Illegitimate HIS Access by Healthcare Professionals Detection System Applying an Audit Trail-based Model

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Abstract: Complex data management on healthcare institutions makes very hard to identify illegitimate accesses which is a serious issue. We propose to develop a system to detect accesses with suspicious behavior for further investigation. We modeled use cases (UC) and sequence diagrams (SD) showing the data flow between users and systems. The algorithms represented by activity diagrams apply rules based on professionals’ routines, use data from an audit trail (AT) and classify accesses as suspicious or normal. The algorithms were evaluated between 23rd and 31st July 2019. The results were analyzed using absolute and relative frequencies and dispersion measures. Access classification was in accordance to rules applied. “Check time of activity” UC had 64.78% of suspicious classifications, being 55% of activity period shorter and 9.78% longer than expected, “Check days of activity” presented 2.27% of suspicious access and “EHR read access” 79%, the highest percentage of suspicious accesses. The results show the first picture of HIS accesses. Deeper analysis to evaluate algorithms sensibility and specificity should be done. Lack of more detailed information about professionals’ routines and systems, and low quality of systems logs are some limitations. Although we believe this is an important step in this field.

1 INTRODUCTION

Healthcare institutions typically imply complex data management processes, where a professional can have multiple roles during a certain period of time (physician, researcher, head of department), leading him or her to access many different patients’ Eletronic Health Record (EHR), that in its turn are accessed by many professionals for different reasons. This complexity makes very hard distinguishing the legitimate accesses from the non-legitimate ones and it is becoming a serious issue for healthcare institutions to solve. Although audit trails (AT) are an important tool for some General Data Protection Regulation (GDPR) requirements’ compliance (EU, 2016), like audit and traceability (Gonçalves-Ferreira et al., 2018), we believe that they can have an important role on detection of suspicious actions on HIS and that can be illegitimate access. Previous studies show that despite the complex environment of data management on healthcare providers it is possible to create rules associated to routines of healthcare professionals and to model their access to Health Information Systems (HIS) through use cases (UC). Taking advantage of information collected on previous investigation (L.Correia et al., 2019) we propose to implement algorithms for detection of suspicious actions on HIS by healthcare professionals giving clues for further investigation by the Data Protection Officer (DPO) and to ensure the patients data privacy.

2 METHODS

Parthing from previous studies (L.Correia et al., 2019) in which were modeled UC for scenarios that described situations of, or that could lead to, illegitimate access, we selected three to implement algorithms for detection of suspicious activity. The choice was based on the available logs in the AT of a hospital from North Portugal after an analysis of variables needed
for each UC. Since we had logs just from the applicational system Obscare we excluded the UC that depend other type of logs. The rules and thresholds applied to algorithms were based on the information gathered on discussions with experts and interviews to healthcare professionals (L.Correia et al., 2019).

We used the Unified Model Language (UML) to design the UC and activity diagrams (AD), and coded in JAVA programming language. Tests were conducted between 23rd and 31st of July 2019, with logs of one applicational system - Obscare that were being collected by the AT HS.REGISTER on an hospital from North Portugal. We analysed the obtained datasets in order to find errors on dates and calculations, inconsistencies and access misclassifications. For each, it was removed duplicated records and it was analysed the impact of N/A existence. For the dataset of UC “Check time of activity” we produced a summary table by professional category with the metrics: (1) total of results, (2) number of professionals without identification, (3) minimum time of activity, (4) 1st and 3rd quartiles and median values of time of activity, (5) mean of time of activity, (6) maximum time of activity; (7) standard deviation and (8) number of results classified as “suspicious”. For the dataset of UC “Check days of activity” we produced a summary table by professional category with the metrics: (1) total of results, (2) minimum days of activity, (3) 1st and 3rd median days of activity, (4) mean of days of activity, (5) maximum of days of activity; (6) standard deviation and (7) number of results classified as “suspicious”. For dataset of UC “EHR read access” we produced a summary table by date with the metrics: (1) total of results, (2) total of results without professional ID, (3) total of results with null patient ID, (4) total of suspicious access classifications, (5) total of suspicious access classifications without professional ID and (6) total of suspicious access classifications with null patient ID, and a table comparing the accesses by professional category.

3 RESULTS

3.1 Use Case “Check Time of Activity”

First, we think of identifying professionals’ activity periods that are longer or shorter than expected for a work shift, since professionals have a schedule to work and should not access to HIS when they are off (Diário da Republica, 2005).

Scenario 1. A professional uses his credentials during his shift to accomplish his tasks. In the end of his shift, he goes home and he did not logout his session on the computer. A colleague uses his open session to access the HIS and take a look at a patient’s EHR that he was curious about.

For this UC we propose to track all activities of a professional and monitor the consecutive time of activity, checking if the total time of activity is normal for a shift duration, or is shorter or longer insted, as showed in the UC (figure 1) and on the SD (figure 2).

![Figure 1: Use case “Check time of activity”](image1)

Our algorithm requests the data to AT between two dates, analyses the data and produces a report with the classification of the results corresponding to periods of consecutive time of activity. As we cannot affirm that the result obtained is in fact an illegitimate access, we classified the access as “suspicious” if it is shorter or longer than expected for a work shift and an alert is launched. The AD (figure 3) shows the proposed algorithm. For each professional, the events are ascending ordered by timestamp. It adds the time between two consecutive timestamps of event logs, if the difference between them is less than six hours. Otherwise we consider that the professional is off and it starts counting a new period of consecutive time of activity. If the total of added time is greater than thirteen hours or shorter than five hours it may indicate that the user is not accessing only during the work shift.

Evaluation. The algorithm was tested between 23rd and 31st July 2019. The results for each professional
and classification as suspicious are shown in table 1. If a professional accesses a period of time less than five hours ($\leq 299$ minutes) and greater than thirteen hours ($\geq 781$ minutes) it is classified as “suspicious”, else the system classifies the access as normal. In the referred period, which counts nine days, after removing the duplicated ones, we got 276 results, of which 176 were classified as suspicious. The data presented show two outliers with different behaviours. For the category “No identified” all cases have a duration completely distinct from the others, but all 6 occurrences have the same behaviour. This happens because this category represent automatic processes that run in system’s background, acording the provider of Obscare system. Another outlier is in “Nurse” category and is similar to “No identified” category, because there are some automatic processes associated to “Nurse” category, as well. Categories associated to management and research tasks have activities with very short duration and few occurrences. Looking to categories that are more related to healthcare delivery and removing the automatic processes from “Nurse” category we can see that the results presented, generally, do not exceed the superior limit fixed as suspicious access. However the categories “physician” and “specialist physician” have some results that exceed that limit. It is also possible to see that there are many accesses that do not go over the inferior limit and those are responsible for most of the suspicious access classifications.

3.2 Use Case “Check Days of Activity”

Secondly, we tried to identify professionals’ consecutive days of activity that are longer than expected for a week work, since professionals are off after a week of work, that can be up to seven consecutive days and in some exceptions even longer, and should not access to HIS when they are off (Diário da Republica, 2005).

Scenario 2. A professional uses his credentials during his shift to accomplish his tasks. In the end of work week, when he is off, another user uses his credential to access a HIS, to take a look at a patient EHR.

For this UC we propose to track all activities of a professional and monitor the consecutive days of his or her work, checking if the total consecutive days of activity is normal for a work week, or longer, as showed in the UC (figure 4). The SD (figure 5) shows that for every activity in the system done by a professional, it is sent a event log for the AT which identifies the professional, his profile, the timestamp, the patient accessed, the action executed among other data. Our algorithm requests the data to the AT between two dates, analyses the data and produces a report with the classification of the results corresponding to the number of consecutive days of activity. Also, as we cannot affirm that the result obtained is in fact an illegitimate access, we classified the accesses as “suspicious” if it is longer than expected for a work week. For each

Figure 3: Activity diagram “Check time of activity”.

Figure 4: Use case “Check days of activity”.

For this UC we propose to track all activities of a professional and monitor the consecutive days of his or her work, checking if the total consecutive days of activity is normal for a work week, or longer, as showed in the UC (figure 4). The SD (figure 5) shows that for every activity in the system done by a professional, it is sent a event log for the AT which identifies the professional, his profile, the timestamp, the patient accessed, the action executed among other data. Our algorithm requests the data to the AT between two dates, analyses the data and produces a report with the classification of the results corresponding to the number of consecutive days of activity. Also, as we cannot affirm that the result obtained is in fact an illegitimate access, we classified the accesses as “suspicious” if it is longer than expected for a work week. For each
## Table 1: Results for UC “Days of Activity”.

<table>
<thead>
<tr>
<th>Professional Category</th>
<th>Nr results</th>
<th>Professional identified</th>
<th>nr of consecutive minutes worked</th>
<th>Median</th>
<th>1st Qu.</th>
<th>Mean</th>
<th>3rd Qu.</th>
<th>Max</th>
<th>Standard Deviation</th>
<th>Suspicious accesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>No identified</td>
<td>6</td>
<td>0</td>
<td>4305</td>
<td>4305</td>
<td>4305</td>
<td>4305</td>
<td>4328</td>
<td>6248</td>
<td>6.12</td>
<td>6 (100%)</td>
</tr>
<tr>
<td>Admin Sirai</td>
<td>5</td>
<td>5</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>2.60</td>
<td>0.00</td>
<td>0.00</td>
<td>0</td>
<td>1 (100%)</td>
</tr>
<tr>
<td>Admin VCOBSGYNV3, Create users</td>
<td>1</td>
<td>1</td>
<td>2.00</td>
<td>2.00</td>
<td>2.00</td>
<td>2.00</td>
<td>2.00</td>
<td>0</td>
<td>1</td>
<td>1 (100%)</td>
</tr>
<tr>
<td>Administrative</td>
<td>36</td>
<td>36</td>
<td>1.00</td>
<td>96.75</td>
<td>338.00</td>
<td>307.54</td>
<td>364.25</td>
<td>713.00</td>
<td>210.83</td>
<td>44 (41%)</td>
</tr>
<tr>
<td>Nurse</td>
<td>108</td>
<td>108</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0</td>
<td>1 (100%)</td>
</tr>
<tr>
<td>Nurse, Admin VCM, Physician, Development team</td>
<td>1</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0</td>
<td>1 (100%)</td>
</tr>
<tr>
<td>Nurse, Administrative, Admin Sirai, Admin Backoffice</td>
<td>4</td>
<td>4</td>
<td>0.00</td>
<td>2.25</td>
<td>8.00</td>
<td>15.00</td>
<td>18.75</td>
<td>36.00</td>
<td>16.31</td>
<td>5 (100%)</td>
</tr>
<tr>
<td>Management, Admin, VCOBSGYNV3, Creat Users, Physician</td>
<td>1</td>
<td>1</td>
<td>197.00</td>
<td>197.00</td>
<td>197.00</td>
<td>197.00</td>
<td>197.00</td>
<td>197.00</td>
<td>1.00</td>
<td>1 (100%)</td>
</tr>
<tr>
<td>Indicators Sirai, Admin Sirai</td>
<td>1</td>
<td>1</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0</td>
<td>1 (100%)</td>
</tr>
<tr>
<td>Physician</td>
<td>28</td>
<td>28</td>
<td>0.00</td>
<td>74.5</td>
<td>230.00</td>
<td>314.60</td>
<td>359.00</td>
<td>1543.00</td>
<td>345.88</td>
<td>21 (75%)</td>
</tr>
<tr>
<td>Physician, Specialist, Physician</td>
<td>65</td>
<td>65</td>
<td>0.00</td>
<td>124.00</td>
<td>338.00</td>
<td>435.40</td>
<td>448.50</td>
<td>4320.00</td>
<td>766.37</td>
<td>45 (68%)</td>
</tr>
<tr>
<td></td>
<td>276</td>
<td>267</td>
<td>0.00</td>
<td>87.00</td>
<td>266.00</td>
<td>422.80</td>
<td>448.50</td>
<td>4320.00</td>
<td>766.37</td>
<td>176 (63%)</td>
</tr>
</tbody>
</table>

Figure 5: Sequence diagram “Check Days of activity”.

classification as “suspicious” an email is sent to the CIS and to the DPO.

The AD (figure 6) shows the proposed algorithm. For each professional, the events are ascending ordered by timestamp and it counts consecutive days using the timestamps of event logs. If the difference between them is more than one day, we consider that the professional was off and it starts counting a new period of consecutive days of activity. If the total of added days is greater than eight days it may indicate that the user is not accessing only during the work shift.

**Evaluation.** The algorithm was tested between 23rd and 31st July 2019. The results of days of activity for each professional and classification as suspicious are shown in table 2. If a professional accesses a period of days greater than 8 days it is classified as “suspicious”, else the system classifies the access as normal. In the referred period, which counts nine days, we got 213 results, of which 17 were classified as “suspicious”. The data presented shows two outliers with different behaviours. For the category “No identified” all the cases have a duration completely distinct from the others, but all the 6 occurrences have the same behaviour. This happens because this category represent automatic processes that run in system’s background. Another outlier is in “Nurse” category and is similar to “No identified” category, because there are some automatic processes associated to “Nurse” category, as well. Categories associated to management and research tasks have activities with very short duration and few occurrences. We can see that automatic processes run every day having no associated category, and there are accesses associated to management and research accesses that occurs generally once or twice a week. Observing the categories that are directly related to delivery of healthcare, such as “Administrative”, “Nurse”, “Physician” and “Specialist Physician”, similarly to what happens in the results of the UC “Check
time of activity”, the suspicious accesses are associated to “specialist physician” category.

3.3 Use Case “Check EHR Read Access”

In this UC, we tried to identify accesses by professionals to read patients’ EHR and did not create or update them. The lack of evidences that can justify such access is already spotted as an issue to solve by healthcare institutions. According to GDPR and Joint Commission International (JCI) for hospitals certification on Management of Information (MOI) 11.5 this type of access should be addressed to mitigate problems related to data breaches (Joint Commission International, 2017).

**Scenario 3. A professional access to a patient EHR. Why does he access? What are the evidences of the healthcare delivering of that professional.**

For this UC we propose to track all accesses of a professional and monitor the patient accessed and the type of action executed between 72 hours (three consecutive days). A EHR may be updated after the end of shift or in the beginning of the shift and the information updated may need to be checked in the end of the shift. If between 72 hours there is an access to read an EHR and there is any update or create action, the access is classified as “suspicious”, else is classified as normal, as showed in the UC (figure 7). The SD (figure 8) shows that for every activity in the system done by a professional, it is sent an event log for the AT which identifies the professional, his profile, timestamp, patient accessed, action executed, among other data. Our algorithm requests the data to the AT between two dates, analyses the data and produces a report with the read actions (yes or no), write actions (yes or no) and results of access classification. Again, as we cannot affirm that the result obtained is in fact an illegitimate access, we classified the access as “suspicious” if there is any update or create actions. For each classification as “suspicious” an email is sent to the CIS and to the DPO.

Figure 7: Use case “Check EHR read access”.

Figure 8: Sequence diagram “EHR read access”.

Figure 9: Activity diagram “EHR read access”.

The AD (figure 9) shows the proposed algorithm. For each professional, it is analysed the patient accessed, and, for each, verifies the action, counts the number of readings and the number of writings. For each patient, if the number of readings is greater than zero and the number of writings are equal to zero the...
The results show that 77 classifications (20%) do not have the professional ID. Such occurrences are related to automatic processes, that run in parallel, to check, get and retrieve necessary data on EHR. The results with N/A “patients id” are 94 (25%), and they are users’ processes that are not related with patients but to other type of reports instead. So we adjusted the values excluding the results of automatic processes and we obtain the values on table 4, which shows that the results classified as “suspicious” grow to 92%.

Analysing the results by categories (table 5), we have those that typically access data for management and research tasks. All these accesses were considered suspicious because they are query actions. Nonetheless all the other categories have a high percentage of access classified as “suspicious”. This indicates that there are a several number of EHR accesses that did not had information updated, and were just consulted.

Table 5: Results for UC “EHR read access” by professional category.

<table>
<thead>
<tr>
<th>Date</th>
<th>Total results</th>
<th>Suspicious access nr</th>
<th>Sr. Access</th>
<th>Access</th>
<th>Suspicious Access</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-07-22</td>
<td>49</td>
<td>27 (93%)</td>
<td>8 (27%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-23</td>
<td>20</td>
<td>19 (95%)</td>
<td>13 (65%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-24</td>
<td>30</td>
<td>29 (97%)</td>
<td>26 (87%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-25</td>
<td>40</td>
<td>32 (80%)</td>
<td>19 (48%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-26</td>
<td>11</td>
<td>11 (100%)</td>
<td>11 (100%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-27</td>
<td>15</td>
<td>14 (93%)</td>
<td>11 (73%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-28</td>
<td>18</td>
<td>17 (94%)</td>
<td>15 (83%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-29</td>
<td>26</td>
<td>24 (92%)</td>
<td>24 (92%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-07-30</td>
<td>27</td>
<td>25 (93%)</td>
<td>24 (89%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The categories related to healthcare delivery like “Administrative”, “Nurse”, “Physician” and “Specialist Physician” have a high percentage of suspicious access classification, all above 70%.

4 DISCUSSION

Previous work showed that there are many reasons for existig concerns about health data access on healthcare institutions (L.Correia et al., 2019) and the health data flow complexity is such that turns very hard to evaluate the ligitimacy of the accesses to EHR. However, despite the complexity of health data management processes, it is possible to describe scenarios, UC and the data flow of the access between users and systems through SD. Based on this information we could develop three algorithms for suspicious activ-
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5 CONCLUSIONS

The scope of this study is very complex and requires a very thorough analysis. Although the difficulties we found it was possible to create a proof of concept of a system to detect suspicious accesses by professionals from healthcare institutions.

Some limitations we have are the lack of detail of the tasks performed by healthcare professionals to create more precise rules for algorithms. An analysis on the field would be also very useful to better understand the results and, probably, change the classification of some accesses. Another limitation is the availability and quality of HIS logs. Obscare system has already logs prepared for GDPR compliance, but many systems have not and institutions need to make a great effort on providers to have this information. The period of test should be longer than nine days to detect more patterns in the results obtained.

Nonetheless it was possible to model the scenarios of undue access and create algorithms to detect suspicious accesses. The results obtained gave a first glance of what is happening at the level of HIS access. A strength of using Obscare system was the fact that it is used on hospital stay, consulting and emergency context. It may explain some of the outliers detected, as the emergency shifts may have different
durations. These results must be confirmed at an ini-
tial stage and, than, take advantage of this information
to create a knowledge base that will allow to apply Ar-
tificial Intelligence (AI) models.

Even at this stage, which is still in a very embry-
onic stadium, the project reveals to be very useful to IS department and to DPO. They are having the first picture of the accesses by professionals in the pre-

tented format. Having the results of access classifi-
cation based on the rules created according to staff routines, the identification number of the professional that made the access, the time the access was made and the patient accessed, it gives clues for DPO and CIS investigate whether the access was in fact ille-
gitimate. Further work must be performed to com-
pletely accomplish the main goal of this project, like perform a more detailed analysis to verify the correct-
ness of classifications, determine its sensibility and specificity and detect the suspicious accesses in al-
most real time. It would be very interesting and use-
ful although the characteristics of technology used in hospitals may be a barrier. Finally, the production of a knowledge base its recommended so that it will be possible to apply AI models in the future.

ACKNOWLEDGEMENTS

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