Utilizing a ML-Enabled EMR Provider Workflow to Improve Non-Clinical Tasks

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Based on CMS data from 2021, the US healthcare system spent $4.3 trillion annually on non-clinical tasks (NCTs). This includes essential non-medical activities such as EMR review, coordinating next steps in care, closing care gaps, admin tasks, and insurance paperwork (Figure 1). These NCTs significantly burden primary care providers (PCPs) – requiring nearly 45 minutes of NCTs for every 30-minute patient encounter. Importantly, increasing documentation demands from private and government insurance hinders PCPs from delivering effective patient care.

**Background**

We hypothesized that ML-based natural language processing (NLP) could streamline non-clinical tasks by automating patient assessment form (PAF) completion for outpatient PCPs.

**Hypothesis**

We developed and internally validated a ML-enabled workflow that combined (1) note extraction from the EMR, (2) protected health information de-identification, and (3) NLP and federated learning to automate PAF completion (Figure 2). PAFs were auto-populated with ICD-10 codes matched directly to patient clinic notes. We externally validated our workflow in a real-world setting by applying it to a primary care clinic serving patients who are Medicare Advantage beneficiaries, following their annual wellness visits. PCPs then reviewed and approved completed PAFs with one click, triggering the workflow to auto-generate screening orders for at-risk patients.

**Methods**

Our ML-enabled workflow was trained on data from 6,000 synthetic notes and achieved a ten-fold cross-validation accuracy of 96%. Over five months (in a real-world, suburban outpatient clinic), PAFs were completed for 179 patients (Figure 3A), requiring only six hours of provider review time with a 99.4% approval rate. Compared to the previous year, the ML workflow decreased manual work from 30 hours across three staff to six hours for one provider, yielding overhead savings of $1,680. The system also led to a 3.2x increase in preventative and diagnostic order submissions for at-risk patients who have historically failed to complete necessary screenings (Figure 3B).

**Results**

**Conclusion**

Our study demonstrated the application of ML in improving PCP operational efficiency and enhanced patient care management in at-risk patients.