Early Engagement Measures Can Accurately Identify Users at Risk of Abandoning Digital Therapeutics

W. Wang[1], K. Crowley[1], M. Dugas[1], A. K. Iyer[2], M. Peeples[2], M. Shomali[2], and G. Gao[1]

[1]Center for Health Information and Decision Systems, University of Maryland, College Park

[2]WellDoc Inc., Columbia, MD

Background and Objective

- Though many individuals are adopting and benefiting from digital therapeutics, attrition rates remain high[1,2]
- Early identification of those likely to abandon a digital therapeutic may help guide targeted identification
- The purpose of this research was to:
  - develop an accurate predictive model of digital therapeutic persistence
  - explore important factors associated with persistence

Methods

Sample and Digital Therapeutic

- Data from 3,142 patients users of BlueStar with Type 2 diabetes (50.3% women; 62.1% aged 40-63 years; 44.1% A1c $\geq$ 8.0)
- BlueStar is an FDA-cleared digital therapeutic for Type 2 Diabetes
- BlueStar is a primarily mobile platform that facilitates self-monitoring of diabetes management and provides automated coaching[3,4]

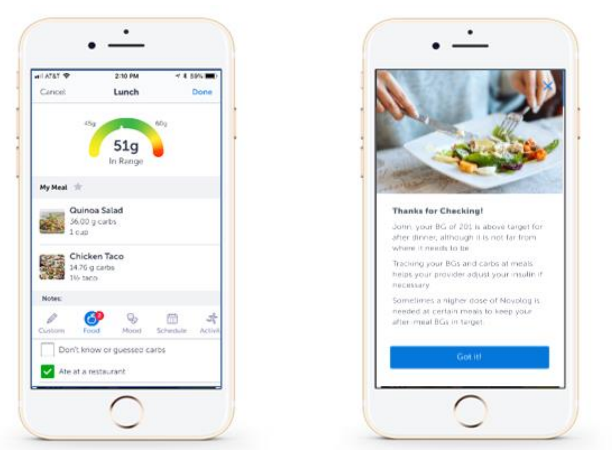

Figure 1. *Screenshots of BlueStar app.*

Modeling Approach

- Tested performance of four machine learning models (logistic regression, ridge regression, random forest, and gradient boosting) in predicting persistence
- Examined whether input features from 7 days of use could predict persistence at: 14, 28, 180 days
- Also examined predictive models using features from 14 days of use to predict persistence at: 60, 180, and 365 days

Table 1. *Examples of input features.*

	Features
Patient characteristics	Age and gender
Diabetes Control	Initial A1c and medication regimen
Self-management tracking	Diet, activity, medication adherence, blood glucose measures, annotations

Results

Table 2. *Accuracy of predictive models.*

Data Input	Retention Period	Overall Sample Observed Retention Rate	Overall Sample Accuracy of Best Model (Improvement over Baseline)	Annotation Sample Observed Retention Rate	Annotation Sample Accuracy of Best Model (Improvement over Baseline)
7 days	14 days	61.3%	85.4% (+24.1%)[GB]	91.9%	91.9% (+0%)[GB,RF,RR]
7 days	28 days	55.9%	82.5% (+26.7%)[RF]	90.3%	89.5% (-0.8%)[GB]
7 days	180 days	25.4%	85.1% (+10.5%)[GB]	58.1%	64.5% (+6.5%)[GB]
28 days	60 days	43.8%	82.2% (+26.0%)[GB]	79.0%	84.7% (+5.7%)[RF]
28 cays	180 days	29.5%	82.9% (+12.4%)[GB]	59.7%	67.7% (+8.1%)[RF]
28 days	365 days	21.9%	84.4% (+6.3%)[GB]	39.5%	71.8% (+11.3%)[GB]

Note. Best models denoted with superscripts. *GB* = Gradient Boosting, RF = Random Forest, RR = Ridge Regression.

- Machine learning algorithms were almost always better at predicting retention than a baseline uniguess model
- Algorithms showed similar levels of performance but gradient boosting was the slightly better model in the majority of tasks
- Exploratory analyses revealed that patients who used the text annotation features of the app were more likely to continue using the app, $F(3, 3095) = 3.13$, $p = .02$.
- Therefore, we also tested whether machine learning models could enhance prediction of retention among this subgroup of patients (n =1,232)

Conclusions

- Early engagement data can be leveraged to accurately identify users at risk of abandoning a digital therapeutic
- Annotation was associated with greater persistence of the digital therapeutic
- Predictive models that incorporate additional information can further improve prediction of persistence in this subgroup

Implications for Policy and Practice

- Early identification of individuals at risk of abandoning digital therapeutics could guide targeted support efforts
- Results suggest that use of annotation features may be a promising avenue to enhance persistence

References

Scan the QR Code to view a list of references cited.