

Forecasting Patient Persistency Behavior: A Comparison of Methodologies

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Abstract: *Patient persistence is a critical factor in the management of chronic diseases and effectiveness of therapies. High levels of persistency are associated with better clinical outcomes and can affect the cost - effectiveness of treatment. Understanding and improving patient persistence are crucial for achieving optimal treatment efficacy and patient health outcomes. There are various methods to calculate persistency, including the medication possession ratio, medication availability at a fixed point in time, and gaps between refills. Different methods provide distinct insights into medication adherence. The (shifted) beta - geometric (sBG) mixture model is based on a storytelling approach and has been shown to offer accurate forecasts and insights into patient dropout probabilities over time. The paper recommends the use of the sBG model as a starting point for understanding and forecasting patient persistence and retention patterns. It is important to validate the model's predictions with real - world data and compare them with other forecasting models or traditional methods of analyzing patient persistence to evaluate its effectiveness and advantages in predicting medication adherence behavior. The paper also suggests that a few key factors, such as time period, therapeutic class, and region, should be considered when calculating patient persistence.*

Keywords: patient persistence, fixed interval, shrinking interval, withdrawal interval, medication adherence

1. Introduction and Background

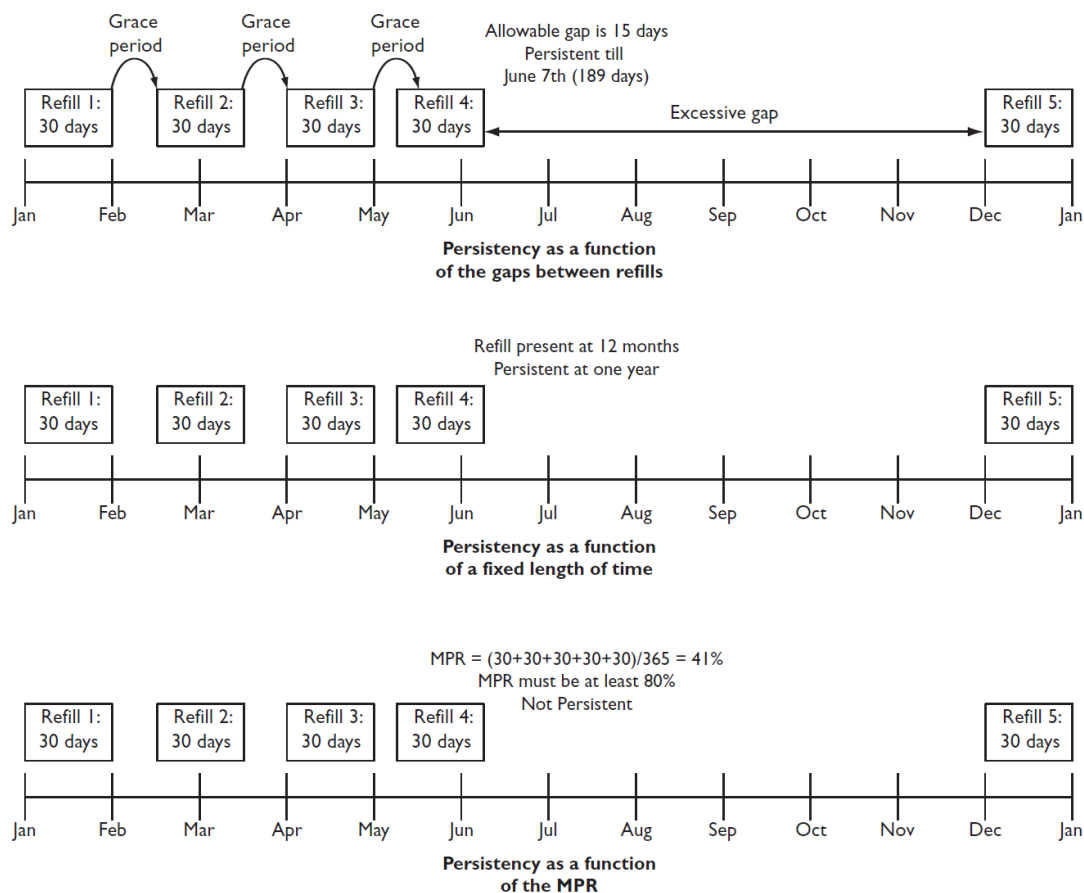
Patient persistence refers to the duration and consistency with which patients adhere to their prescribed medical treatment. It is a critical factor in the management of chronic diseases and effectiveness of therapies. Persistency is defined as the time from initiation to discontinuation of therapy, with factors affecting persistence including prior medication use, physician visits, and hospitalization after therapy initiation [1]. Patient persistence is a multifaceted concept that plays a significant role in the treatment of various conditions, including chronic diseases, such as Alzheimer's disease, glaucoma, and HIV [2]. It is influenced by factors such as medication side effects, the complexity of the treatment regimen, and patient interactions with healthcare providers. High levels of persistency are associated with better clinical outcomes and can affect the cost - effectiveness of treatment. Understanding and improving patient persistence are crucial for achieving optimal treatment efficacy and patient health outcomes.

Applying methodological rigor to measure patient persistency allows for more refined interpretations that can inform decision - makers on how to improve disease management [3]. Pharmaceutical companies use persistency projections to understand the patterns of medication refills,

which aids in forecasting and improving patient outcomes [4].

There are various methods to calculate persistency that depend on the type of analysis performed. Medication persistence can be assessed as a function of the medication possession ratio, medication availability at a fixed point in time, or the gaps between refills, with the latter providing a robust assessment across various medications and diseases [5]. Persistency can be measured using Markov models, net benefit regression models, and discrete event simulations, which offer flexibility and direct inclusion in pharmacoeconomic analyses [6]. The Kaplan - Meier method and Cox proportional hazards models are used to determine persistence rates over time and to identify factors influencing persistence [7]. Persistency can be modeled as a discrete optimization problem under uncertainty, providing insights into stochastic discrete optimization problems and choice modeling [8].

Given the various methods in persistence calculation, it is important to use the right method to fit the required analysis. This paper attempts to evaluate different methodologies for patient persistence calculation. The focus of this paper is to suggest a methodology that allows researchers to forecast patient behavior. This would be helpful for pharmaceutical companies to understand their target patient populations and accurately forecast revenue projections for their drugs.



MPR indicates medication possession ratio.

Figure 1: Sikka et al. Compares Different Persistency Methodologies

2. Literature Review

Multiple research papers explain different persistence calculation methods. Three research papers have been selected that provide insights into the applicability of patient persistence calculation to forecasting.

2.1 (Shifted) Beta - Geometric (sBG) Mixture Model

Ka Lok Lee, Peter Fader, and Bruce Hardie provide a structured framework for forecasting patient persistency behavior. By combining elements of the beta distribution and geometric distribution, the (shifted) beta - geometric (sBG) mixture model offers accurate forecasts and insights into patient dropout probabilities over time [9]. The model is based on a storytelling approach, in which patients are metaphorically described as flipping a coin to decide whether to refill their medication. This simple yet effective narrative helps understand and predict patient persistency patterns. The sBG model demonstrated remarkable accuracy in forecasting patient persistence levels. By estimating model parameters and projecting persistence curves, stakeholders can make informed decisions to improve medication adherence and patient outcomes. The model accounts for heterogeneity in patient dropout probabilities, indicating variability in persistence behavior across different patient populations. Understanding this variability can lead to targeted interventions that enhance medication adherence. The model can be implemented using simple tools, such as

Excel, making it accessible and applicable across various managerial domains. This ease of implementation allows for its practical use in pharmaceutical forecasting and healthcare decision - making. The authors recommend the use of the sBG model as a starting point for understanding and forecasting patient persistence and retention patterns. It is important to validate the model's predictions with real - world data and compare them with other forecasting models or traditional methods of analyzing patient persistency to evaluate its effectiveness and advantages in predicting medication adherence behavior.

2.2 Persistency Calculation using Real - World Data

Rishi Sikka, Fang Xia and Ronald E. Aubert highlight the importance of real - world data in persistence calculations. Real - world data, derived from sources such as electronic health records and pharmacy claims, are instrumental in medication persistence studies, as they provide a window into real - world medication adherence behaviors, treatment effectiveness, and healthcare utilization within authentic clinical environments. These datasets offer a rich repository of information on how patients take and refill their medications in diverse populations. Researchers can use real - world data to monitor medication adherence over time, capturing the nuances of actual clinical practice and patient habits. By harnessing these data sources, researchers can compare the effectiveness of different treatments, establish connections between medication adherence and patient

outcomes, and identify areas where healthcare delivery can be improved. Ultimately, the integration of real - world data into medication persistence studies enhances the understanding of medication adherence behaviors and enables the development of targeted interventions to enhance patient outcomes and optimize healthcare services. The authors outlined three primary approaches for measuring medication persistence: persistency based on the Medication Possession Ratio (MPR), medication availability at a specific time point, and the intervals between refills. The MPR method defines persistency as meeting a set threshold, often 80%, which indicates consistent medication availability across refill periods. Examining medication possession at a fixed moment offers a snapshot of adherence but may not capture long - term behavior. Calculating persistency using refill gaps focuses on the regularity and promptness of refilling, distinguishing between individuals who adhere to their medication regimens and those who do not. Each method provides distinct insights into medication adherence behaviors, with the refill gap approach offering a more comprehensive evaluation of refill compliance across various medications and health conditions [5].

2.3 Key Factors in Persistency Calculation

Persistence calculations can vary depending on the timeframe considered. Studies may assess persistence over different durations, such as 12 months, and show trends of decreased persistence over time. Persistence rates may differ across different therapeutic classes, but overall, there can be similarities in persistence rates among classes, such as antihypertensives, oral antidiabetics, and lipid - lowering therapies. Studies conducted in different regions reported varying persistence rates. For example, differences in persistence rates were observed between European and North American studies. The study design can impact the calculation and reporting of persistence. Prospective studies may provide different insights into persistence than retrospective studies. Considering these factors is crucial for understanding the nuances of medication persistence calculations and accurately interpreting the results in the context of managing different disease conditions [10].

3. Conclusion

This paper on forecasting patient persistency behavior highlights the critical role of patient persistence in managing chronic diseases and optimizing treatment effectiveness. Various methodologies, such as the medication possession ratio, medication availability, and refill gaps, provide valuable insights into medication adherence behaviors. The (shifted) beta - geometric (sBG) mixture model, developed by Ka Lok Lee, Peter Fader, and Bruce Hardie, emerges as a powerful tool for forecasting patient persistency patterns, offering accurate predictions and insights into patient dropout probabilities over time. Real - world data, including electronic health records and pharmacy claims, play a crucial role in medication persistence studies, enabling researchers to monitor adherence behaviors and optimize healthcare services. By understanding and improving patient persistence, stakeholders can enhance medication adherence, improve patient outcomes, and make informed decisions to forecast the revenue projections for pharmaceutical products.

The integration of advanced forecasting models such as the sBG model with real - world data enhances our understanding of medication adherence behaviors and paves the way for targeted interventions to optimize patient health outcomes.

4. Next Steps

The next steps can be aimed at improving the accuracy of persistence predictions, enhancing the understanding of medication adherence behaviors, and optimizing healthcare decision - making to benefit patient health and treatment efficacy. These steps include validating and comparing the (shifted) beta - geometric (sBG) mixture model with real - world data to ensure its reliability, conducting further research to identify additional factors influencing patient persistence, implementing advanced forecasting methodologies in clinical and pharmaceutical settings, conducting longitudinal studies to monitor persistency trends over time, and developing tailored patient engagement strategies based on forecasting insights to boost medication adherence and improve patient outcomes in chronic disease management. By undertaking these actions, researchers and healthcare professionals can refine persistence predictions, gain deeper insights into adherence behaviors, and enhance healthcare strategies to improve patient health and treatment effectiveness in chronic disease management.

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