Predictive Analytics for Chronic Disease Medication Adherence

Tresna Dey

Abstract

In the quiet mornings of rural Narail and the bustling aisles of pharmacies in Dhaka, a silent yet profound health crisis is unfolding. For millions of Bangladeshis living with chronic conditions such as hypertension and diabetes, the efficacy of a prescription is contingent not merely on the availability of medicine, but on the patient's ability to adhere consistently to the treatment regimen.

As we advance through 2026, research is revealing a sobering reality: nationwide medication adherence for chronic illnesses hovers around 52.4%, implying that nearly one in two patients risks suboptimal disease control or treatment failure. This adherence gap is not simply a matter of personal discipline—it is a structural determinant of health outcomes, reflecting socioeconomic disparities, healthcare access, and the effectiveness of communication between providers and patients.

Historically, interventions to improve adherence have relied on simplistic measures such as SMS reminders or pamphlets. While these strategies have value, they fail to address the underlying system-level determinants of non-adherence. In 2026, predictive analytics and machine learning (ML) are transforming the field, allowing healthcare systems to anticipate adherence lapses and intervene before a patient misses a dose. By integrating prescription refill records, socioeconomic indicators, comorbidity data, and prior adherence behavior, algorithms are capable of generating individualized "non-adherence risk scores," enabling a proactive, data-driven approach to chronic disease management.

Quantitative analyses underscore the breadth of the adherence challenge. Recent studies from 2025–2026 indicate that income remains a significant determinant of adherence. Patients in lower-income brackets, earning below 20,000 BDT per month, are disproportionately represented among non-adherent populations, whereas those earning above 40,000 BDT achieve adherence rates approaching 63.4%. Chronic conditions themselves present unique challenges: in sub-district health facilities, nearly 43.9% of hypertensive patients fail to follow their prescribed regimens, with forgetfulness (20.29%) and demanding work schedules (7.71%) cited as primary contributors. For individuals living with Type 2 Diabetes Mellitus (T2DM),

adherence is further complicated by treatment complexity, limited access to professional healthcare guidance, and lack of insurance, rendering 81% of such patients at elevated risk of missed doses. These data highlight that non-adherence is rarely random; it is systematically influenced by socioeconomic context, clinical complexity, and patient engagement.

Machine learning algorithms provide an unprecedented lens to decode these complexities. Several modeling approaches have been benchmarked to identify the most effective predictive tools for the Bangladeshi context. Random Forest (RF) consistently demonstrates robust performance, with a median area under the curve (AUC) of approximately 0.83, adeptly capturing the non-linear relationships between variables such as age, income, and treatment burden. Boosting algorithms like XGBoost and CatBoost are particularly valuable for detecting “tipping points” where adherence begins to decay, allowing timely intervention. Logistic regression remains critical for its interpretability, enabling clinicians to understand how factors like “distance to pharmacy” or “number of concurrent medications” influence a patient’s risk score. Collectively, these models facilitate a shift from reactive monitoring to proactive risk management.

One of the most insightful outputs of machine learning is the identification of feature importance using methods such as SHAP (Shapley Additive exPlanations). Analyses consistently show that prior adherence behavior is the strongest predictor of future compliance. Patients with dense comorbidity profiles, taking five or more medications, are more likely to struggle with adherence, highlighting the cognitive and logistical burdens of complex regimens. Furthermore, trust in healthcare providers and satisfaction with physician consultations are powerful protective factors; longer, more informative consultations are directly associated with improved adherence. This underscores the critical role of interpersonal communication in supplementing technological solutions—predictive analytics is most effective when coupled with human-centered healthcare delivery.

As predictive analytics becomes integrated into patient care, ethical considerations regarding data privacy emerge. Personal prescription records, socioeconomic profiles, and health behaviors constitute sensitive information, necessitating privacy-conscious strategies for data handling. Anonymized aggregation allows researchers to analyze trends at the community or pharmacy-cluster level without compromising individual identity. Secure Health Exchanges, facilitated through national digital infrastructure, ensure that patient-level data is encrypted and accessible only to authorized providers. Data sovereignty is equally important: behavioral insights derived from Bangladeshi patients must remain under local jurisdiction, protected by national ICT regulations, and insulated from external exploitation. Ethical stewardship ensures that predictive models serve public health goals without compromising individual rights.

The practical application of predictive analytics extends beyond identification of at-risk patients; it informs targeted interventions designed to enhance adherence and reduce preventable complications. AI-driven refill reminders, timed to align with each patient’s specific prescription cycle, surpass generic SMS blasts in

effectiveness. Strategic counseling becomes more precise: pharmacists prioritize patients with high-risk scores for in-depth “medication reconciliation” and education, addressing both cognitive and logistical barriers. In cases where cost is a primary determinant of non-adherence, predictive insights allow healthcare authorities and social programs to deploy targeted subsidies or discounts, ensuring equitable access to essential medications.

This integrative approach reframes medication adherence not as a failure of will, but as a predictable system friction. It recognizes the intersection of socioeconomic pressures, health literacy, access challenges, and individual behavioral patterns. By preemptively identifying potential lapses, the healthcare system can intervene strategically, transforming adherence from a reactive challenge to a proactive, manageable metric of system performance.

The quantitative impact of such predictive systems is significant. Modeling indicates that targeted interventions informed by AI-driven risk scoring could improve overall adherence rates by 15–20%, translating into measurable reductions in avoidable hospitalizations, complications, and long-term treatment costs. For hypertensive patients, even modest improvements in medication continuity can dramatically reduce the incidence of stroke and heart attack. For patients with diabetes, better adherence decreases the likelihood of renal failure, neuropathy, and cardiovascular comorbidities. Beyond individual outcomes, system-level efficiencies are realized through reduced burden on tertiary hospitals and a lower incidence of acute care crises, contributing to the broader goals of Universal Health Coverage and sustainable healthcare resource management.

Equally important is the human dimension. By identifying patients at risk before non-adherence occurs, healthcare providers can prioritize counseling, nurture patient trust, and deliver personalized interventions that acknowledge the social and cultural context of care. In rural areas, this may involve home visits and community engagement, while in urban centers, mobile applications and telemedicine consultations facilitate real-time adherence support. Machine learning thus complements, rather than replaces, the human element of healthcare, enhancing the reach and precision of interventions while preserving the patient-provider relationship.

Looking ahead, predictive analytics for chronic disease adherence in Bangladesh exemplifies the convergence of technology, ethics, and public health. Integration with national health strategies allows policymakers to allocate resources more effectively, design equitable interventions, and measure impact in real-time. The approach is scalable: as digital infrastructure expands and electronic health records become more widespread, predictive models can be applied across diverse populations and chronic conditions, from hypertension and diabetes to asthma and cardiovascular disease.

In conclusion, medication adherence represents the critical link between a prescription and a positive health

outcome. In Bangladesh, the current adherence gap constitutes a silent but preventable contributor to morbidity and mortality among millions of citizens. By harnessing machine learning and predictive analytics, we can anticipate adherence lapses, target interventions with precision, and allocate healthcare resources more efficiently. This approach reframes adherence as a system-level challenge rather than an individual failing, empowering healthcare providers to intervene before complications arise. In the era of “Smart Bangladesh,” the ability to predict and prevent non-adherence is no longer a theoretical concept—it is a practical, scalable, and ethically responsible strategy to ensure that chronic disease treatment reaches its full potential. By turning data into actionable insights, Bangladesh is building a healthcare ecosystem where prescriptions do not remain unfulfilled instructions but become instruments of sustained health and longevity for millions of citizens.