Complementing the Impact and Economic Potential of Patient Support Programs through Artificial Intelligence (AI) Augmentation

Daniela Zanni
Department of Health Outcomes
HealthNet Homecare UK Ltd.
Swadlincote, Derbyshire, UK
Email: daniela.zanni@healthnethomecare.co.uk

Joshua Hinton
School of Psychological and Behavioural Sciences
London School of Economics (LSE)
London, UK
Email: j.d.hinton@lse.ac.uk

Ejike Nwokoro
Department of Patient Insights & Data Strategy
HealthNet Homecare UK Ltd.
Swadlincote, Derbyshire, UK
Email: ejike.nwokoro@healthnethomecare.co.uk

***Abstract* - Patient adherence to medication has been a long-sought health outcome measure, with the demonstrable benefits of reduced disease-related complications, improved quality of life, and reduced mortality. However, when not adequately supported, chronic disease patients often experience a downward trend in their adherence over time. Patient Support Programs are designed to address this issue by keeping patients engaged throughout their chronic disease management journey and supporting them in developing increasing accountability for their own health and wellbeing. Although these Patient Support Programs have been shown to be a viable tool in supporting treatment retention and adherence, there remains sparse evidence relating to quantifiable economic benefit, both from a pharmaceutical revenue and a health system cost-saving perspective. To this end, this study sought to explore the impact of Patient Support Programs on treatment retention as well as the medicine revenue implication of any observed impact of these programs. We found that adoption of Patient Support Programs reduces patient drop-off from treatment (1.1% drop off compared to 2.8% when patients are not enrolled in the program). Additionally, the observed impact translates to economic benefits, in terms of medicine revenue, of between £2,156,561 and £4,714,787, over a 6-month period. Furthermore, our analysis suggests that complementing these Patient Support Programs with prior prediction of patient risk of poor adherence (through machine learning) can result in the generation of additional medicine revenue of almost £500,000 over a 6-month period. We opine that this enhancement is made possible through early deployment of the programs, as well as their deployment in a manner that is guided by a better understanding of individual patient risk of poor adherence.**

Keywords-Patient Support Program; medication adherence, artificial intelligence; predictive analysis.

I. INTRODUCTION

Patient Support Programs are increasingly popular in the healthcare sector. For most pharmaceutical companies, these Patient Support Programs are intended as wraparound services for new medicines, with a view to supporting patients with treatment compliance. In general, initiatives that support improved access and adherence to medicines are expected to help drive better patient outcomes and positive experience with treatments.

Needless to say, adherence to treatments for chronic diseases is of public health relevance - it is estimated that there would be 18 million people in the UK living with a chronic physical illness by 2025 [1] and it is widely cited that up to 50% of medications are not taken as prescribed [2], with these rates possibly varying considerably across different conditions [3].

Crucially, it has been argued by other authors that AI can support early deployment of Patient Support Programs, thus making them more effective [4], as well as enhance the potential of Patient Support Programs to improve medication adherence [5].

The rest of the paper is structured as follows. In Section 2, we establish the objectives of this paper. In Section 3, we assess the methodology used to achieve the objectives of the study. In Section 4, we discuss the results in greater detail, and in Section 5, we conclude by highlighting the implications of our findings, as well as indicating areas of future research.

II. OBJECTIVES

This study had three overarching objectives:

- To examine the efficacy of Patient Support Programs in mitigating patient drop-off from treatment (as an indicator of non-adherence)
- To understand the medicine revenue implications of reduced drop-off rates
- To explore the potential of AI augmentation in enhancing the impact and economic potential of Patient Support Programs, etc.

 ISBN: 978-1-68558-180-0

III. METHODOLOGY

A. Study dataset and patient categories

The study population data pertains to patients diagnosed with chronic diseases and who are receiving one of three possible service levels from a Clinical Homecare company (n=97,795) between January 2016 and March 2024. The three possible service levels were: (1) Level 1 Service - entails a direct-to-patient delivery of prescribed medication at a frequency dictated by their prescription (2) Level 2 Service - entails Level 1 service plus a nurse-led training of a patient to correctly self-administer their medication independently (3) Level 3 Service – entails Levels 1 and 2 services plus a Patient Support Program designed to facilitate sustained medication adherence.

Only services that had 100 or more patients were included in the analysis. The period covered was for patients enrolled in one of the above three services between May 2016 and March 2024.

B. Inclusion criteria for Treatment drop-off categorisation

Patient drop-off from treatment was analyzed across all three service levels. In the context of this study, "drop-off" is defined as patients who are no longer receiving their medication either due to: their unwillingness to engage with the service, a no-response to engagement attempts from the service provider and where patients have requested the service to be put on hold. In these three instances, the patients is considered as no longer taking their medication as prescribed and thus classed as non-adherent.

C. Analysis approach for Medicine revenue impact

The study extrapolated maintenance posology for all medicines prescribed to the patients whose data were part of the study and calculated the applicable dose per week. Then, the NHS England indicative price was collected for each medicine, with cost per unit subsequently calculated. Following this, cost per dose was identified for each medicine, both on a weekly and a 6-monthly basis. Finally, bearing in mind the treatment drop-off across all three service levels, potential additional medicine revenue (over 6 months) was calculated for scenarios where level 1 and Level 2 service patients are instead enrolled in a Level 3 service.

D. Analysis approach for Impact of AI augmentation

AdherePredict [6][7] (an AI platform designed to predict which patients are most likely to drop off their prescribed medicine and therefore enabling the early and targeted deployment of impactful Patient Support Programs) estimates that one of the benefits of an early deployment of a Patient Support Program that is based on predictive insight includes better patient engagement and reduced drop-off from treatment.

This Machine Learning model, which utilizes a Convolutional Neural Network, identifies the patients most at risk of non-adherence. In this context, non-adherence is defined by using the metric known as Proportion of Days Covered (PDC) of 100% for the period covered by the patient's prescription. Therefore, a patient is deemed non-adherent if they do not have any medication at any point within the period the period that they are supposed to, based on their prescription. Accurately predicting the patients most at risk of non-adherence allows a more purposeful, and early, deployment of Patient Support Programs, in a manner that is better tailored to each individual patient risk. Research has shown that such early and proactive deployment of patient support initiatives makes them more impactful [8] [9].

We calculated the additional medicine revenue implication, over 6 months, of an assumed 0.2% less drop-off in targeted Patient Support Programs that are complemented by AI-based predictive insight.

IV. RESULTS

A. Treatment drop-off rate across Service Levels

Fewer patients drop off from treatment when they are on Patient Support Programs, i.e., Level 3 service (1.1%), compared to those that are on Level 2 service (2.1%) or Level 1 service (2.8%).

B. Medicine revenue implications of drop-off across Service Levels

The medicine revenue analysis shows that if the Level 1 and Level 2 service patients were instead enrolled into a Level 3 service, and as a result are subject to a similar drop-off rate as the current Level 3 service patients, then this translates to an additional drug revenue, over 6 months, of £2,156,561 compared to Level 1 service, £2,558,226 compared to Level 2 service, and £4,714,787 compared to both Level 1 and 2 services together.

C. Additional Medicine revenue from AI-augmented Patient Support Programs

Assuming a further decrease of 0.2% in the Patient Support Program drop off rate due to targeted and early deployment driven by predictive insight, the medicine revenue analysis showed an additional medicine revenue, over 6 months, of £5,206,399 compared to £4,714,787 for a Patient Support Program not complemented by such AI-based prediction.

V. CONCLUSION

Investing in Patient Support Programs and AI integration potentially not only improves medication adherence but also produces significant financial benefits. Further research is required to understand how such benefits may vary across different therapy areas and within primary, secondary and homecare settings.

REFERENCES

[1] C. Abraham, M. Conner, F. Jones, and D. O'Connor, "Health Psychology," Topics in Applied Psychology (2nd ed.), Routledge, doi: 10.4324/9781315776453, April 2016.

[2] E. Sabaté, "Adherence to long-term therapies: Evidence for action," World Health Organization, 2003.

[3] B. Vrijens et al., "A new taxonomy for describing and defining adherence to medications," British Journal of Clinical Pharmacology, vol. 73 no. 5, pp. 691–705, doi: 10.1111/j.1365-2125.2012.04167, 2012.

[4] V. Koesmahargyo et al., “Accuracy of machine learning-based prediction of medication adherence in clinical research,” Psychiatry Research,, vol. 294, no. 113558; ISSN0165-1781. doi: 10.1016/j.psychres.2020.113558, December 2020

[5] A. Bohlmann, J. Mostafa, and M. Kumar, “Machine Learning and Medication Adherence: Scoping Review,” JMIRx Med, vol. 2, no. 4, p. 26993. doi: 10.2196/26993, November 2021.

[6] B. Malin, T. Kalganova, E. Nwokoro, and J. Hinton, ”Medication Adherence Prediction for Homecare Patients, Using Medication Delivery Data,” HEALTHINFO 2023, The Eighth International Conference on Informatics and Assistive Technologies for Health-Care, Medical Suppot and Wellbeing, IARIA 2023, pp. 30-38.

[7] HealthNet Homecare UK Ltd. “How HealthNet are driving patient safety and positive experience through cost-effective Clinical Homecare,” HealthNet Homecare, 2023.

[8] T. Patel, “Medication nonadherence: Time for a proactive approach by pharmacists,” Canadian Pharmacists Journal, SAGE Publications Ltd, vol. 154, no. 5,, pp. 292–296, doi: 10.1177/17151635211034216. September 2021.

[9] A. G. G. Stuurman-Bieze, E. G. Hiddink, J. F. M. van Boven, and S. Vegter, “Proactive pharmaceutical care interventions decrease patients’ nonadherence to osteoporosis medication,” Osteoporosis International, vol. 25, no. 6, pp. 1807–1812, 2014, doi: 10.1007/s00198-014-2659-8.