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Clinical Interactions in Electronic Medical Records Towards the Development of a Token-Economy Model

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Abstract

The use of electronic medical records (EMRs) plays a crucial role in the successful implementation of the Universal Healthcare Law which promises quality and affordable healthcare to all Filipinos. Consequently, the current adoption of EMRs should be studied from the perspective of the healthcare provider. As most studies look into use of EMRs by doctors or patients, there are very few that extend studies to look at possible interaction of doctor and patient in the same EMR environment. Understanding this interaction paves the way for possible incentives that will increase the use and adoption of the EMR. This study uses process mining to understand simulated doctor-patient interaction, with the goal of developing interaction features and a token economy framework to increase EMR adoption. Results from the process mining showed that current EMR interaction remains low, and highlighted the need for interaction features to promote preventive healthcare. Moreover, process mining from the simulated logs showed that consistency and time are important factors in encouraging usage. Activity category, relative frequency of activity, relative case frequency of activity and average time spent on activity are features that may serve as the foundation for a token economy framework for EMRs.

Keywords: Token Economy; Blockchain; Healthcare; Electronic *Medical* Records; Process Mining

1. Introduction

The Universal Health Care Law, instituting universal health care for all Filipinos, prescribing reforms in the health care system, and appropriating funds, therefore, was signed into law last February 20, 2019. The law mandates that all

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health service providers and insurers must maintain a health information system, including electronic medical records or EMR systems.

Since then, most of the focus has been on the adoption of EMR systems. This study aims to promote preventive healthcare through EMR interactions where instead of just using EMRs to manage and monitor the patient activities when they initiate the contact with health service providers, continuity of care for the patients from prevention, diagnosis, and treatment to monitoring should be taken into account in an effective healthcare delivery model.

With this, the goal of the study is to identify the key activities that exist in the doctor-patient interactions based on the information obtained from process mining. Moreover, the study selects and develops new interaction features for the EMR systems. Lastly, the study aims to implement a token economy framework on the NEM Symbol Blockchain and to develop a token economy framework to sustain and increase active use of an EMR, by defining the method of allocating and circulating tokens in the system.

This study serves as a way to facilitate and improve information exchange among the different stakeholders in the clinical interaction. The study also promotes the idea of "preventive healthcare" among patients. Lastly, the study serves as a foundation for future studies for a usable implementation of a token economy built on blockchain especially since this field has not been completely studied yet.

2. Review of Related Literature

2.1. Understanding Preventive Healthcare

Four levels of preventive healthcare are present. Primordial prevention focuses on a nationwide approach, where prevention is done through actions to prevent future health hazards which are known to increase the risk of disease. Primary prevention focuses on reducing the risk factors of developing chronic illnesses. Secondary prevention focuses on the detection and treatment of pre-clinical changes. Tertiary prevention focuses on the reduction, reversing, or delaying the impact of the disease on the patient's life [1, 2]. Given the current low adoption of EMRs, there needs to be a way to encourage the use of important features that aid in addressing all four levels.

2.2. Token Economies

One way is through the integration of a token economy. To implement a token economy, first, determine the target behaviors that would induce a token reward for every initiation of the user. Second, choose the format of the token to be given. Third, plan out a list of rewards as it is best when participants have options for the rewards. Fourth, set the frequency of redeeming rewards properly. Ideally, having less redemption of items with a more fulfilling reward is the goal. Fifth, make sure the reward system is achievable or no one will be motivated to participate and adjust accordingly while the token system is already being implemented. A token economy should prevent the occurrence of both the floor effect or the ceiling effect [3], where the requirements are either too difficult or too easy. Lastly, create rules for the token economy to have a true-to-life flow [4, 5, 6].

2.3. *Understanding Process Mining*

Building a token economy model entails the need to obtain user activity data as a foundation. Process mining is a method of extracting knowledge from data generated and stored in information systems in order to understand how activities are executed within the system. Activity refers to a step in a process. A set of activities is called an event log and it should contain data, usually through the timestamp, on the order of how the activities were executed [7, 8]. Because process mining relies on system-generated event logs, there can be instances of hidden tasks, duplicate tasks, non-free-choice constructs, loops, time, noise, and lack completeness that challenges process mining [9].

In healthcare, these processes are the series of activities that are performed to diagnose, treat and prevent diseases, including non-clinical work, like encoding and reporting, that supports the delivery of healthcare services from doctor to patient. With a multi-disciplinary, ad-hoc, complex, and dynamic healthcare ecosystem, process mining is often used to improve health facilities' capability to meet demands, reduce waiting times, maximize resources, and increase transparency [10].

There are three main types of process mining. The first is process discovery where a new model is created from analyzing extracted event logs. The second is conformance checking where an existing model is compared to the extracted event logs to see if there are any deviations. The third is enhancement where an existing model is extended or optimized through the analysis of event logs [10, 11]. In this study, process discovery is used as event logs on clinical interaction and is the basis of creating a new process specification containing activities performed by the stakeholders.

2.4.*Patient Behavior in the Context of Healthcare*

While process mining helps understand how users behave in a process, it also helps to have an idea of the common patient behavior in healthcare as a starting point. First, a registration clerk records the patient's arrival time and his/her symptoms. Then, a nurse will check the patient's records and will try to determine the illness. After, the patient will be assigned to a doctor for medical treatment consultation and bed assignment if confinement is deemed necessary. Next, necessary tests will be performed in the laboratory. Doctors will then decide if patients need to be admitted or not. If the patient will be admitted, then the records and treatment will be done by the assigned doctor. If not, the patients will receive prescriptions for over-the-counter medicine treatment, and records in the hospital will end from that point. Scheduled checkups are then performed for feedback and results [12, 13].

3. Methodology

3.1.Data Collection and Preprocessing

This study used a total of 9542 usage logs from an electronic medical record as a baseline analysis of the current state of interaction in an EMR. The data collected were logs from November 11, 2020, to November 30, 2020. This data was contained in a JSON file. Inside this JSON file were the columns for the API endpoints accessed by the user thus providing already organized usage logs for the activities done in the system.

This was loaded into a Pandas Dataframe which enabled it to be exported in a .csv file that was used as the input for the process mining algorithm. Once loaded into the process mining algorithm, the data then was run through another processing where the final set of data only includes the URL, curvalue, element_label, element_type, element, action, datetime, user_id, facility_id, and session_id. These were the fields that give information about the path a user takes whenever the user interacts with the system and the fields that differentiate case instances.

3.2.Defining Possible Scenarios

Aside from actual logs, possible scenarios logs were defined to illustrate levels of interaction in an EMR. Assumptions were based on the study of patient behavior [12, 13]. In low interaction, doctors and patients use only the basic and required features of the EMR. Basic features refer to records, telemed, eclaims, and HFSRS only. In medium (doctor) interaction, all features are being used by the doctor and patient. This means that aside from the basic features found in the low interaction scenario, health programs, referrals, and broadcast are added. However, the doctor only does 50 percent of his/her activities compared to the high interaction scenario. Similarly, in medium (patient) interaction, the patient only does 50 percent of the tasks assigned to him/her by the doctor. Lastly, in high interaction, all features are being used by both agents where 100 percent of the activities are completed.

Five columns in a CSV file were made, in order to create input files for these simulation scenarios. The first column is CaseID, which acts as the session identifier. The second column is User, which points to which account is doing the activities. The third column is Agent, which is used to identify whether it is a doctor or a patient who does the activity. The fourth column is Activity. The letters "D" and "P" are used as prefixes for the activity names to be able to distinguish between BluEHR and BluPHR activity instances, respectively. Lastly, the fifth column is Datetime, which stores when the activity was done. Each row in the CSV file corresponds to one activity instance. Sample rows are generated based on the scenarios definitions of each interaction above.

3.3. Running Process Maps Functions

This study performed process mining on the pre-processed .csv files derived from the usage logs and the simulated datasets using the bupaR package. The following measures were used as parameters for the process maps that served as a foundation for the token economy framework. Relative frequency measures the relative number of instances per activity and the relative outgoing flows for each activity for the nodes and edges, respectively. Compared to relative frequency, the relative case frequency shows the relative number of cases per activity and flow, instead of the number of instances per activity. Time performance measures the time users spent in each activity. This was calculated by subtracting the start time of the next activity from the end time of the current activity. If there are multiple activity instances, the average time was taken.

3.4. Developing Interaction Features and Token Economy Prototype

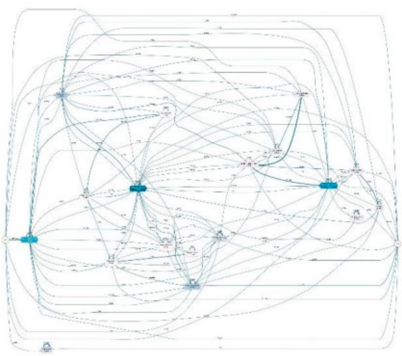
After identifying gaps and opportunities in the process maps, this study developed personal health program features in addition to the current features that existed in the doctor and patient EMRs, which served as the interaction features. Personal health program features include health tasks, health check-ins, and analytics. Aside from creating interaction features, this study also emphasizes increasing the engagement for those interaction features with a token economy framework. The prototype for the token economy framework was developed on the NEM Symbol Blockchain with the NEM SDK, as a stand-alone module, for re-usability to show how a reward system can benefit from the decentralized characteristic of a blockchain. Each user is provisioned a NEM account. Digital assets, called mosaics, were used to represent tokens. An API is created for each interaction feature in the EMR, which is responsible for calculating and transferring tokens into the user's NEM account. APIs were exposed from the blockchain side for the EMR systems to be able to call the functions in this module.

3.5. Testing and Validation

This study tested all the functions on EMR to see if the functions were able to call and perform the correct transactions on the NEM Symbol Blockchain. The testing of this system was done in March 2021. Due to time constraints, this study will limit the testing and validation of this usage of the token economy framework.

4. Results

4.1. EMR Usage Logs



Activity	Count
View_List_Records	67071
View_Patient	45884
Eclaims	43468
Edit_Health_Record	25189
Access_Dashboard	23266
Create_Health_Record	8587
Search_Records	5039
Log_in	3420
Add_Patient	2494
View_Referrals	87
View_Calendar	72
View_Reminders	33
View_Laboratory	19
View_Extentions	14

Fig. 1. BluEHR Process Map.

Figure 1 shows the process map coming from the usage logs which indicates that a large population of the users is mostly using Access_Dashboard, Edit_Health_Records, and View_List_Records, respectively. Patient_Print and View_Calendar also belong to the top functions used by the users, where these functions are essential for the users to be able to print prescriptions and create appointments. Most users use these functions more frequently compared to the other activities present in the system, such as View_Referrals, View_Reports, View_Broadcast, and View_Reminders. Currently, Open_Telemed and Join_Telemed are found in between these two usage comparisons.

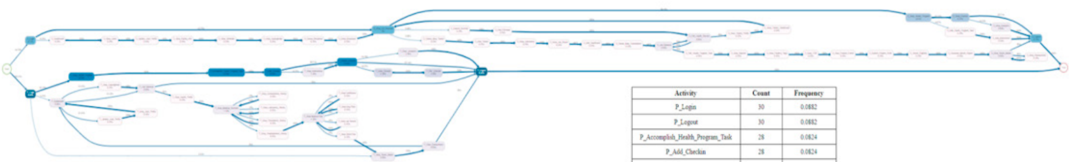
4.2.Low Interaction Simulated Logs

Activity	Count	Frequency
P_View	4	0.0667
P_View_Medical_Records	4	0.0667
P_Dashboard	3	0.05
D_Edit_Health_Record	2	0.0333
D_Join	2	0.0333
D_Login	2	0.0333
D_Logout	2	0.0333
D_View_List_Records	2	0.0333
P_Join	2	0.0333
P_Login	2	0.0333
P_Logout	2	0.0333
D_Add_Followup	1	0.0167
D_Add_Healthcare	1	0.0167
D_Add_Patient	1	0.0167
D_Check_Eligibility	1	0.0167
D_Create_New_Consultation	1	0.0167
D_Create_New_Patient	1	0.0167
D_Dashboard	1	0.0167

Fig. 2. Low Interaction Process Map.

In this process map, where the doctor and patient only used the basic features of an EMR, it was observed that the doctor would be using D_View_List_Records, D_Edit_List_Records, and D_Join_Telemed the most. The most frequent activities for the patient were P_View_Medical_Records and P_View_Medical_Files as these were the basic features present in the EMR. P_Join_Telemed had the same amount as D_Join_Telemed as it was crucial for the patient to first initiate a telemed consultation appointment with his or her doctor before it happens.

4.3.Medium (Reduced Doctor Engagement) Interaction Simulated Logs

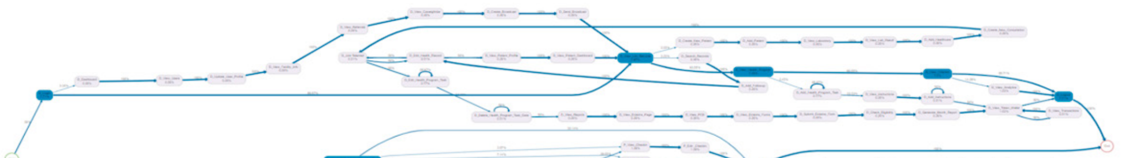


Activity	Count	Frequency
P_Login	30	0.0882
P_Logout	30	0.0882
P_Accomplish_Health_Program_Task	28	0.0824
P_Add_Checkin	28	0.0824
P_Submit_Checkin	28	0.0824
P_View_Health_Program	28	0.0824
D_View_List_Records	17	0.05
D_Login	16	0.0471
D_Logout	16	0.0471
D_View_Health_Program	15	0.0441
D_View_Checkin	14	0.0412
P_Edit_Checkin	8	0.0235
P_View_Checkin	8	0.0235
P_View_Analytics	4	0.0118
P_View_Medical_Files	4	0.0118
P_View_Instructions	4	0.0118
P_View_Medical_Records	4	0.0118
P_Dashboard	3	0.0088

Fig. 3. Medium (Reduced Doctor Engagement) Process Map.

In this process map, P_Login was more frequent than D_Login, because the patient was using the EMR more than the doctor in this scenario. The doctor's most frequent activity was D_View_List_Records. This was because most of the doctor's interactions with the patient go through D_View_List_Records. For instance, the doctor had to navigate to D_View_List_Records first to add or edit a patient, consultation, and health program. On the other hand, the most frequent activities for the patient were P_View_Health_Program, P_Accomplish_Health_Task, P_Add_Checkin, and P_Submit_Checkin, showing evidence in the consistency of the patient in doing his/her task.

4.4.Medium (Reduced Patient Engagement) Interaction Simulated Logs

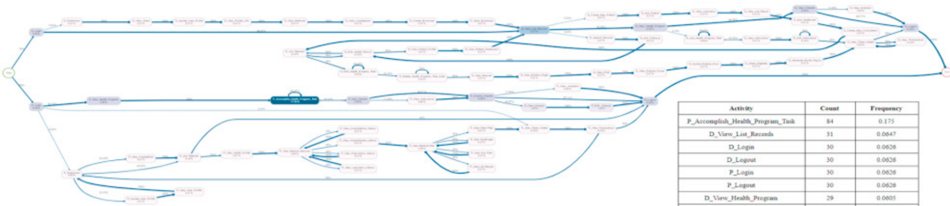


Activity	Count	Frequency
D_View_List_Records	31	0.0797
D_Login	30	0.0771
D_Logout	30	0.0771
P_Login	30	0.0771
P_Logout	30	0.0771
D_View_Health_Program	29	0.0746
D_View_Checkin	28	0.072
P_Accomplish_Health_Program_Task	28	0.072
P_View_Health_Program	28	0.072
P_Add_Checkin	14	0.036
P_Submit_Checkin	14	0.036
P_Edit_Checkin	5	0.0129
P_View_Checkin	5	0.0129
D_View_Analytics	4	0.0103

Fig. 4. Medium (Reduced Patient Engagement) Process Map.

In this process map, where the patient does 50 percent of his/her tasks, the doctor's most frequent activity was still View_List_Records, as most of the doctor's interactions with the patient go through D_View_List_Records. Compared to the process map for reduced doctor medium interaction, the frequency for D_View_List_Records increased from 5 percent to 7.97 percent. Here, it can be implied that initiative from the doctor-side to interact with the patient increased from the previous scenario. D_View_Health_Program and D_View_Checkin also have higher frequencies for the same reason. On the other hand, the most frequent activities for the patient were P_View_Health_Program and P_Accomplish_ Health_Task. Comparing the process map for reduced doctor medium interaction the frequencies for P_View_Health_ Program and P_ Accomplish_Health_Task decreased from 8.34 percent to 7.2 percent and the frequencies for P_Add_Checkin and P_Submit_Checkin decreased from 8.24 percent to 3.6 percent, which indicated the reduction in engagement from the patient-side illustrated by this scenario.

4.5.High Interaction Simulated Logs



Activity	Count	Frequency
P_Accomplish_Health_Program_Task	84	0.175
D_View_List_Records	31	0.0647
D_Login	30	0.0626
D_Logout	30	0.0626
P_Login	30	0.0626
P_Logout	30	0.0626
D_View_Health_Program	29	0.0605
D_View_Checkin	28	0.0585
P_Add_Checkin	28	0.0585
P_Submit_Checkin	28	0.0585
P_View_Health_Program	28	0.0585
P_Edit_Checkin	8	0.0167
P_View_Checkin	8	0.0167
D_View_Analytics	4	0.0084
D_View_Token_Wallet	4	0.0084
P_View_Medical_Files	4	0.0084
P_View_Analytics	4	0.0084
P_View_Instructions	4	0.0084
P_View_Medical_Records	4	0.0084
D_Add_Health_Program_Task	3	0.0063
D_Edit_Health_Program_Task	3	0.0063

Fig. 5. High Interaction Process Map.

In this process map, where both agents do all their tasks, the doctor's most frequent activity would be D_View List_Records as it is the main activity for the doctor to view every day to access the data of patients. Subsequently, the next would be D_View_ Health_Program and D_View_Checkin for the doctor to check up on the patient's progress on their health program. Other interaction activities would be D_Add_ Health_Program_Tasks which were done to create the health program of the patient at the start and D_View_Analytics which was useful at the end of the health program for comparison of the patient's progress. Lastly, the doctor would check their token wallet and transactions through D_View_Token_Wallet and D_View_ Transactions.

On the other hand, it was seen that the patient's most frequent activity would be P_Accomplish_Health_Program such that the patient would accomplish their health program provided by the doctor on a daily basis, followed by P_View_Health_Program, P_Add_Checkin, and P_Submit_Checkin as these are the main activities that are consequently done to accomplish their health program. Other activities related to the health programs would be P_View_Checkin and P_Edit_Checkin. The least frequent activities for the health program would be P_View_Instructions and P_View_Analytics as the patient would only view instructions at the start and view analytics towards the end when data are already sufficient for analytics.

4.6.Time Performance

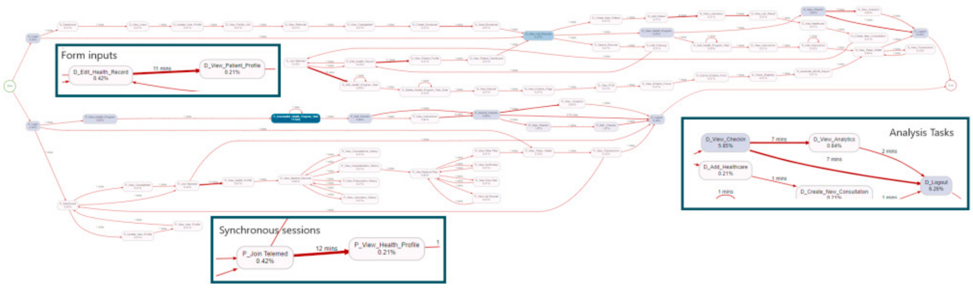


Fig. 6. Time Performance Process Map.

Here, Join_Telemed took the longest as the only direct and synchronous interaction between the two agents. Longer form inputs, such as D_Add_Patient, D_Edit_Health_Record, P_Add_Checkin, and P_Edit_Checkin, would take a longer time than other activities because accomplishing these took more effort. Lastly, D_View_Laboratory, D_View_Checkin, and P_View_Instructions were activities that would also require time to view and analyze the content, hence, the longer timespan indicated in the edges.

5. Conclusion

This study aimed to understand doctor-patient interactions in an electronic medical record with the use of process mining through the bupaR package. System usage logs were converted to bupaR's event logs, then were transformed into visual graphs that illustrate the flow of all the actions from the time logged in to the time they logged out. Using process mining, the following insights were derived from the data available in this study. First, the current state of EMRs, from the November 2020 process mining, was shown to be low interaction. After analyzing, one of the main problems with the low interaction scenario was the lack of features for both agents to interact between consultations.

Since preventive healthcare requires consistent monitoring beyond just consultations as defined in [1, 2], a personal health program was introduced and developed to address this. It includes a health tasks checklist that is flexible enough to adapt to the type and frequency of tasks, with categorization (physical activities, nutrition and diet, wellness activities and vitals), priority levels, and a customizable scheduling system, daily check-in, and analytics so any discrepancies in the health data can be identified and instruction on how to properly accomplish tasks.

For the medium interaction scenario, the doctor enables most of the features available on the patient side, so less activity from the doctor-side automatically impacts the patient's activities as well. However, the doctor has to do the same number of activities, whether or not the patient followed through with the program. It can also be seen that failure to maximize these interaction features either from the doctor-side or patient-side reduces the effectiveness of the newly added features. There must be a way to encourage doctors and patients to be consistent with their usage of these features. This is where the token economy framework comes in.

If the doctor enabled an effective end-to-end program for the patient and the patient was diligent in accomplishing that entire program, the doctor was constantly aware of the health condition of the patient. In the high interaction scenario, we are able to target all four levels of preventive healthcare. Another insight is that consistency of usage also matters more than just frequency. It would be more effective to have doctors and patients log in at regular intervals than accumulate all their tasks in a short time period. Lastly, it shows that synchronous sessions, form inputs, and analysis tasks require more time to accomplish, thus can be rewarded more.

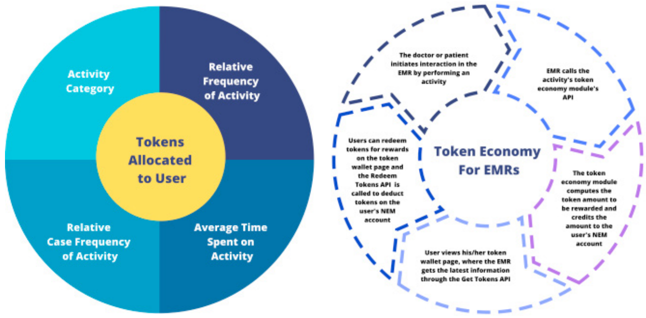


Fig. 7. (a) Token Economy Framework (Left); (b) Token Economy for EMRs (Right).

Figure 7a illustrates the features of the framework. First is the categorization of activities. As defined before, basic activities refer to the “required" features of the EMR, which are records, telemed, eclaims, and HFSRS (hospital facility statistics reporting system) only, while the rest are considered advanced activities. Advanced activities should weigh more than basic activities. Next are the individual frequencies of each activity from the process map, which can have an indirect relationship in relation to the frequency. Lower frequency implies less usage, hence, the weight of this activity should be higher in the equation to encourage its use more, and vice versa. This feature can also be further split into relative frequency and relative case frequency. While relative frequency could show the count of interactions, relative case frequency can balance out potential discrepancies, such as when functions are used merely for transitioning to pages, rather than doing the activity itself. Another feature could be the time spent on each activity. Since more time usually implies more effort was needed to complete an activity, then higher time spent can correlate to a higher weight in the equation. Lastly, Figure 7b illustrates how the framework described integrates into the EMR. In the end, the application of this token economy framework to EMRs would allow for the attainment of the preventive healthcare goal of this study, through more interaction and wider and more consistent adoption of the system.

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