**Original article**

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# THE EFFECT OF COVID-19 CRISIS ON CHRONIC DISEASE TRACKING: BRIDGING A DATA GAP

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COVID-19 negatively shifted chronic disease tracking and general data collection in primary healthcare facilities. The focus was moved to support the counter-pandemic efforts, while the number of registered general examinations and those dedicated to chronic diseases dropped.

In that light, the results of the algorithms dedicated to helping identify potential new chronic patients become less relevant. With a lower number of registered visits, the results of the estimate become less relevant with the increased number of unidentified patients with chronic medical cases. This research aims to improve the existing data summarization methods and increase their relevance by adding new criteria, using the potential to integrate with other medical information systems, and making them more configurable up to the patient level.

The updated data aggregation tools are evaluated against results collected in Niš Primary and Ambulatory Care Center and compared with the results from the initial version of the algorithm.

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**Key words:** *medical information system, history of disease summarization, chronic disease management, data gap identification*

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## Introduction

Chronic medical conditions such ashigh blood pressure and diabetes hit a significant percentage of the population worldwide. In European countries, the percentage of registered patients suffering from chronic hypertension is between 30% and 45% (1, 2). Unfortunately, the Republic of Serbia is in the top 10 countries with an estimated prevalence of hypertension of one-half in the adult population (3). In many cases, the chronic disease is not discovered early enough, leading to the significant deterioration of the health status of the affected individuals (4). For this reason, any improvement in the detection of chronic diseases is of immense importance for the public health system as a whole (5). We identified this problem during the pandemic and our first result ofthe identified gap was presented in the study by Rajković P. et al.(6). From the thematic point of view, this paper represents the follow-up of the mentioned research and shows the latest results and recommendations in our research, which should bring more effective data summarization processes and routines that would help identify patients with chronic diseases.

This situation has beena well-known fact for decades, but with the COVID-19 pandemic outbreak, it worsened (7). Since, during that period, most of the medical workforce was engaged in COVID-19 units, the positions in general and specialist care became understaffed. The series of lockdowns reduced the general population's mobility which reflected in the reduction in the number of registered visits with general practitioners (GP) and specialist doctors (8).

Besides the usage of Medical Information Systems (MIS) during the pandemic period in GP and specialist units dropped in terms of quantity, the quality of collected data remains. This means the identification of the early warning signs of chronic disease, especially hypertension and diabetes (9, 10), remains possible. The early warning signs for the chronic disease could be various medical record items associated with it—like diagnosis on some examination, prescription of the specific medication, treatment, change in patient's data, etc.

Our research group has worked on developing MIS for primary care, named Medis.NET, and supplementary software tools since 2009. The installation base consists of 25 installations in the region of Southern and Eastern Serbia (11) covering a population of approximately 1.5 million and supporting both general practitioners and specialist services (12–14). Recognizing the potential to extend the basic MIS with the data analytic features we introduced an extension that provided a Data Summarization Method (DSM), integrated into an auxiliary tool. Its main aim was to detect potential patients with chronic diseases on the base of registered medical services and prescribed medications (15).

The structure of the base MIS and the mentioned extension is shown in Figure 1. The effect of the proposed methods was published by Aleksić D.et al.(15) and the designed algorithm was based on data collected between the years 2012 and 2015. The approach was proven effective in the coming years. The results for the years 2016 to 2019 were within the expected boundaries.

The transition to the updated version of DSM tool would be necessary since the structure of the collected data as well as collection methods gets changed. The COVID-19 pandemic influenced the habits of software users, and the integration services extended the software landscape. Speaking about changed user habits, our MIS has a reduced set of directly registered data, as the result of the focus shift to COVID-19-related medical services. Oppositely, the integration with the external systems brought additional data that must be treated a bit differently. The internal transition would be seamless for the end users and would come through one of the regular software releases.

The updated algorithm was tested in parallel for the period 2016-2019 with the COVID crisis from 2020 to 2021 (6). The mentioned summarization algorithm has been further extended (Figure 2), and its present form is discussed in this paper. In this paper, we wanted to compare the results we got from the two algorithms and point out the differences and improvements we implemented. Furthermore, the updated DSM offers a higher level of customization. This will give the end user better control over the identification process.

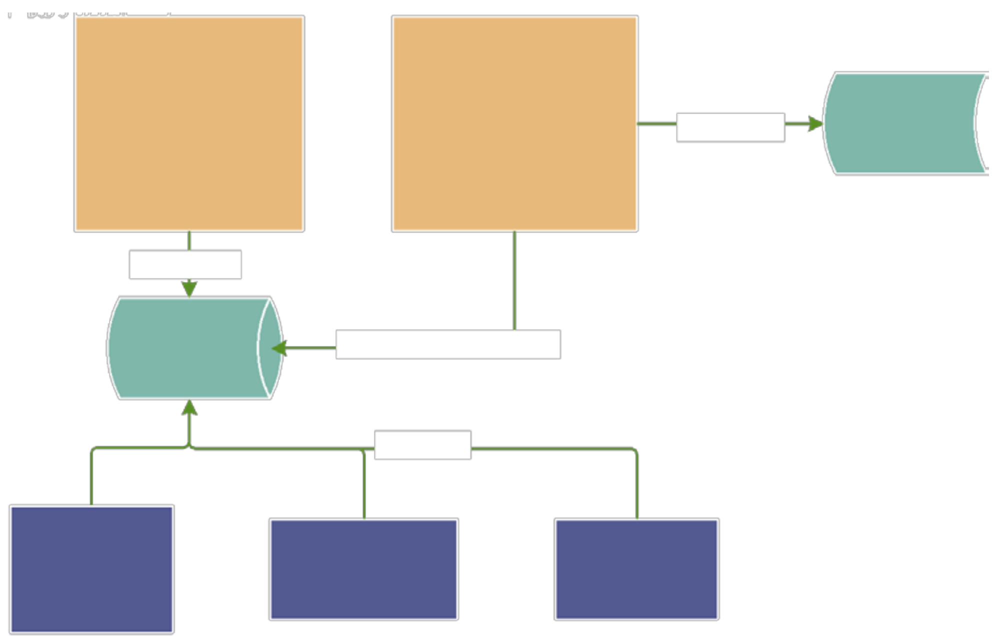

**Figure 1.** The extended system architecture

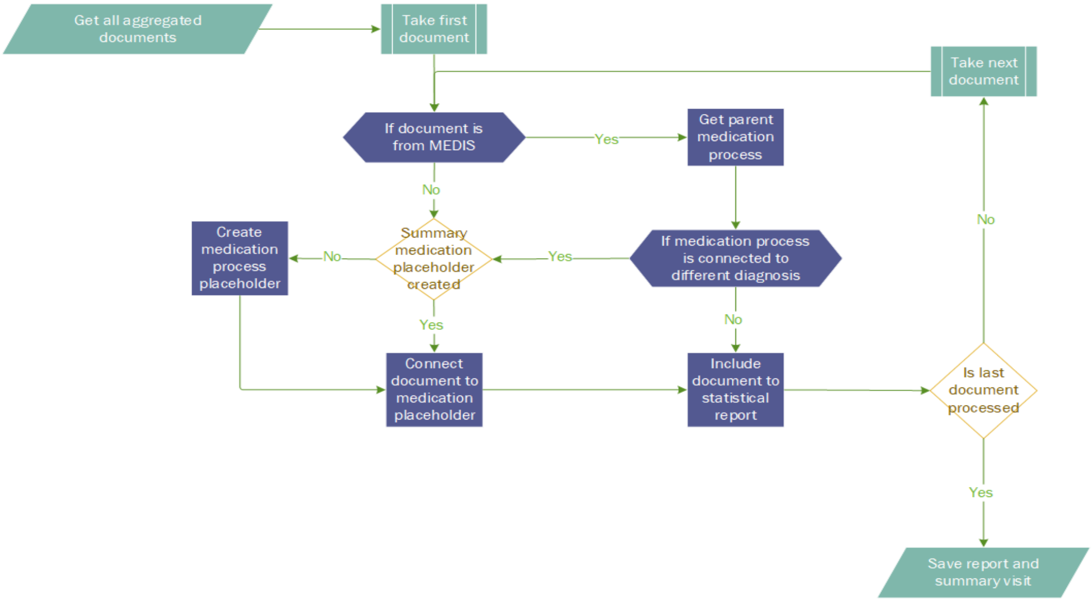


**Figure 2.** The adaptation of the data extraction/summarization algorithm originally presented in the study by Aleksić D. et al. (15)

### Related work

The challenge started with the COVID-19 outbreak in March 2020 (16). In the following months, the reduction of registered medical care institutions dropped worldwide (17) to one quarter, and in some cases (18) even to one-tenth. Due to the reduced number of registered medical services, the number of identified patients dropped too, making the already designed and implemented algorithm less effective. To bridge the potential gap, we decided to improve our DSM, by improving its routine and by adding new identification parameters.

The studies of MIS systems used during the pandemic (19) show a dramatic activity decrease in March and April 2020. This period was then followed by a significant increase in pandemic-related activity (as added support tools emerge) which partially covered the reduction in the number of medical services related to non-COVID-19 patients.

The research by Patel S.Y. et al. discusses one different consequence of the pandemic: the growth of telemedicine (18). Analyzing data from the United States, the authors concluded a rise of close to 20% in the first half of 2020, while the number of patient visits dropped to close to one-third. Combining telemedicine with regular visits, the overall reduction in visit registration ended at 10% looking at the situation from 2020.

The overall data summarization paradigm is often extended nowadays with the analysis of different medical images presented by Wang S. et al.(20). The authors modified the existing image processing methodology, used to detect common pneumonia, by including deep learning techniques to make the algorithm that could help in early detection of COVID-19. The positive influence of such an approach to our work was the suggestion to use an adaptive estimation approach which allows the system to propose different setup parameters when number of false positives increases. Unfortunately, the downside of such approach is the high number of false positives which requires further adaptation by including images of the pathogenic negative patients in the analysis.

Cases like the COVID-19 pandemic prove that medical professionals cannot rely only on direct data collection from MIS systems, but any additional tools prove to be helpful and bring an additional level of data collection quality. The collateral benefit of all these scenarios is that they could remain active during regular and general emergencies, making the healthcare system more effective.

### Aim

The main objective of our research was to improve the existing data summarization methods and increase their relevance by adding new criteria and making them more configurable. The outbreak of COVID-19 made a negative impact on medical research (21) as well as regular healthcare routines (17, 18), including chronic disease tracking (19). The entire health system switched its focus to support the counter-pandemic efforts (22). Medical personnel were reassigned from their regular duties to COVID care (23), and the potential number of medical examinations was reduced significantly. In some periods, the number of non-COVID-19-related treatments dropped to under one-third of the usual number (24).

Facing the significantly reduced data set, the data summarization systems identified fewer potential patients than expected. The immediate consequence was that the results of the algorithms dedicated to helping in the early detection of potential new chronic patients became less relevant. Since the general lifestyle during the pandemic becomes more stressful, the number of chronic patients will grow at least the same rate as during the regular situation. To overcome this problem, we launched research that should improve our data search algorithms to identify more patients who should be summoned for the control check-ups.

## Material and Methods

The material used in our research was a set of data gathered by Niš Primary and Ambulatory Care Center (in Serbian *Dom zdravlja Niš*, in further text DZN) personnel from 2010 to 2022, using MIS Medis.NET. For the most accurate data analysis, we relied on DZN, our largest user with the highest number of registered patients. DZN is a public healthcare facility and the main primary medical care provider for a quarter-million-sized city and its surrounding area.

The collected data were organized and well-structured according to open EHR (25) standards. The choice of the international standard during the system design and development helped in later integration and made all the developed algorithms useful for other MIS instances based on the same set of standards. Our primary interest was focused on medical records that were connected to the most frequent chronic diseases in the area covered by DZN—namely I10 Essential (primary) hypertension, E11 Type 2 diabetes mellitus, I49 Cardiac arrhythmia, I20 Angina pectoris, and E10 Type 1 diabetes mellitus (Table 1). As it has been mentioned in the previous section, our main objective was to help in the early detection of chronic diseases based on the data collected both in DZN and external sources.

The initial methodology for the support in the detection of potential patients suffering from chronic diseases relied on the data summarization methods and tools that we proposed in our research (15). Due to the applied standards, the solution could be used for the development of the different extensions of any open EHR based MIS. For example, the approach was used for the visualization of the clinical structure document (26). Our research group continued development to support the pandemic effort (27) during 2020, but the method itself was acknowledged as part of the general clinical decision support paradigm (28).

It is important to point out that the summarization algorithms werenot intended to automatize the decision but to act as a warning and suggestion tool in cases when patients hadmany simultaneous diagnoses and frequently visited multiple medical professionals. The secondary benefit wasthe possibility to generate lists of the patients that could be summoned for the periodical preventive medical exams.

The base summarization algorithm was built on the analysis of medical documents generated within DZN for patients who have not yet been marked as ones with chronic diseases. The algorithm would analyse all the documents created within the predefined period and generate a warning to the medical practitioner if there were a number of medical documents related to a chronic diagnosis. The level of the warning depended on the number of discovered medical documents. When the doctor received the warning, he could decide whether to consider further action or discard the notification. Considered documents included all kinds of medical notes, prescriptions, treatments, or requests for further specialist examinations.

**Table 1.** The number of patients with the most common chronic diseases identified and officially verified in the period 2018-2022—2022 is given as an estimate followed by the value until November 30$^{th}$

| Diagnosis | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|
| Number of newly identified patients | 14127 | 13208 | 9044 | 9232 | 9246 (8476) |
| E10 Type 1 diabetes mellitus | 515 | 506 | 337 | 285 | 272 (249) |
| E11 Type 2 diabetes mellitus | 3433 | 3234 | 2246 | 2779 | 2970 (2723) |
| I10 Essential (primary) hypertension | 6834 | 6668 | 4434 | 4315 | 4573 (4192) |
| I20 Angina pectoris | 1543 | 1226 | 829 | 715 | 602 (553) |
| I49 Cardiac arrhythmia | 1802 | 1577 | 1198 | 1138 | 829 (760) |

Unfortunately, the accuracy of the suggestion tool, designed in such a way, depended mostly on the volume of the collected data. During the regular situation, when people regularly visit their GPs, the number of registered medical services and documents is stable, maintaining the required level of precision. When the pandemic started, the number of visits related to non-COVID-19 cases dropped, in some months, to one-third of the usual. The additional problem with the summarizing tool is that many patients nowadays visit multiple medical institutions, and their data are scattered across multiple databases. This problem is more notable in specialist departments than GPs since one patient usually visits one GP, but specialist examinations are requested from several specialists. This led to a data gap that could be easily identified during the simple data analysis (6). All the mentioned problems led to the requirements for the extension of the data summarization algorithms, tools, and usage approaches to reduce the identified data gap.

The first point was to make the data range between two identified occurrences of the document with the chronic diagnosis configurable. This would give us the immediate ability not to look at the few predefined periods (14, 30, and 90 days (about 3 months) as in the initial research), but to try with the extended periods, such as 120 or 180 days (about 6 months).

This proved beneficial for periods such as the spring/summer of 2020. The next update was not to include only diagnosis and the length between occurrences, but also patient demographic data such as age, living location, working location, family status, and whatever could be identified as important.

The next point was to include data from external institutions whenever possible. Developed integration services provided by the Serbian Ministry of Health allowed merging data from various sources (Figure 3). In this way, the number of checked documents grew higher giving a better success rate for the results.

Regarding usability improvements, two main points were suggested—raise the warning when the number of visits was too low according to predefined parameters and suggest the aggregated care process containing all the extracted data from various visits that gave the results with the chronic diagnosis.

The definition of the “too low” number of visits must be left to medical professionals to determine according to the patient’s demographic data, such as age and/or gender. The MIS could give the initial suggestion according to the statistics shown in Table 2, but the final decision must be in the hands of medical professionals.

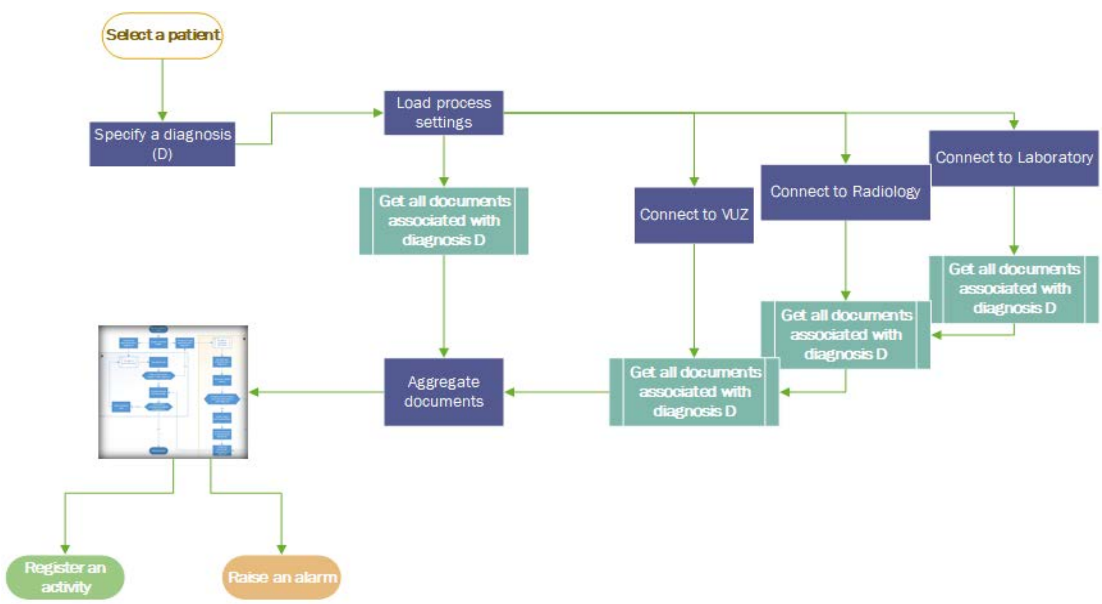


**Figure 3.** The extension of the identification process around the data summarization algorithm

**Table 2.** The number of potentially identified new patients (old method/new method) summarized for the period 2018−2022

| Row Labels | Number of verified patients | Number of potential new patients (old method) | Number of potential new patients (new method) |
|---|---|---|---|
| **2018** | 14127 | 2926 (20.71) % | 5069 (35.88)% |
| **E10** | 515 | 87 (16.89) % | 167 (32.43) % |
| **E11** | 3433 | 420 (12.23) % | 850 (24.76) % |
| **I10** | 6834 | 1775 (25.97) % | 2717 (39.76) % |
| **I20** | 1543 | 267 (17.3) % | 640 (41.48) % |
| **I49** | 1802 | 377 (20.92) % | 695 (38.57) % |
| **2019** | 13211 | 3438 (26.02) % | 5433 (41.12) % |
| **E10** | 506 | 127 (25.1) % | 210 (41.5) % |
| **E11** | 3234 | 527 (16.3) % | 941 (29.1) % |
| **I10** | 6668 | 2115 (31.72) % | 3072 (46.07) % |
| **I20** | 1226 | 261 (21.29) % | 544 (44.37) % |
| **I49** | 1577 | 408 (25.87) % | 666 (42.23) % |
| **2020** | 9044 | 2494 (27.58) % | 3693 (40.83) % |
| **E10** | 337 | 104 (30.86) % | 167 (49.55) % |
| **E11** | 2246 | 366 (16.3) % | 644 (28.67) % |
| **I10** | 4434 | 1531 (34.53) % | 2021 (45.58) % |
| **I20** | 829 | 175 (21.11) % | 371 (44.75) % |
| **I49** | 1198 | 318 (26.54) % | 490 (40.9) % |
| **2021** | 9232 | 3162 (34.25) % | 4580 (49.61) % |
| **E10** | 285 | 131 (45.96) % | 195 (68.42) % |
| **E11** | 2779 | 504 (18.14) % | 938 (33.75) % |
| **I10** | 4315 | 1906 (44.17) % | 2444 (56.64) % |
| **I20** | 715 | 213 (29.79) % | 411 (57.48) % |
| **I49** | 1138 | 408 (35.85) % | 592 (52.02) % |
| **2022** | 9246 | 2594 (28.06) % | 3601 (38.95) % |
| **E10** | 272 | 90 (33.09) % | 128 (47.06) % |
| **E11** | 2970 | 491 (16.53) % | 847 (28.52) % |
| **I10** | 4573 | 1591 (34.79) % | 1978 (43.25) % |
| **I20** | 602 | 188 (31.23) % | 318 (52.82) % |
| **I49** | 829 | 234 (28.23) % | 330 (39.81) % |
| **Grand Total** | 54860 | 14614 (26.64) % | 22376 (40.79) % |

Regarding aggregated care, it would be displayed as the existing medication process but highlighted properly. Data that already existed in Medis.NET were displayed through the standard layout, and the data retrieved from the external source would be displayed as imported using VUZ service (VUZ abbreviated from Serbian *Vertikalno Upravljanje Zdravstvom* meaning Vertical Healthcare Management) as shown in Figure 4. When the GP receives the warning, a simple click on it will include all the identified records as part of the separate medication as shown in Figure 5.

The structure of the improved algorithm is shown in Figure 2. The most notable improvement compared with the previous version is that the algorithm is focused on documents themselves, reducing the number of data access by ignoring all the non-relevant sources. This becomes possible after adapting the overall data summarization process, which took all the documents from MEDIS.NET and external systems and combined them into a single list that becomes a single list source for the data aggregation algorithm Figure 3.

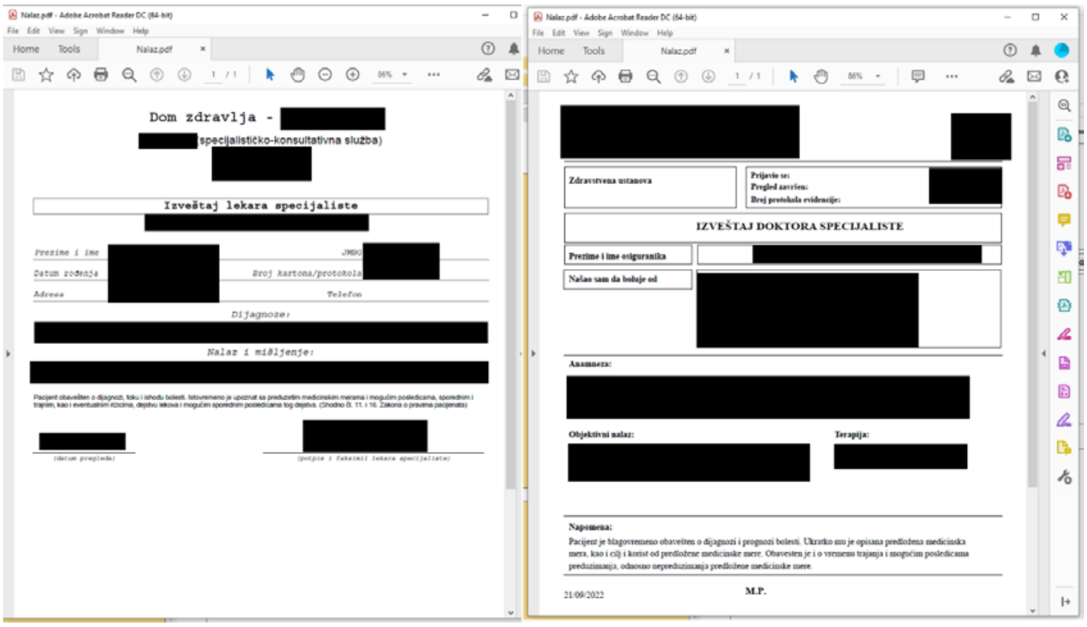


**Figure 4.** Examples of documents downloaded from external systems (patient-related data had to be blacked out since we could not get publication permission from the data owner until the finalization of this paper)

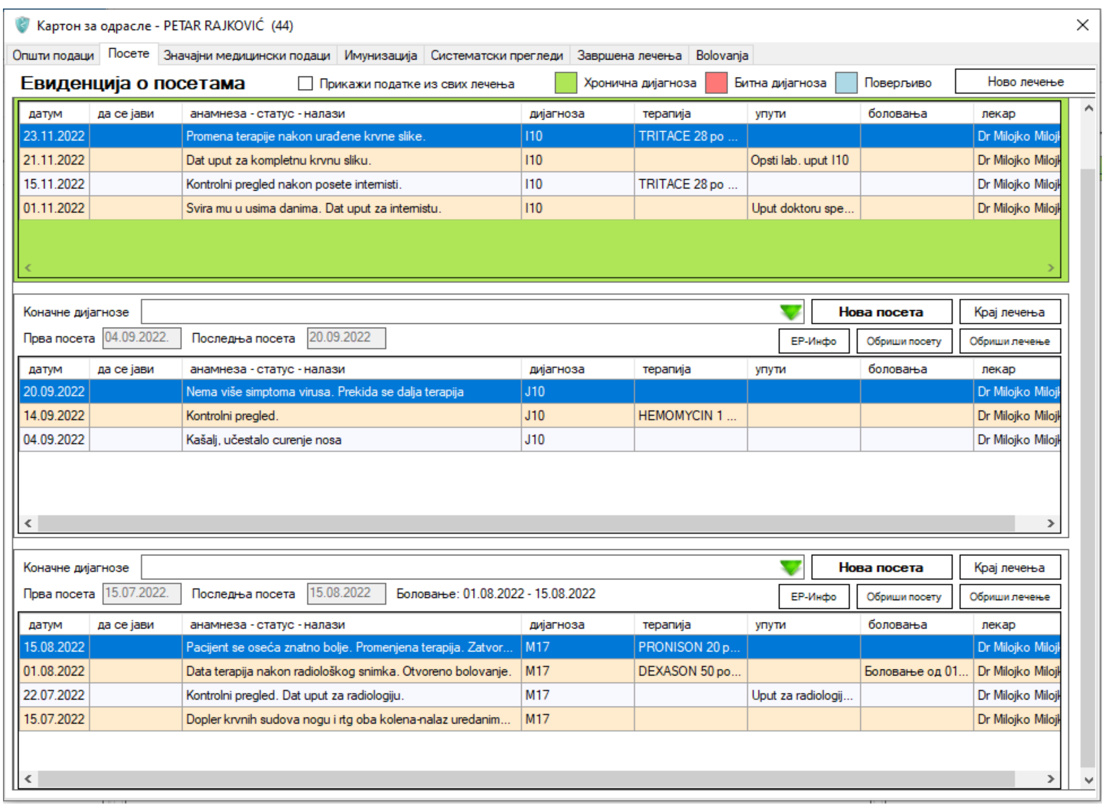


**Figure 5.** The example of the active medication process overview—the first medication (the one with green background) is related to the aggregated inputs for the chronic diagnoses

## Results

The numbers dropped significantly in March 2020, and the situation got even worse in April. Starting from May 2020, numbers continued to recover, but except for the data collected in September (which was the month with the best epidemiological situation in Serbia in 2020) they were still under the average. In 2021, the situation tended to get normalized from April to August, but COVID-19 peaks from January and September/October reduced the total number of registered patients (Figure 6).

Checking the data in the last two years, we established that the average gap was close to 30% overall, whereas the difference in 2020 was even higher. In that situation, it was certainthat the existing data collection methods needed to be updated. Our initial approach was based on counting the number of patient visits, medical prescriptions, and specialist examinations within periods of 14, 30, and 90 days and joining the records for the selected patient by diagnosing. In addition, we provided treatment of patients with primary chronic diagnoses and secondary chronic diagnoses in separate medical services.

Joined data helped us to identify the patients and general practitioners and then decide whether to call them for the reference examinations.

With the displayed data gap, we could assume that potentially one-third of the patients could have remained unidentified. The situation was slightly better since most patients always visited the same doctor. The bottom line is that the gap was still too high to be ignored, since numerous common chronic diseases represented physical states that could deteriorate overall health status if not treated properly.

We identified the data gap and made an initial assessment using the original data summarization method (15). After including the new parameters, we reassessed the results and identified the set of parameters that brought us close to the results we had with the full data set. Recovering the number of medical examinations in the last quarter of 2021 made it possible to validate the updated method in close-to-regular conditions.

The improved method helped medical professionals to overcome the gap that was created because of the pandemic. The effect of the improved method on the reduced data set was close to the original method with a slightly higher number of false positives. Applying the updated method to situations with regular datasets increased the precision of the results.

## Discussion

MIS Medis.NET started with pilot deployment in DZN in 2010. The MIS was initially installed in the GP department and later expanded to pediatrics, gynecology, laboratory, and specialist services. The system reached its full operational capability in 2012. During the system usage observations, we identified room for various improvements. One direction for such an update is the development of suggestion tools that could help medical professionals to bring important decisions.

One notable usage gap was the way in whi chchronic diseases were tracked. Besides, the GPs could mark the diagnosis as chronic; unfortunately, this feature was rarely used. The significance of such a problem becomes obvious when the patient changes the doctor. Patients are likely to miss important medical examinations or treatments during the transition as the newly chosen doctor do not have proper data upfront. Another notable case is when the patient frequently visits different doctors in different medical institutions, which could result in non-consolidated data.

The introduction of a data summarization tool was one step forward that could support users in daily activity. Using reports from our tool, we identified between 13,000 and 14,500 new potential chronic patients yearly, from 2013 to 2019. The deviation from the median number of the discovered patients was under 5%, which was the expected quality level for the results. The year 2012 was not a regular case, because that year was associated with all the patients registered since the start of the system usage. It is also important to mention that in the initial period MIS was not in use in all the departments, and only GPs actively collected data. The next important fact to point out is that in the initial period the GPs did not mark the diagnoses as chronic, despite conducting therapy and history of the disease as chronic. In later years, as the system usage became routine for all the departments in DZN, the number of potential new patients decreased to values with low variance.

For the next four years 2016–2019, the reports that came from the data summarization tool were in line with the initial findings. Unfortunately, the COVID-19 pandemic broke out in the Republic of Serbia in February/March 2020. At the end of the year, the total number of patients identified by our data summarization method dropped to slightly around one-half of the number in 2019. Periods January–March and during the summer were on the level of 2019, but during the pandemic peaks and the lockdown in April–June and in the autumn, the number was lower than one-third of the expected. The situation in 2021 was slightly better than in 2020, but the gaps created in the mentioned year still need to be overcome.

The year 2022 gave a better result and could bring the number of discovered patients closer to the pre-pandemic period, but the total number of registered patient visits was still lower than before 2020 (Figure 6 and Figure 7). There were multiple reasons for this (6). One of the problems was the constant reduction of the number of medical professionals in DZN. The next potential reason was the change in the patient's behavior. Due to several reasons, patients chose private practice—increased number of private specialist ordinations, fear of being in the waiting room as the result of the pandemic, longer waiting time in public healthcare institutions, and increased number of patients choosing private practice as default. This analysis could lead to an interesting conclusion. However, it is outside the scope of this paper and should be considered for future research.

The proposed improvements are important in the sense that they will give an additional set of potential patients with chronic diseases compared with the original data summarization algorithm (15).

The extension of the monitoring period together with the additional demographic parameters will increase the number of identified medical documents connected with chronic diagnoses, bringing a higher number of identified patients (Figure 8). For further development of this feature, it would be necessary for it to be moved to a live environment where the doctors could use it in a real environment with the ability to provide feedback and dynamically influence the discovery rules.


**Figure 6.** Total number of patients with one of the five chronic diseases per year and per month in the period January 2018–November 2022

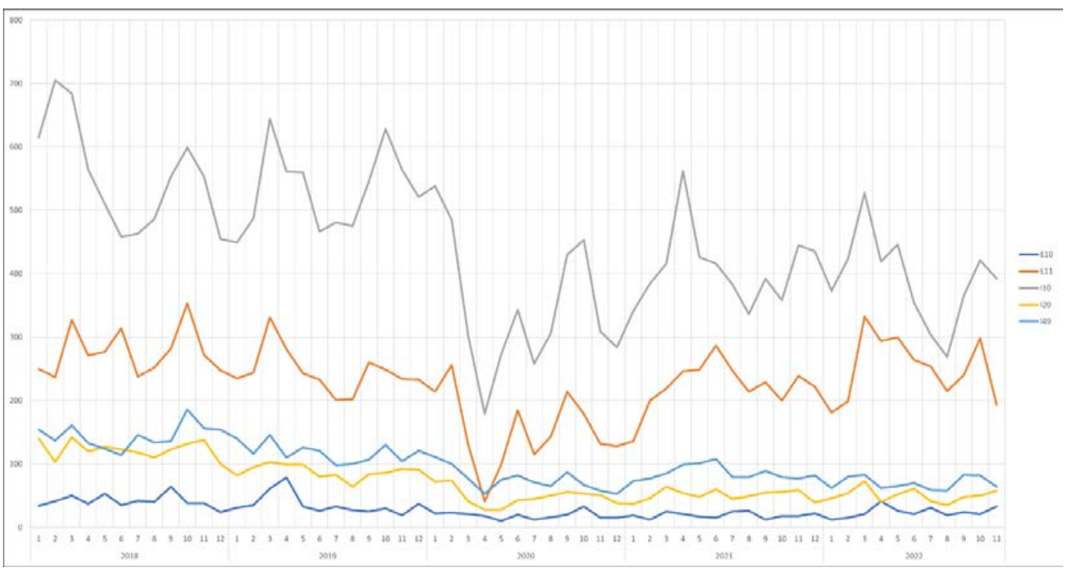


**Figure 7.** Number of patients with registered chronic disease (distribution per diagnosis)

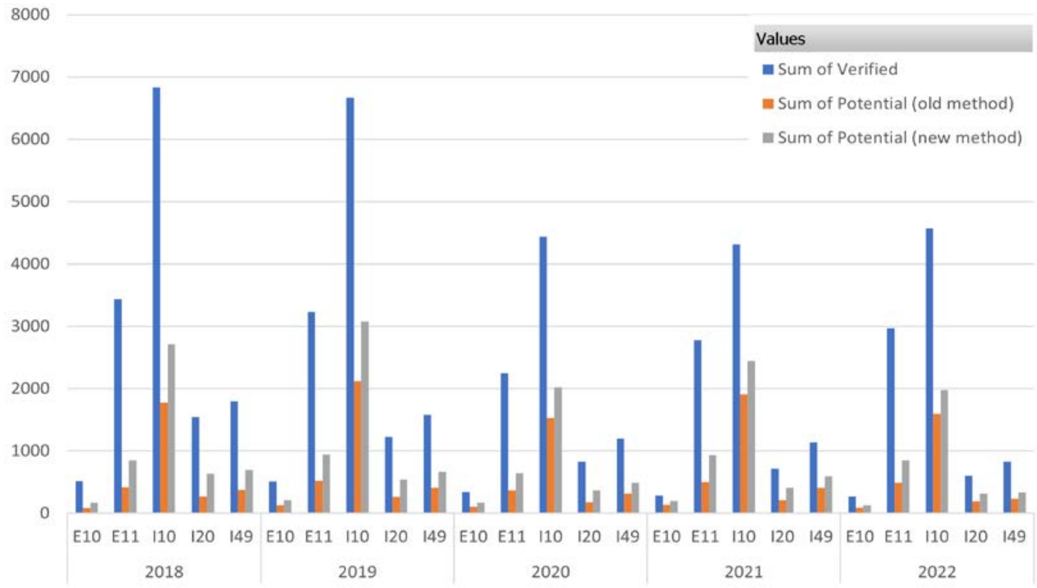


**Figure 8.** Comparison between the number of verified patients with chronic diseases with the number of potential patients using old and new summarization methods

The improvement in user interface should make the medical professionals work more effective. They will get the warning promptly if the patient can be marked as having chronic medical conditions. The scattered data, collected from various sources, and during a predefined period will be presented as the regular medication process, but notably marked as the data aggregation, not as the actual medication process.

All these improvements should bring new data for the integration with external medical institutions as necessary nowadays. Bidirectional communication between medical institutions is becoming a reality with the successful integration of different web services provided by the Serbian Ministry of Health. This integration will allow for the collection of scheduled patient data and display of records for specific chronic diseases from multiple sources, giving users of MIS a much better overview. The aggregated medication view will be more complete and the possibility that doctors make decisions based on the reduced data set will be lower.

With the mentioned improvements, doctors will have a powerful additional tool that could help them make better decisions for patients suffering from chronic medical conditions. This would eventually lead to more effective medical practices and improved quality of life for the patients. With further development, the doctors will be able to fine-tune their reporting services and working environment as best as possible.

## Conclusion

After the change in the quantity of collected data in DZN, the existing data collection algorithm seems not to fully fit in the situation when the gap in data retrieval becomes significant. To overcome the gap, we identified a few scenarios that should be included in the filtering stage of the algorithm (Figure 2) and the preparation stage of the complete process (Figure 3). Extending the collection range will bring more people into a set of potential chronic patients. Our preliminary examination shows that if the target period gets extended to 180 days (in contrast to 90 days as we had before) it is possible to identify up to 15% more patients, with a certain number of false positives.

Many patients have started using private medical practices, and the data collected in these institutions could potentially be synchronized with data from the medical center. The problem is more administrative than technical, as the infrastructure is already implemented. Administrative decisions related to medical data sharing need to be made. Additional filtering parameters will increase the complexity of running queries, but the benefit is expected to be in the range of 10 to 15%. However, much general demographic data is missing, which makes it difficult to establish the connection between all requested data sets.

The drawback of this approach is the increased number of false positives, but it is better to call more people for preventive examinations and prove they are not suffering from chronic medical conditions, than not to identify them and start the medication process when the diseases progress. For future work, we plan to incorporate our additional criteria fully and run more simulations before implementing the update to the real system.

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# EFEKAT COVID-19 KRIZE NA PRAĆENJE HRONIČNIH BOLESTI – PREDVIĐANJE PODATAKA KOJI NEDOSTAJU

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Pandemija COVID-19 imala je izrazito negativan uticaj ne samo na praćenje hroničnih bolesti nego i na prikupljanje podataka kroz medicinske informacione sisteme u ustanovama primarnog zdravstva. Opravdano, fokus je inicijalno prebačen na antipandemijske mere, dok je broj poseta vezanih za službu opšte prakse, posebno radi praćenja hroničnih bolesti, opao.

Sa manjim brojem raspoloživih podataka, algoritmi koji se bave identifikovanjem potencijalnih novih hroničnih bolesnika na osnovu prikupljenih zahteva postali su manje relevantni, a broj bolesnika koje više nije bilo moguće identifikovati je porastao.

U ovom radu prikazali smo unapređenje pomenutih algoritama za sumiranje podataka i identifikovanje hroničnih bolesnika kroz dodavanje novih kriterijuma za pretraživanje, koristeći mogućnosti integracije sa drugim medicinskim informacionim sistemima.

Unapređeni algoritam je evaluiran na podacima prikupljenim u Domu zdravlja u Nišu i upoređen sa rezultatima koje je dala inicijalna verzija algoritma.

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***Ključne reči***: *medicinski informacioni sistemi, sažetak istorije bolesti, hronične dijagnoze, identifikacija podataka koji nedostaju*