User Engagement in Mobile Health Applications

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ABSTRACT
Mobile health apps are revolutionizing the healthcare ecosystem by improving communication, efficiency, and quality of service. In low- and middle-income countries, they also play a unique role as a source of information about health outcomes and behaviors of patients and healthcare workers, while providing a suitable channel to deliver both personalized and collective policy interventions. We propose a framework to study user engagement with mobile health, focusing on healthcare workers and digital health apps designed to support them in resource-poor settings. The behavioral logs produced by these apps can be transformed into daily time series characterizing each user’s activity. We use probabilistic and survival analysis to build multiple personalized measures of meaningful engagement, which could serve to tailor contents and digital interventions suiting each health worker’s specific needs. Special attention is given to the problem of detecting churn, understood as a marker of complete disengagement. We discuss the application of our methods to the Indian and Ethiopian users of the Safe Delivery App, a capacity building tool for skilled birth attendants. This work represents an important step towards a full characterization of user engagement in mobile health applications, which can significantly enhance the abilities of health workers and, ultimately, save lives.

CCS CONCEPTS
• Applied computing → Life and medical sciences.

KEYWORDS
engagement; mobile health; churn; survival analysis

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1 INTRODUCTION
Digital health solutions have disruptive potential for precision public health and improved health outcomes [1, 3, 4, 21, 25], as they allow for the collection of large quantities of behavioral and health-related data that can be used to design and evaluate evidence-based policies. In particular, in low- and middle-income countries [15, 29], the growing mobile penetration has led to the deployment of an increasing number of digital tools to assist patients and healthcare providers [7, 11] and help them overcome the scarcity of resources. Such mobile health solutions include capacity building tools, apps that provide healthcare workers with needed supplies (e.g. drug delivery services) or medical resources (e.g. arrangement of test appointments), tools that connect them to patients (e.g. for a remote follow-up) or physicians (e.g. to get their opinion on test results), and even apps to assist them in clinical triage and diagnosis.

Understanding engagement, its drivers and deterrents, is key to properly assisting essential workers and patients. We are interested in meaningful engagement, the optimal level of engagement that leads users to provide the best care to the communities they work with. Grasping and predicting engagement at the user level is a first step towards defining personalized interventions (such as adaptive learning journeys, suitable reminders, incentives for better practices, or drug recommendations) that can be delivered through the app just when they are needed. By boosting the performance of healthcare workers in greater need of support, these interventions can have a great impact on the community, in the form of improved care for patients.

This work proposes different methods to study user engagement. Special attention is paid to understanding churn (user attrition) and its risk, understood as a marker of total disengagement. We pursue a multidimensional approach to the problem and illustrate it by analyzing user activity from the Safe Delivery App [9], a digital training tool developed by Maternity Foundation [8], the University of Copenhagen, and the University of Southern Denmark that contains evidence-based obstetric and newborn guidelines for skilled birth attendants.

The paper is organized as follows. In the remainder of this section, we describe related works and our contribution. In Section 2, we present our dataset and framework. Its application to the Safe Delivery App is discussed in Section 3, where various churn definitions are compared. Finally, in Section 4 we deliver our conclusions.

1.1 Related works
Previous analyses of user engagement in digital health contexts can be found in [28], where classification trees are employed to divide the user population by their different levels of engagement, and in [23], a survey on app abandonment. However, both studies focus on apps designed for the public, and thus not specific to healthcare...
workers. Other related studies propose mobile health solutions inspired on gaming research, or health games [5, 6].

While there is limited work on general engagement, churn in non-contractual settings has been profusely studied for different products and services. Churn is usually defined in terms of a period of inactivity, which can be fixed (e.g. a calendar month with no logins) or rolling. For instance, in [22], 35 days without a gaming session, sport betting ticket or deposit are deemed evidence of churn in an online game, while [18] defines churn as no music downloads for a year. In the context of video games, different methods to predict churn were explored in [27], with other works using survival analysis [12, 26] and time-series [2] approaches. In the latter studies, the period of inactivity that determines churn is computed through the returning churners’ method (see Section 2.2), which serves as a baseline for churn detection in this paper.

User behavior in the Safe Delivery App has been studied in [13], which predicts the demand for specific in-app contents by certain groups of users, and in [14], which explores the use of deep learning click-through-rate prediction models for content recommendation.

1.2 Our contribution

To the best of our knowledge, this is the first time that probabilistic and engagement score methods are explored in the context of app engagement, or that time-to-churn is predicted through a survival ensemble method with time-varying covariates. We are not aware either of any previous work discussing various methods to measure user engagement and personalized ways of characterizing it.

2 DATASET AND METHODOLOGY

We propose a multifaceted approach to study user engagement, applying various methods to selected activity indicators and different churn risk definitions. The analysis can be performed from diverse angles, and we considered the following main dichotomies:

Frequency vs. intensity. Engagement involves the frequency with which users perform certain actions (e.g. logging in), but also the intensity they devote to an activity (e.g. how long they are connected).

Generic vs. specific. Engagement can be defined in terms of generic metrics relevant to all apps, such as login frequency, number of sessions, time spent on the app or average number of clicks per session. But we can also focus on app-specific measures of engagement, such as the time spent trying to solve quizzes in an e-learning app.

Exogenous vs. endogenous. To characterize the engagement of a given user, we can compare their present and past activities, using endogenous (self-referential) indicators or scores. But we can also compare their activity to that of a group they belong to, and then their level of engagement is defined exogenously.

Historical vs. snapshot. In exogenous approaches, we can extend the comparison to all past behavior of the group (a historical perspective), or restrict it to the behavior of the group users at a certain moment (taking a snapshot of the engagement at that time).

Analytic vs. predictive. Most of this work revolves around analytic measures that characterize user engagement from observed behavior. But the application of survival analysis to predict the probability that users will remain active in the future is also explored.

2.1 Dataset

Our dataset comes from usage logs of the Safe Delivery App [9], a digital learning tool providing skilled birth attendants with up-to-date evidence-based clinical guidelines, whose effectiveness has been evaluated in clinical trials [20, 24]. The content of the App is divided into clinical modules, which are each comprised of educational videos, easily referenceable action cards, drug list, and practical procedures, as well as a gamified learning platform containing a series of tests of increasing difficulty to assess the users’ acquired knowledge and skills.

The analyzed dataset comprises 58,195 users from India (95%) and Ethiopia (5%) and shows their in-app activity between January 2018 and August 1, 2021. The user activity logs were processed into daily user metrics characterizing daily user behavior and engagement.

The specific daily metrics we considered include lifetime (number of days between first login and a certain moment), daily connection time, action count (number of clicks), e-learning action count (number of clicks on videos, action cards and testing features), progress (number of tests successfully passed), video view count (number of videos watched), video watch time, loyalty index (fraction of days with login), and days since last login.

The analysis in Section 3 assumes all this user history is available, and explores what it tells us about the engagement of individual users and of the user population as a whole on the last observed date (August 1, 2021).

2.2 Returning churners and missed metrics

The approaches to define churn risk presented in this work will be compared to a baseline method previously used in the context of video games [12, 26], which considers that a user has churned after k consecutive days without login. The goal of this method is to find a churn definition, i.e. a reasonable way of setting the value of k.

The idea is to choose a value as small as possible, while satisfying constraints on the number of users we wrongly classify as churners. This is tantamount to setting thresholds on the fraction of false or returning churners (users identified as churners that nonetheless will log in again in the future). We can also enforce that these returning churners will not contribute significantly to any considered activity by setting additional thresholds on relevant missed metrics (the fraction of a particular metric coming from returned churners).

There is always a tradeoff between accuracy and efficacy when selecting a specific churn definition: the longer we wait before we label inactive users as churned, the more certain we can be that they have actually quit. However, quickly detecting churn is more useful, as attempts to reengage the user are more likely to succeed.

In terms of the angles discussed at the beginning of this section, such a churn definition is analytic (as it relies exclusively on observed behavior), historical and exogenous (as it considers the past behavior of large groups of users). It always uses a generic measure of frequency (through the threshold on returned churners), that can be combined with additional constraints on generic or specific measures of intensity (through thresholds on missed metrics). It is probabilistic in the sense that it constrains the probability of
wrongly classifying a user as churned, but it does not involve probabilistic statements about individual user behavior, as the empirical cumulative function (ECDF) or survival methods described below.

The specific churn definitions for our dataset are discussed in Section 3.1. The missed metrics considered are connection time, action count, and progression. And we set thresholds of 30% and 10% on returning churners and missed metrics, respectively.

2.3 Empirical cumulative distribution function

Probabilistic approaches use the available distributions of observed behavior to find the likelihood of a certain activity level for a user, as well as their resulting engagement. The ECDF method is an analytic probabilistic approach, where we can consider the distribution for (i) the same user in the past (ECDF endogenous, ECDF-endo); (ii) the group they belong to (ECDF exogenous, ECDF-exo), or (iii) that group on a particular day (ECDF snapshot exogenous, ECDF-snp). Daily user behavior distributions do not fall clearly into a parametric family of distributions and tend to be left-skewed, and thus we will focus on non-parametric methods, which make no underlying assumptions about the probability distribution.

The cumulative distribution function (CDF) is defined as $F(x) = P(X \leq x) = \sum_{i \leq x} f(t)$ for a discrete random variable $X$, and as $F(x) = \int_{x}^{\infty} f(t) dt$, where $F(x)$ is a non-decreasing continuous function, for a continuous random variable (which here corresponds to a specific activity metric). Given $N$ ordered data points $y_1, y_2, \ldots, y_N$, the empirical cumulative distribution function (ECDF) takes the form $E_X = n(i)/N$, where $n(i)$ is the number of points less than $y_i$, and the $y_i$ are arranged in ascending order. This is a step function that increases by $\frac{1}{N}$ at each ordered data point and converges to the CDF when enough data is collected. The ECDF indicator is defined as the value of the ECDF at time $t$, i.e., the probability with which that level of activity or less was to be expected:

$$s^i_t = F^i(z^i_t | z^i_1, \ldots, z^i_{t-1}),$$

where $F^i$ is the empirical cumulative distribution function for the user $i$, and $z^i_t$ is the user metric that reveals engagement. Note that we are considering the user’s behavior as compared to themselves, and hence taking an endogenous approach.

For example, let us consider a frequency-related feature typically used in this analysis: the days between a (generic or specific) activity for a single user. We intuitively know that anomalously large values are pointing to disengagement and potential churn, so we can treat the situation as an anomaly detection problem. The ECDF indicator allows us to make claims like 9 times out of 10, a user will perform this activity again within z days (for an ECDF indicator value of 0.9 at z). If the period of inactivity extends beyond z, we can thus deem it an unusually low engagement for that user. For intensity metrics, we can build an intensity ECDF indicator that will allow us to make similar claims, such as 9 times out of 10, a user will correctly reply to less than x test questions daily (where an ECDF indicator value of 0.9 describes a very engaged testing behavior).

The previous statements refer to the likelihood that a user shows a certain level of activity as compared to their past behavior. By considering the ECDF distribution for all users, the statements would become about how usual or unusual user behavior is as compared to the conduct of their group—their country, in our case—, either in general or on a certain day (in the snapshot approach).

The results described in Section 3.2 consider exclusively a frequency measure, namely days between logins, looking at it from endogenous, historical exogenous, and snapshot exogenous perspectives. These combined give us an indication of the likelihood of the user’s time since last login.

To study churn detection using these ECDF approaches, we can set a threshold on the likelihood of a certain engagement trait, and consider users inactive (i.e. at least temporarily churned) if the level of activity is deemed unusually low. Here (see Section 3.4) we consider any observed behavior with a probability equal or greater than 0.1 (the 10 or 90 percentiles described in the examples above) not suspicious of inactivity. If an unusually low activity has been observed in the past with a likelihood of less than 0.1, it is considered to signal high churn risk.

The ECDF approach offers a very flexible way to understand engagement along different angles of interest, yielding a quite intuitive interpretation of both measures of engagement and churn definitions. Its main limitation is that, even if it can be used to provide a collection of measures characterizing the engagement of a user on a given day (in general and for specific activities, as compared to themselves or to their group, either on that day or in the past), these are not easily reconciled into a single unified measure.

2.4 Engagement scores

Another analytic approach to characterize user engagement is to build engagement scores (which typically range between 0 and 1). Different engagement measures (intensity and/or frequency related, generic and/or specific) can be combined into a single indicator by taking their harmonic mean:

$$s^i_t = \frac{n}{\sum_{j=1}^{n} \left(\hat{z}^i_{jt}\right)^{-1}},$$

where $n$ is the number of metrics combined into the indicator, and $\hat{z}^i_{jt}$ are the scaled metric component values for user $i$ at time $t$.

To keep the score bounded between 0 and 1, we apply min-max scaling to all features used to build the indicator. The scaling is performed as compared to the past values of the same user if we want that component of the score to reflect endogenous engagement, or as compared to the past group of users (introducing thus exogenous historical components), or to the behavior of a group of users at time $t$ (exogenous snapshot components). Note that whenever one of the component metrics is zero, the engagement score goes to zero, and thus it will always vanish on days without activity if we are using intensity measures.

The greatest strength of this approach is its ability to combine components of different types, which allows us to discriminate non-meaningful engagement even in days with activity. It uses a single unified quantification of engagement, thus leading to a single engagement measure that can be, however, based on different metrics. The main weakness lies in the difficulty of having an intuitive understanding of what the score represents and how it relates to churn.

The engagement score used in Section 3.3 is built from the following user metrics: weekly loyalty index, video view count, video watch time, action count, progression, and e-learning connection.
time. One could also set thresholds on the score for churn risk detection (e.g., considering all users with scores between 0 and 0.1 are in high risk of churn, even if they have activity on that day).

2.5 Survival analysis
Survival analysis can also be used to characterize user engagement, and is the only predictive approach considered in this work. Survival models seek to predict the time to an event of interest, and output the probability that such event has not occurred yet as a function of time. Hence, if we set the models to predict time-to-churn, we obtain the probability that each user is still actively using the app as time goes by. Survival analysis is particularly well-suited to deal with censored data, meaning that, while for many users we do not know the time-to-churn because they are still active, these models can learn from the fact that these users have not churned yet (as opposed to standard regression approaches).

This methodology is frequency-based in that login frequency over time is what determines the user lifetime, understood as the days between their first and last logins. Nonetheless, it incorporates information on both intensity and frequency through the use of both types of metrics for feature engineering, and both generic and specific quantities can be considered. This approach is historical and exogenous by definition (models learn about the expected behavior from the past observed behavior of a group of users).

An additional decision that needs to be made when using this method is what definition of churn we will use, in order to identify whether the event of interest occurs or not. In this paper, a churn definition of 31 days is used for both Ethiopian and Indian users. This is just a convenient choice, and it can be modified depending on the use case. It represents roughly a month, and is also, as we will see, what the ECDF exogenous approach described in Section 2.3 points to (see Section 3.4). This means users will be labeled as churned after 31 consecutive days without logging in. This method can thus never be used to define churn, as it relies on an already existing churn definition. However, it can be combined with any other of the methods precisely by using the churn definition they provide. In Section 3.5 we will discuss how to use the survival curves to characterize user engagement, and the accuracy of the models in predicting churn.

Figure 1 shows the Kaplan–Meier estimates for the whole user population in India and Ethiopia. It depicts the fraction of users that are still using the App as time goes on, as well as the time windows that capture their variation over a day, a week, and time periods. To develop good predictive models (IBS close to 0), we created additional time-series features, such as week of the year, connection time, action counts, or session counts in the past 3, 7 and 15 days. We then fit the CSF model on $b = 25$ bootstrap rounds (this is done by taking multiple samples with replacement from a single random sample), a number chosen to minimize computation time. Subsequently, we calculate the average IBS as $\text{IBS}_{\text{boot}, \text{avg}} = \frac{1}{b} \sum_{j=1}^{b} \text{IBS}_{\text{boot}, j}$. For each bootstrap round, the model was trained using 75% of the users’ data and validated on the remaining 25%.

In the LTRC case, we proceed similarly: for the time-varying covariates, we use relevant engagement metrics (as discussed above) and time windows that capture their variation over a day, a week, or a month. Lastly, we use the top 30 features with the highest feature importance scores across all the bootstrap rounds to fit the final CSF and LTRC models analyzed in this study.

2.5.1 Conditional Survival Forests (CSF). This is an ensemble method that recursively partitions the feature space to maximize the difference between the survival curves of users belonging to different nodes [16, 30]. The split is performed in terms of Kaplan–Meier estimates. CSF models avoid the split variable selection bias (favoring variables with many possible split points) present in random survival forests [17] by using linear rank statistics as the splitting criterion at each node.

2.5.2 Left-Truncated and Right-Censored (LTRC) Forests. The LTRC conditional inference forest (LTRC-CIF) model [10, 31] is similar to the static feature CSF, but can handle left-truncated data and time-varying covariates. The LTRC relative risk forest (LTRC-RRF) [10, 31] is another model apt to deal with right-censored data, an adaptation of the relative risk forests discussed in [19] to time-varying covariates. Conceptually, both LTRC models, the time-varying covariates are used to generate different pseudo-user observations out of observations of the behavior of a single user. While the LTRC-CIF model performs the split using Kaplan–Meier estimates, the LTRC-RRF resorts to the Nelson–Aalen estimator.
Table 1: Various engagement measures for two selected users on August 1, 2021. ECDF-endo-CD gives the equivalent churn definition for the users as per their ECDF-endo, and SurP is the survival probability predicted by the CSF model.

| User | ECDF-endo | ECDF-exo | ECDF-snp | ES       | ECDF-endo-CD | SurP |
|------|-----------|----------|----------|----------|--------------|------|
| 1    | 0.98      | 0.99     | 1        | 0.029    | 29 days      | 0.82 |
| 2    | 0.76      | 0.55     | 0.29     | 0.331    | 6 days       | 0.69 |

3 RESULTS AND DISCUSSION

In this section, we apply our framework to study user engagement among the Indian and Ethiopian users of the Safe Delivery App. We try to illustrate how the discussed methods can provide a multidimensional description of the engagement of specific users at a given time, but also how they can characterize the engagement of the whole population. We take the last day with data, August 1, 2021, as the day of interest, to replicate a production environment where one wants to assess user and population engagement in terms of the latest information available.

As the methods described can be applied to different metrics or metric combinations, and through different angles (as discussed at the beginning of Section 2), the possibilities are literally endless and need to be carefully chosen for the specific use case at hand.

To demonstrate our approach, we have focused on:

1. The ECDF indicator through different angles—endogenous (ECDF-endo), historical exogenous (ECDF-exo), and snapshot exogenous (ECDF-snp)—for a generic frequency metric (days between logins). In exogenous approaches, the group will always consist of all the users from the same country.
2. The engagement score (ES) combining frequency and intensity metrics, both generic and specific, with only endogenous components.
3. Survival curves in days since first login, as predicted by a collection of frequency and intensity, generic and specific features (and comparing three different models).

The results of applying these measures of engagement to two selected users of the Safe Delivery App (to whom we will refer as users 1 and 2) on August 1, 2021, are summarized in Table 1. In the next sections, we will present additional figures and information to illustrate the kind of discussion allowed by this approach.

3.1 Returning churners and missed metrics

To find a suitable churn definition, in Figure 2 we plot the percentage of returning churners and of missed progression (tests successfully taken tests) in bursts separated by relatively long pauses. If we choose the churn definition that will keep the fraction of returning churners below 30% and of relevant missed metrics (connection time, action count and progression) below 10%, we find that $k$ should be 74 days for Ethiopia and 64 days for India. (Different thresholds on different metrics can be chosen depending on the specific use case.) Note that these churn definitions are hardly actionable: if we need to wait over two months to decide a user has quit, it will be almost impossible to reengage them, as they will have probably lost all their interest long ago. Therefore, in Section 3.4, we will explore the possibility of combining this method with the ECDF approach in order to detect churn risk much earlier. The baseline churn definition, however, remains the most robust way of unequivocally spotting users who are not going to come back (the situation we seek to minimize).

3.2 ECDF indicator

We applied the ECDF method to the frequency metric of days between logins, whose histogram is depicted in Figure 3. We enforce a cutoff at 200 days to limit the bias and noise introduced by the arbitrarily large values that churners would keep contributing. Note that the most typical pattern is a few days between logins, and most instances are below two weeks. However, there is also a very long tail, implying that some users will log in again after many months of inactivity. This distribution would be used to compute the user ECDF under the exogenous historical (ECDF-exo) approach.

Figure 4 shows the ECDF-endo cumulative distribution of days between logins for our two selected users. The graph has a much longer tail for user 1, implying a larger uncertainty as regards the
number of days typically expected between logins. User 2 logs in more frequently and consistently, with almost no instances of more than 30 days between sessions, while user 1 displays a more erratic behavior, with longer periods between logins (up to 6 months).

For those two users, the August 1, 2021, values of the three ECDF engagement indicators discussed in Section 2.3 are presented in Table 1. The very high values of all ECDF indicators for user 1 result from a long period of inactivity before the day considered. Indeed, the last login prior to August 1 happened 175 days before for user 1 (and 2 days before for user 2). The indicator values for user 2 show this user is particularly engaged as compared to the rest of users on that day (ECDF-snp), pretty disengaged as compared to their own past activity (ECDF-endo), and moderately engaged when taking into account the whole group’s history (ECDF-exo).

Figure 4 also includes the 0.9 threshold we set to infer a high risk of inactivity or churn. Note that the use of this particular metric (days between logins) from an endogenous perspective is analogous to finding an equivalent churn definition for each user, similar to that obtained through the returning churners’ method. The values of $k$ corresponding to that equivalent definition (which are also included in Table 1) are 29 days for user 1 and 6 days for user 2. This means that, in the observed history of each user, nine out of ten times they have logged in again after less than those days. For user 2, a week without logins already points to a lower-than-expected engagement, while in the case of user 1 we need to wait for almost a month to conclude the same. In contrast, the exogenous approach results in a fixed churn definition for the whole user population, as will be discussed in Section 3.4.

Figure 5 shows the values of the ECDF-snp indicator on August 1, 2021, across India and Ethiopia. The marked bimodal behavior for India indicates that there are two large groups whose last login took place roughly 20 and 40 days earlier.

### 3.3 Engagement score

As described in Section 2.4, we built an endogenous engagement score relying on weekly loyalty index, video view count, video watch time, action count, progression and e-learning connection time. Figure 6 compares the time series of the daily values of this engagement score for the two selected users. Larger values of the engagement score correspond to a higher level of engagement, as the metrics considered increase with engagement (contrary to the days between logins discussed in the previous section). The engagement score for August 1, 2021, is included in Table 1 and shows that—as compared to their own past behavior—user 2 is moderately engaged, while user 1 is at risk of churn, even if they registered some activity on that day. Therefore, this method also captures that user 2 is more engaged than user 1, just as the ECDF indicators.

Figure 6 also depicts the 0.1 threshold that marks an unusually low engagement, indicative of a high risk of churn. While we will not explicitly consider the engagement score for churn detection, it could be used to that end in the same way as the ECDF indicators. However, when discussing churn, we prefer to focus on the frequency ECDF approach as, by construction, it will yield values more easily comparable to our baseline churn definition (since both
We have discussed other ways of detecting churn besides our base-line method (whereby a user has churned after a certain number of consecutive days without logins), besides covering the endogenous, exogenous and snapshot angles.

Figure 7 compares the distributions of engagement scores across the user populations of India and Ethiopia for August 1, 2021. While both graphs are similar, India’s is more skewed to the left, indicating a more disengaged population (as compared to their own past behavior) on that day. This is consistent with a longer history of use for most Ethiopian users, which makes the current ones relatively loyal. Both India and Ethiopia distributions are bimodal, with a large peak associated to relatively low engagement, and another smaller concentration of more engaged users. Note that this second group is more engaged (higher engagement score) in the Indian case.

### 3.4 Churn detection

We have discussed other ways of detecting churn besides our baseline method (whereby a user has churned after a certain number of consecutive days without logins, found by imposing thresholds on the percentage of returning churners and missed metrics). These alternative definitions are based on the ECDF endogenous approach (where we set a 0.9 probability threshold on the distribution of days between user logins) and both exogenous ones (where we compare the typical days between logins for a user and for the group, either historically or on the day of interest, also using a 0.9 threshold). Note that any churn definition relies on determining a meaningful level of activity, so that users below a certain threshold are considered to be inactive.

The use of the ECDF equivalent churn definitions to complement the returning churners’ baseline one is schematically represented in Figure 8. The diagram shows user activity (days with logins are represented as green or red dots), and the day when churn is detected using the baseline method is marked with a red cross (according to that method, all users churn at the same time). In the diagram, users 3 and 4 are examples of returning churners, and activity corresponding to the days after they were marked as churned (red dots), will contribute to missed metrics. The ECDF-indicator-based churn definitions will typically detect high risk of churn (through atypically disengaged behavior) earlier. The precise moment is marked with exclamation marks, surrounded by a circle, hexagon, and triangle for the endogenous, snapshot, and exogenous indicators, respectively. The two latter methods still detect churn at the same time for all users. The former, however, yields a personalized churn definition, which will identify churn much earlier for very engaged users—but perhaps later than the baseline churn definition, as in the case of user 3, for users with a low engagement pattern.

Table 2 presents the confusion matrix as of August 1, 2021. That is, it shows the number of users classified as churned/not churned by the RCMM approach, and in high/low risk of churn according to the ECDF indicators (endogenous, exogenous and snapshot) threshold method. Note that the ECDF-exo approach finds 20 additional users in high risk of churn (for whom the number of days since their last login is larger than the number of days observed 90% of the time, for all users and all times) who are not identified by the RCMM method. This is also the case for 16 users when considering the self-referential engagement (ECDF-endo) indicator. Interestingly, there are 12 users who are deemed churners by our baseline method (which roughly means they have not logged in within the previous two months) while appearing significantly engaged as compared to their own past activity, as per the ECDF-exo indicator.

As we applied the ECDF method to a metric that is frequency-based and equivalent to detecting churn through a number of consecutive days without logins (as in our baseline approach), we can compare the resulting equivalent churn definitions. Note that, since exogenous methods characterize churners as inactive as compared to the group, the equivalent churn definition will be the same for all users. In contrast, in the ECDF endogenous approach, each user has their own churn definition to mark unusually low inactivity. Table 3 shows the churn definition values arising from the different methods considered (in the ECDF-endo case, the average is presented) as of August 1, 2021. Note that, for more engaged populations, we normally need shorter periods of time to detect churn (if the login frequency is high, relatively short periods of no activity already signal disengagement).

The equivalent churn definitions that we found are consistent with the picture already described. Note that the baseline method yields the stricter definition, as a longer period of inactivity is needed to conclude that a user is not going to come back. On the other extreme are the average values for the ECDF-endo method—although we know some users may have churn definitions longer than the baseline ones, as for the 12 users discussed above. As for the remaining methods, the snapshot approach yields greater engagement (lower churn definition) than the exogenous one among Ethiopian users, while the contrary is true for India. This means that, in India, the period of time needed to detect churn is significantly longer now than in the past (disengaging population), while Ethiopian users appear slightly more engaged nowadays.

Table 2: Number of users labelled as churned and not churned by the ECDF-endo and ECDF-exo methods as compared to the returning churners and missed metrics (RCMM) baseline for August 1, 2021, across India and Ethiopia.

| RCMM         | ECDF-endo | ECDF-exo |
|--------------|-----------|----------|
|              | Not churned | Churned | Not churned | Churned |
| Not churned  | 223       | 16       | 220         | 20      |
| Churned      | 12        | 6        | 0           | 18      |
Table 3: Churn definitions (number of consecutive days without logins needed to determine churn or high churn risk) for India and Ethiopia, calculated using the returning churners and missed metrics (RCMM), ECDF-exo, ECDF-snp, and ECDF-endo methods. (For the latter, average values are given.)

| Country | RCMM | ECDF-exo | ECDF-snp | ECDF-endo (Avg) |
|---------|------|----------|----------|-----------------|
| Ethiopia | 74   | 29       | 20       | 20              |
| India   | 64   | 31       | 52       | 19              |

When comparing both countries, Ethiopian users are more likely than Indian ones to use the App again after long periods of inactivity (as indicated by the longer RCMM definition). The average engagement of users as compared to their own past activity (ECDF-endo) and that of their compatriots (ECDF-exo) is very similar in both countries. However, Indian users are significantly more engaged than their Ethiopian counterparts when considering only August 1, 2021, as reference (ECDF-snp).

3.5 Survival Analysis

Predictions of the survival probability—the probability of not having churned yet, i.e., of having logged in within the previous 31 days (where the number of days is determined by applying the ECDF exogenous approach to the days between logins)—as a function of days since first login (lifetime) are calculated using conditional inference ensembles, as well as the two LTRC forest models with time-varying covariates described in Section 2.5.2.

An example of the resulting survival curves for the selected users is depicted in Figure 9. These represent the predicted probability of each of the users not having churned (i.e., of having logged in at least once in the previous 31 days). The actual predicted lifetime would be given by the median value. While user 2 is shown to be more engaged than user 1 by all our analytical measures, this user is also predicted to disengage relatively quickly and quit around 250 days after first login. However erratic and less consistent was user 1’s behavior in the past, their survival probability never falls below 0.5, meaning that (with the available data) the model does not predict this user will ever churn. This is reasonable if we consider that this user has been active for most of the available data period and has always returned, even after long periods of inactivity. Note that, as we are looking at lifetime predictions, we are considering frequency of connection rather than intensity. The survival probability for users 1 and 2 on August 1, 2021, is also included in Table 1. As we have just discussed, the not-too-engaged user 1 still has a survival probability significantly larger than 0.5, while the moderately engaged user 2 only has a 0.69 probability of still being active at that point (even if they are actually active).

Table 4 collects the IBS scores of the different models. Note that, as expected, the accuracy of both LTRC forests is better than that of the CSF model, due to their ability to deal with time-varying covariates. Among the two, the LTRC-RRF performs best.
4 SUMMARY AND CONCLUSIONS

We have proposed three methods to study user engagement in mHealth applications intended for frontline healthcare workers, and tested them with data from the Safe Delivery App, a digital training tool for skilled birth attendants. These methods can be applied to a variety of engagement-related metrics (dealing with frequency or intensity, generic across apps or use case-specific) in order to understand user behavior as compared to their past behavior, that of the whole group, or the population engagement on a particular day. This provides a very flexible and versatile multidimensional framework to explore engagement and churn, with the downside of yielding limitless possibilities and combinations. Additionally, the two analytic approaches can be used to detect churn by setting appropriate thresholds and comparing them to the baseline method considered (based on constraints on the fraction of returning churners and missed metrics). We also added a predictive dimension to this study by considering survival analysis models to foresee time-to-churn in days since first login.

This results in a holistic, well-rounded approach to study engagement and churn, which can be customized to suit the specific needs of different mobile apps and use cases. Both the ECDF and score methods are flexible and versatile, allowing us to incorporate different engagement indicators and angles to the analysis. While ECDF approaches yield an intuitively understandable measure of user engagement, it is not trivial to use them to produce a single, unified measure of engagement (and hence a single magnitude in terms of which to define churn). The engagement score approach has the enormous advantage of providing such a single measure of engagement, but is not as easy to interpret.

Survival analysis yields the expected user disengagement profile. It incorporates different engagement indicators through the use of features, providing additional insights that help to characterize a user’s engagement, given by the survival probability at a certain time as compared to their previous history and expected future. Furthermore, it serves to predict when each user will churn, an additional quantity that can be used to describe engagement.

The methods presented in this work may serve to enhance engagement among health workers using online learning and capacity building tools. This, in turn, could translate into improved care for their patients and have a significant impact on global health.

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