estimated results of the intervention effect are not very valid. We thought it was necessary to verify prediction accuracy by using data before the system was introduced, where correct answer data exists, for the counterfactual prediction value after the system was introduced and devised a method to accurately predict the outcome variable before the system was introduced. Specifically, we introduce two learning models as in the development workflow of a general machine learning model, one for learning and the other one for accuracy verification. However, since CausalImpact does not include the function to verify the prediction accuracy, a separate code was prepared for that purpose to improve the prediction accuracy. As a result, we were able to confirm that the prediction accuracy was almost acceptable.**

Keywords*—Intervention time series analysis; causalimpact package; counterfactual prediction value; general machine learning model

I. Introduction

In a typical hair salon, the reception method is for staff to introduce the treatment menu verbally, have the customer select a menu, and then guide the customer to the treatment table. This method of manual reception is a burden on the staff. By introducing a reception system, customers can also register their name and phone number on a tablet device at the time of reception and receive a call after the estimated waiting time.

To evaluate sales, number of customers, and churn before and after the introduction of this reception system, we performed an intervention time series analysis. We used CausalImpact[1] (Package software tool) for the intervention time series analysis. This package makes it easy to estimate and visualize the effects of the intervention, but it does not guarantee the accuracy of the prediction (the validity of the estimated results of the intervention effect).

It is necessary to be careful about the predicted value of the counterfactual scenario after the start of the measure, as there is no correct data. In this regard, the compromise would be to use data before the implementation of the measure, for which correct data exists, and verify the accuracy of the prediction. The assumption is that if the outcome variables before the implementation of the measure (i.e., if we did not implement any of the measures). It predicted accurately. Thus, the counterfactual scenario after the implementation of the measure will also be predicted accurately.

Specifically, as in the general machine learning model development workflow, the data before the implementation of the measures is divided into training data and accuracy verification data, and the model is built and its accuracy verified. However, since the CausalImpact package does not include a function to verify the prediction accuracy, the code for this purpose must be prepared separately. In this study, we devised a new code for improving prediction accuracy and the accuracy was verified.

In the next section, related research works are overviewed followed by the proposed method. Then, experiments with the actual sales, the number of customers, and churn as well as hourly productivity at three hair salons are described followed by conclusion with some discussions.

II. Related Research Works

As for the related research works on the causal impact analysis, there is GitHub software code also called “tfcausalimpact”[2] [1]. It is the GitHub license and there is PyPI version of Pyversions[3]. This package software code is Google’s Causal Impact Algorithm Implemented on Top of TensorFlow Probability. Also, there is the related research work on causal time series analysis software package also called “CausalImpact”[4] [2].

There are the following studies which deal with intervention time series analysis:

The study [3] introduced a classic in intervention analysis and explained the methodology for evaluating changes in time series data before and after the introduction of a policy or system. The study [4] discussed methods for detecting outliers in time

[1] https://zenn.dev/pe/articles/12be20efdaed40
[2] https://github.com/WillianFuks/tfcausalimpact?tab=readme-ov-file accessed on 27 March 2025.
[3] https://github.com/badges/shields/issues/5550
[4] https://qiita.com/iitachi_tdse/items/24119464b73992cd4abc Accessed on 27 March 2025.

series data, and verifying level and variance changes, and are also related to detecting the effects of interventions.

The study [5] evaluated the impact of service system enhancements on customer retention. This is an intervention time series analysis. This study uses intervention analysis to evaluate the change in customer retention rate before and after the introduction of improvements to a service system (e.g., a reception system), and is a useful application example for service industries such as hair salons.

The study [6] proposed an integrating survival analysis into customer churn prediction models. This is a model that combines survival analysis and time series techniques to predict customer churn. The study suggests relevance to evaluations using AI and machine learning.

A survey report was published for financial time series forecasting with deep learning [7]. On the other hand, analytical frameworks for COVID-19 impact assessment on retail sales using intervention time series analysis was conducted [8].

Forecasting change in customer behavior and sales performance based on AI-driven time series analysis was discussed [9]. Meanwhile, digitalization of the service encounter using AI-based analytics for customer churn prediction was conducted [10].

The effects of customer experience management systems in service industries were developed [11]. This is an intervention analysis approach. Assessing business impact of technology implementation using time series intervention analysis was evaluated as a case study in beauty service industry [12].

Other than these, there are some following URL sites which provide related information on AI-based hair salons:

As for a retailing of hair salons, an intelligent customer retention was provided (https://torontodigital.ca/blog/ai-for-salons-intelligent-customer-retention-strategies/) [13].

For enhancing salon experiences with an AI receptionist, demonstrations are now available with the URL (https://talkforceai.com/demos/hair-salon.html) [14].

Customer characterization for mitigation of customer churn was investigated and was available from the URL site (https://thesai.org/Downloads/Volume14No6/Paper_13-Method_for_Characterization_of_Customer_Churn_Based_on_LightBGM.pdf) [15].

Eight of the practical ways AI can boost salon and spa revenue are available from the URL site (https://www.zenoti.com/blogs/using-ai-to-boost-salon-and-spa-revenue) [16].

Nine ways to use AI for salon automation are provided from the URL site (https://truelark.com/salon-automation-with-ai/) [17].

As for the related research works on customer characterization, recently, a customer profiling method with big data based on Binary Decision Tree: BDT and clustering for sales prediction was proposed and evaluated the accuracy [18].

Modified Prophet [5] +Optuna [6] prediction method (predict sales with Prophet with hyperparameter optimization with Optuna) for sales estimations was also proposed and evaluated its accuracy [19]. Meanwhile, churn customer estimation method based on LightGBM[7] for improving sales was proposed [20] together with method for characterization of customer churn based on LightBGM and experimental approach for mitigation of churn [21]. Method for predictive trend analytics with SNS information for marketing was conducted [22].

III. Proposed Method

A. Reception System

We developed a management system that allows hair salon reception work (done on tablet devices). The aim is to streamline reception work with simple operations and improve customer satisfaction by streamlining reception, calling, and work analysis. Another aim is to reduce the amount of work done by staff.

Fig. 1 shows the outlook of the reception system tablet terminal and the display image of the tablet device. Salon name, date, called customer's name, the number of waiting customers and reception start button appeared on the screen.

Fig. 1. Outlook of the reception system tablet terminal and the display image of the tablet device.

After key-in the required information through the reception system, reception number, customer's name, phone number, ordered menu, status, and cancellation are displayed as shown in Fig. 2. There are four statuses: Accepted: the acceptance via the tablet has been completed; Called: the staff will call the customer; Guided: the customer will be guided to the treatment seat; and Treatment Completed: the treatment has been completed. These reception systems are developed at three hair salons and operated for more than nine months, from March 2024 to November 2024 until now. The sales, the number of customers, churn customers and the hourly productivity for each salon are recorded for these dates and the past dates from the beginning. Therefore, intervention analysis for the sales, the number of customers, and the hourly productivity can be evaluated.

B. Method for Intervention Time Series Analysis

We used a method called CausalImpact, which is useful when you want to verify the change in the effect of introducing a reception system over time. To predict counterfactual scenarios, CausalImpact builds a model that can manage time

[5] https://facebook.github.io/prophet/docs/quick_start.html
[6] https://optuna.readthedocs.io/en/stable/installation.html
[7] https://github.com/microsoft/LightGBM

series data, called a Bayesian structural time series model. To build the model, we use time series data of outcome variables before and after the intervention, as well as data that is likely to be useful for predicting counterfactual scenarios (called covariates).

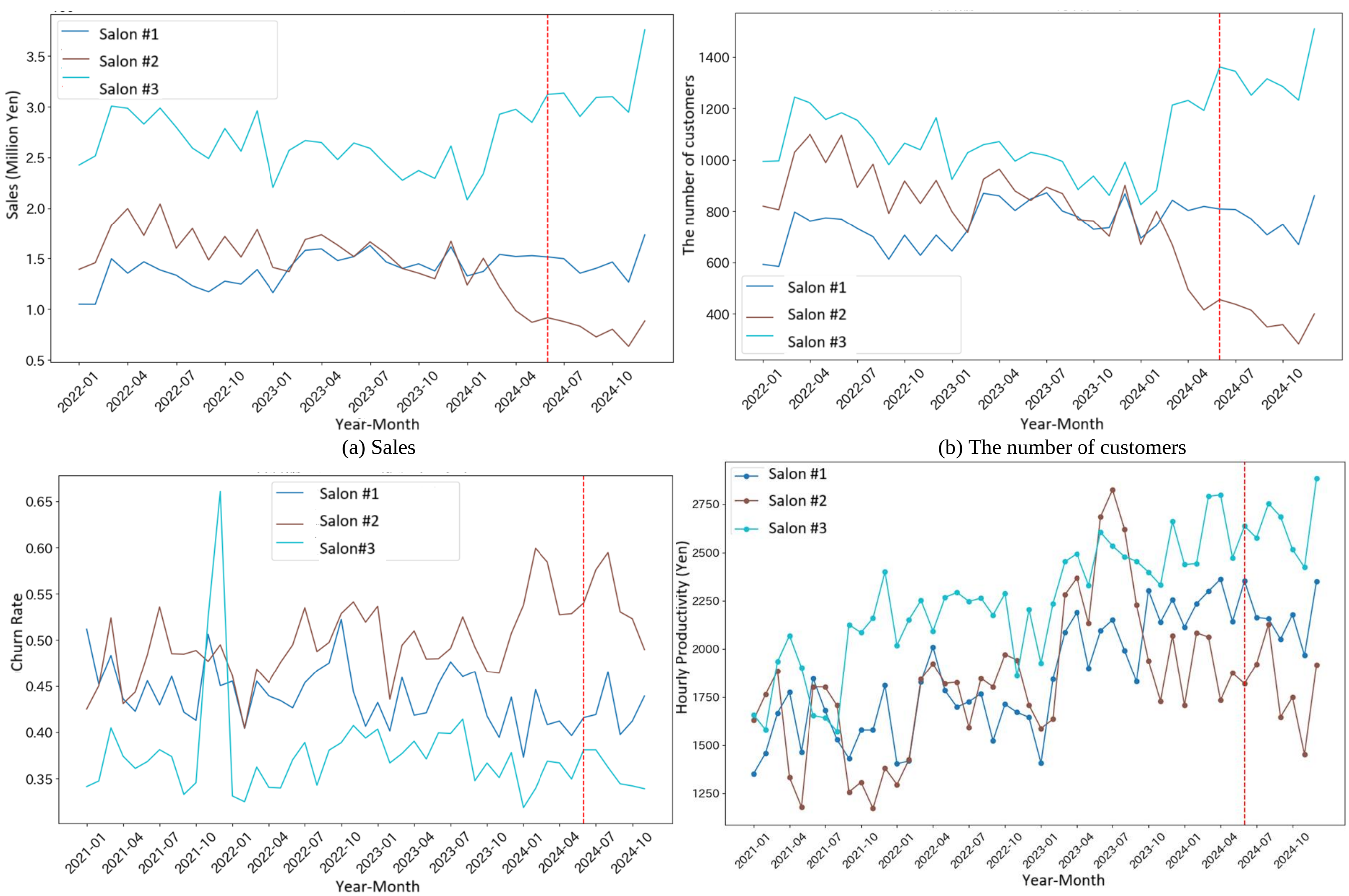
Fig. 2. Display reception number, customer's name, phone number, ordered menu, status, and cancellation.

We will not go into details of the model, but it combines a state space model that expresses the change in outcome variables over time, a local linear trend that is often used in time series data analysis, and a regression model that uses covariates. Covariates must be selected that are not affected by the intervention and whose relationship with the outcome variable does not change before and after the intervention.

IV. Experiment

A. Data Used

Three hair salons, Salons #1, #2, and #3 are selected for the intervention time series analysis. The sales, the number of customers, and churn rate as well as hourly productivity are shown in Fig. 3[(a), (b), (c), (d)] respectively. Red dotted line shows the date for the reception system which will be introduced.



(a) Sales
(b) The number of customers
(c) Churn rate
(d) Hourly productivity

Fig. 3. Sales, the number of customers, and churn rate as well as hourly productivity of the Salons #1, #2, and #3.

The sales of Salon #1 are almost flat, and the effect of the introduction is negligible. The sales of Salon #2 are declining due to the introduction, while the sales of Salon #3 seem to have improved significantly due to the introduction effect. We thought that one factor behind these which increases and decreases is personnel transfers and shortened business hours in February 2024, which are the cause of the appearance of some salons with rising and falling sales. Looking at the trend in customer numbers, we can see that they are trending in the same way as sales.

On the other hand, looking at the time series data for the churn rate, we can see that Salon #2 is increasing, while Salons #1 and #3 are trending sideways. It is noticeable that only the churn rate up to 2024-11, but this is because, due to the definition of churn, it is not possible to measure it until ninety days have passed. Regarding hourly productivity, we can see that Salon #3 is on an upward trend, while Salons #1 and #2 are flat or downward trends.

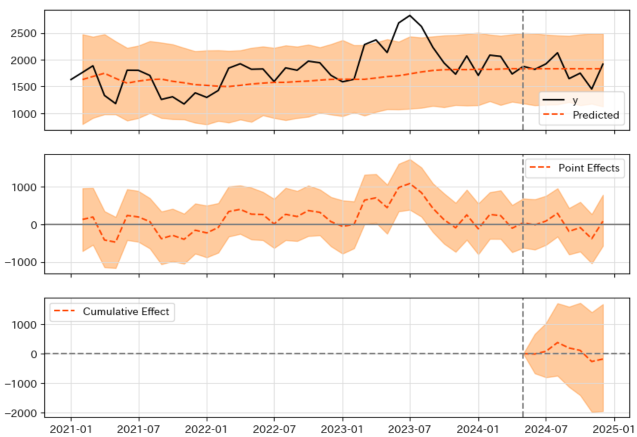
B. Software Code Used

The intervention time series analysis method is to build a predictive model using data from before the intervention and quantify the causal effect from the difference with the actual results after the intervention, and to examine the intervention effect estimated by CausalImpact. Currently, the predictive model uses a Bayesian structural time series model (Causalimpact default).

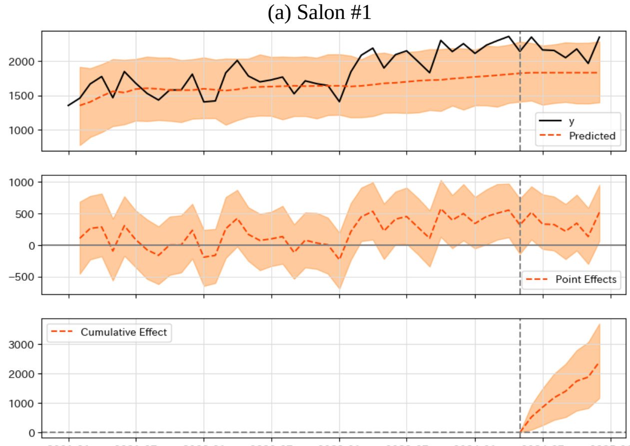
C. Result from the Intervention Time Series Analysis

1) Hourly productivity: Regarding hourly productivity, the evaluation result of the effect of introducing the reception system at Salon #3 was significant. One plausible reason for this is the effect of personnel transfers and insufficient sample size. There are no noteworthy results at other salons. The predicted value for Salon #3 is 2,222 yen (95% confidence interval is [1998.21, 2445.41]). As the average actual result after the intervention was 2,639.54 yen, we conclude that the introduction of the reception system improved hourly productivity by 417.08 yen.

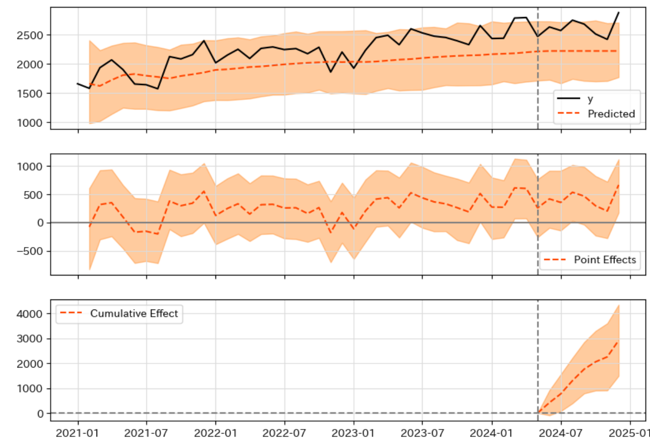
Fig. 4[(a), (b), and (c)] shows actual hourly productivity: y, predicted hourly productivity point by point effects and cumulative effects for Salon #1, #2, and #3.



(a) Salon #1



(b) Salon #2



(c) Salon #3

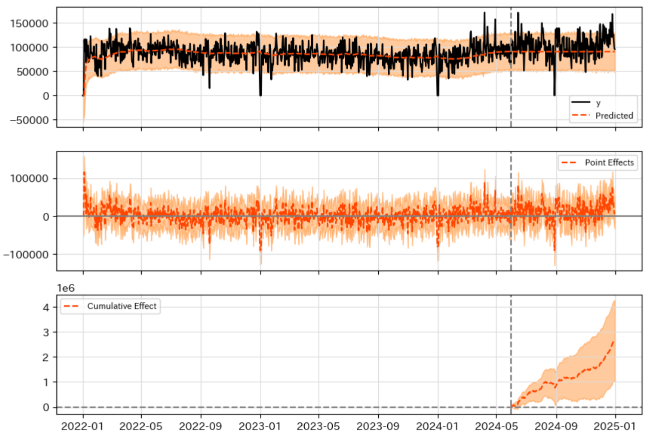
Fig. 4. Actual hourly productivity: y, predicted hourly productivity, point by point effects and cumulative effects for Salon #1, #2, and #3.

2) Sales: On the other hand, we investigated sales and the number of customers. To increase the sample size before and after the intervention in sales, we decided to use daily data for the analysis of sales and number of visitors. For Salon #1, the predicted sales were approximately 89,000 yen (95% confidence interval: [82720.69 yen, 95481.59 yen]) as shown in Fig. 5(a). The average actual result after the intervention was 103,082 yen. In conclusion, the effect of introducing the reception system was statistically significant, and it was true that the introduction increased sales by 13,691 yen. Note that, as with hourly productivity, we would do better to consider the intervention effect of personnel transfers.

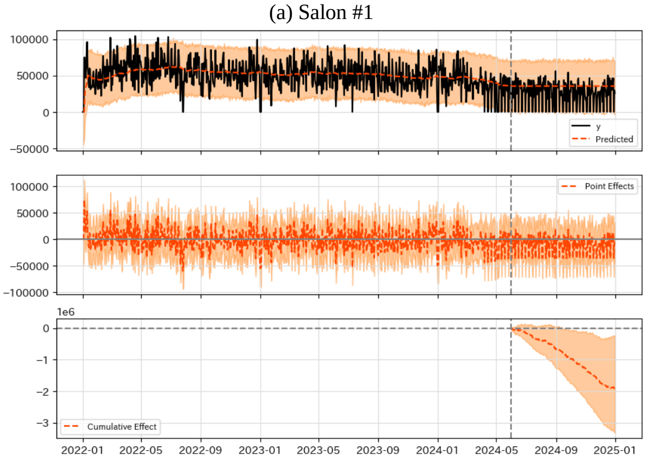
Meanwhile, the predicted sales value for Salon #2 was approximately 37,000 yen (95% confidence interval: [31077.53, 42973.61]), and the average actual sales after the introduction of the reception system was 26,495 yen as shown in Fig. 5(b), so the result is statistically significant, and it can be said that the introduction of the system reduced sales by 10,460 yen. Note that this evaluation result also reflects the intervention effects of personnel transfers and shortened business hours.

As for the Salon #3, during the post-intervention period, the response variable had an average value of approx. 47821.46 yen as shown in Fig. 5(c). In the absence of an intervention, we would have expected an average response of 49049.87 yen.

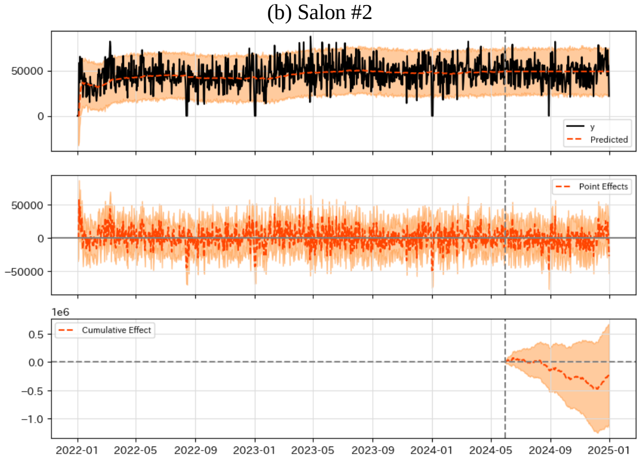
The 95% interval of this counterfactual prediction is [44359.24 yen, 53015.54 yen]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -1228.41 yen with a 95% interval of [-5194.09 yen, 3462.21 yen].



(a) Salon #1

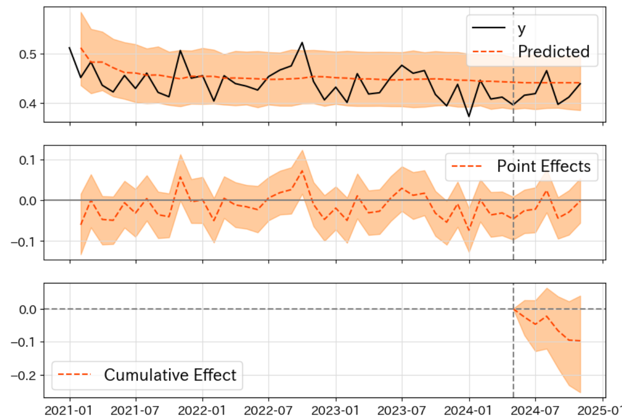


(b) Salon #2

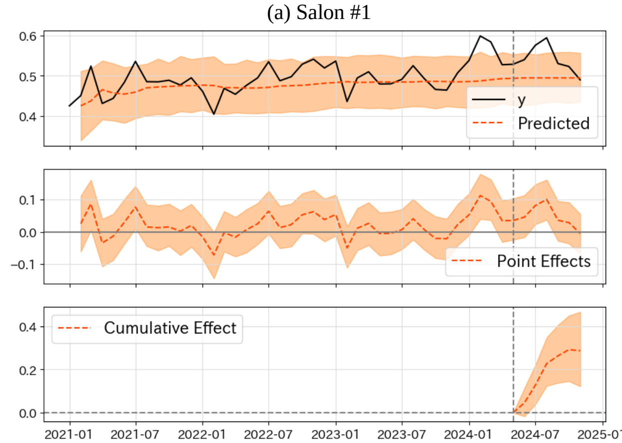


(c) Salon #3

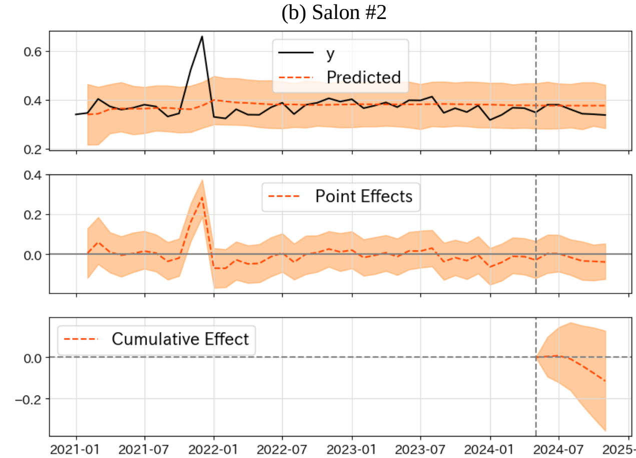
Fig. 5. Actual sales: y, predicted sales point by point effects and cumulative effects for Salon #1, #2, and #3.



(a) Salon #1



(b) Salon #2



(c) Salon #3

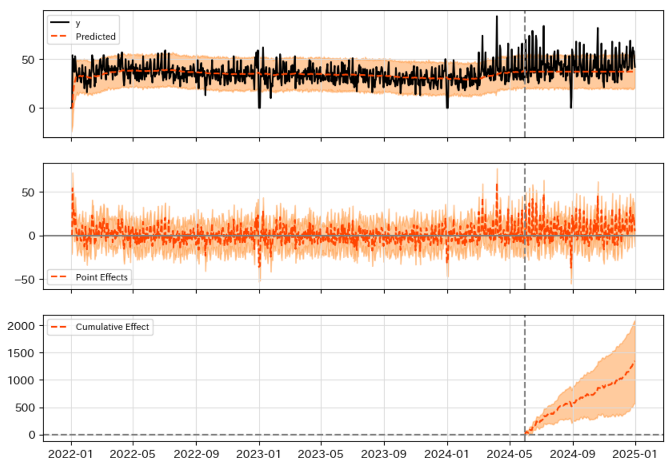
Fig. 6. Actual churn rate: y, predicted churn rate point by point effects and cumulative effects for Salon #1, #2, and #3.

3) Churn rate: As for Salon #1, during the post-intervention period, the response variable had an average value of approximately 0.42 as shown in Fig. 6(a). In the absence of intervention, we expected an average response of 0.44. The 95% interval of this counterfactual prediction is [0.42, 0.46]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -0.02 with a 95% interval of [-0.04, 0.01].

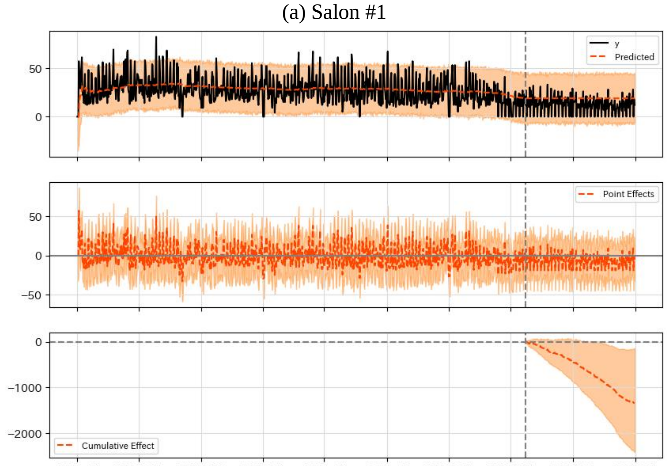
On the other hand, during the post-intervention period, the response variable had an average value of approximately 0.54 for Salon #2 as shown in Fig. 6(b). By contrast, in the absence of an intervention, we would have expected an average response of 0.49. The 95% interval of this counterfactual prediction is [0.47, 0.52]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 0.05 with a 95% interval of [0.02, 0.07].

The increase in churn rate for Salon #2 is statistically significant because the prediction was 0.49 (95% confidence interval [0.47, 0.52]) and the post-implementation mean was 0.54. Meanwhile, during the post-intervention period, the response variable had an average value of approximately 0.36 for Salon #3 as shown in Fig. 6(c). In the absence of an intervention, we would have expected an average response of 0.38. The 95% interval of this counterfactual prediction is [0.34, 0.42]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -0.02 with a 95% interval of [-0.06, 0.02].

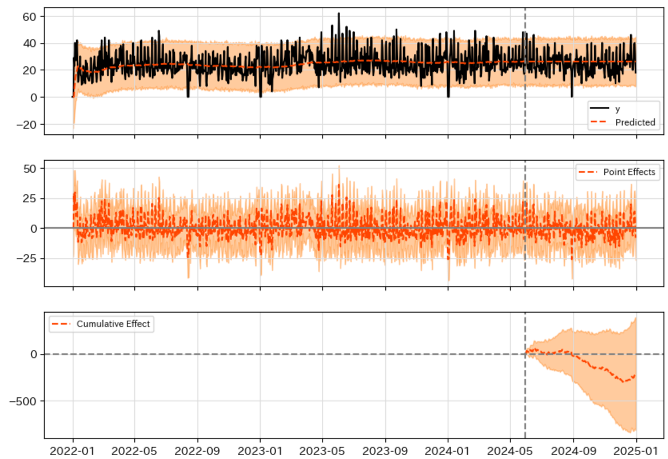
4) Number of customers: As for Salon #1, during the post-intervention period, the response variable had an average value of approximately 43.44 as shown in Fig. 7(a). By contrast, in the absence of an intervention, we expected an average response of 37.16. The 95% interval of this counterfactual prediction is [33.85, 41.19]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 6.29 with a 95% interval of [2.25, 9.6].



(a) Salon #1



(b) Salon #2



(c) Salon #3

Fig. 7. Actual number of customers: y, predicted number of customers, point by point effects and cumulative effects for Salon #1, #2, and #3.

Meanwhile, during the post-intervention period, the response variable had an average value of approximately 12.6 for Salon #2 as shown in Fig. 7(b). By contrast, in the absence of an intervention, we would have expected an average response of 18.88. The 95% interval of this counterfactual prediction is [13.53, 23.41]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -6.28 with a 95% interval of [-10.82, -0.93].

On the other hand, during the post-intervention period, the response variable had an average value of approximately 25.1 for Salon #3 as shown in Fig. 7(c).

In the absence of an intervention, we would have expected an average response of 26.18. The 95% interval of this counterfactual prediction is [23.5, 28.94]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -1.08 with a 95% interval of [-3.84, 1.59].

V. Conclusion

The effect of the introduction of the reception system on sales, number of customers, and hourly productivity has a positive significant difference in Salon #1, and a negative significant difference in Salon #2. However, one of the possible reasons is due to the influence of personnel transfers and business hour changes, even when looking at the visualization of monthly trends.

It is unclear whether there is a significant difference in the actual effect of the introduction of the reception system, so it is necessary to at least look at the difference with the intervention effect of February 2024. When we look back to one-year since the introduction in June 2025, Salon #3 will show some difference.

There is room to consider the possibility that it is effective for large stores like Salon #1, but not effective for small stores. Reasons for their effectiveness in large stores include the fact that it is easier to benefit from the organization of receptions for large numbers of people and the visualization of the number of people waiting.

The effect of the introduction of the reception system on the attrition rate was significant at Salon #1 (significant for increasing the attrition rate), although the sample size was also small. In other cases, we obtained no remarkable results.

We expected that older customers would have more defects, but overall, Salon #3 and Salon #1 saw a decline in defection rates.

FUTURE RESEARCH WORKS

The effect of the introduction of the reception system on the attrition rate was significant in Salon #2 (significant for increasing the attrition rate) and insignificant in other stores, although the sample size was also small. Although we expected that older customers would have more attrition rates, overall, the attrition rates were declining in Salon #1 and Salon #3. We will formulate hypotheses about the reasons for this and verify them in the future.

REFERENCES

[1] https://github.com/WillianFuks/tfcausalimpact?tab=readme-ov-file, Accessed on 27 March 2025.

[2] https://qiita.com/iitachi_tdse/items/24119464b73992cd4abc Accessed on 27 March 2025.

[3] Box, G. E. P. and Tiao, G. C., "Intervention Analysis with Applications to Economic and Environmental Problems" Journal of the American Statistical Association, Vol. 70, No. 349, pp. 70–79, 1975.

[4] Tsay, R. S., "Outliers, Level Shifts, and Variance Changes in Time Series" Journal of Forecasting, Vol. 7, No. 1, pp. 1–20, 1988.

[5] Lee, S. H. and Chen, C. Y., "Evaluating the Impact of Service System Enhancements on Customer Retention: An Intervention Time Series Analysis," Journal of Service Management, Vol. 21, No. 2, pp. 192–215, 2010.

[6] Coussement, K. and Van den Poel, D., Integrating Survival Analysis into Customer Churn Prediction Models, European Journal of Operational Research, Vol. 184, No. 3, pp. 1109–1126, 2008.

[7] Sezer, O. B., Gudelek, M. U. and Ozbayoglu, A. M., Financial Time Series Forecasting with Deep Learning: A Survey, Applied Soft Computing, Vol. 90, Art. No. 106181, 2020.

[8] Liu, X., Chen, H., & Montewka, J. (2021). "Analytical frameworks for COVID-19 impact assessment on retail sales using intervention time series analysis." International Journal of Retail & Distribution Management, 49(8), 1130-1151, 2021.

[9] Park, S., Lee, J., & Song, W. (2019). "Forecasting change in customer behavior and sales performance based on AI-driven time series analysis." Journal of Service Research, 22(3), 245-263, 2019.

[10] Schmidt, J., Drews, P., & Schirmer, I. (2018). "Digitalization of the Service Encounter: Using AI-based Analytics for Customer Churn Prediction." Journal of Service Management, 29(4), 592-616, 2018.

[11] Kim, Y., & Lee, H. (2020). "The Effects of Customer Experience Management Systems in Service Industries: An Intervention Analysis Approach." Service Science, 12(1), 31-49, 2020.

[12] Wang, C., Zhang, X., & Hao, Y. (2018). "Assessing Business Impact of Technology Implementation Using Time Series Intervention Analysis: A Case Study in Beauty Service Industry." Journal of Business Analytics, 6(2), 118-135, 2018.

[13] https://torontodigital.ca/blog/ai-for-salons-intelligent-customer-retention-strategies/ Accessed on 27 March 2025.

[14] https://talkforceai.com/demos/hair-salon.html Accessed on 27 March 2025.

[15] https://thesai.org/Downloads/Volume14No6/Paper_13-Method_for_Characterization_of_Customer_Churn_Based_on_LightBGM.pdf Accessed on 27 March 2025.

[16] https://www.zenoti.com/blogs/using-ai-to-boost-salon-and-spa-revenue Accessed on 27 March 2025.

[17] https://truelark.com/salon-automation-with-ai/ Accessed on 27 March 2025.

[18] Kohei Arai, Zhang Ming Ming, Ikuya Fujikawa, Yusuke Nakagawa, Ryoya Momozaki, Sayuri Ogawa, Customer Profiling Method with Big Data based on BDT and Clustering for Sales Prediction, International Journal of Advanced Computer Science and Applications, 13, 7, 22-28, 2022.

[19] Kohei Arai, Ikuya Fujikawa, Yusuke Nakagawa, Ryoya Momozaki, Sayuri Ogawa, Modified Prophet+Optuna Prediction Method for Sales Estimations, International Journal of Advanced Computer Science and Applications, 13, 8, 58-63, 2022.

[20] Kohei Arai, Ikuya Fujikawa, Yusuke Nakagawa, Ryuya Momozaki, Sayuri Ogawa、Churn Customer Estimation Method based on LightGBM for Improving Sales、International Journal of Advanced Computer Science and Applications, 14, 2, 119-125, 2023.

[21] Kohei Arai, Ikuya Fujikawa, Yusuke Nakagawa, Ryoya Momozaki, Sayuri Ogawa, Method for Characterization of Customer Churn Based on LightBGM and Experimental Approach for Mitigation of Churn, International Journal of Advanced Computer Science and Applications, Vol. 14, No. 6, 112-118, 2023.

[22] Kohei Arai, Ikuya Fujikawa, Yusuke Nakagawa, Sayuri Ogawa, Method for Predictive Trend Analytics with SNS Information for Marketing, International Journal of Advanced Computer Science and Applications, Vol. 15, No. 2, 419-425, 2024.

AUTHOR'S PROFILE

Kohei Arai, He received BS, MS, and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January 1979 to March 1990. During 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post Doctoral Fellow of National Science and Engineering Research Council of Canada. He moved to Saga University as a Professor in Department of Information Science in April 1990. He was a counselor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology from 1998 to 2000. He was a councilor of Saga University during 2002 and 2003. He was also an executive councilor for the Remote Sensing Society of Japan from 2003 to 2005. He is a Science Council of Japan Special Member since 2012. He is a Visiting Professor at Prishtina University. He is also a lecturer at Nishi-Kyushu University and Kurume Institute of Technology. He wrote 134 books and published 745 journal papers as well as 584 conference papers. He received ninety-eight of awards including ICSU/COSPAR Vikram Sarabhai Medal in 2016, and Science award of Ministry of Education of Japan in 2015. He is now Editor-in-Chief of IJACSA and IJISA. http://teagis.ip.is.saga-u.ac.jp/index.html