# IoT Health Data in Electronic Health Records (EHR): Security and Privacy Issues in Era of 6G

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## **Abstract**

Millions of wearable devices with embedded sensors (e.g., fitness trackers) are present in daily lives of its users, with the number growing continuously, especially with the approaching 6G communication technology. These devices are helping their users in monitoring daily activities and promoting positive health habits. Potential integration of such collected data into central medical system would lead to more personalized healthcare and an improved patient-physician experience. However, this process is met with several challenges, as medical data is of a highly sensitive nature. This paper focuses on the security and privacy issues for such a process. After providing a comprehensive list of security and privacy threats relevant to data collection and its handling within a Central Health Information system, the paper addresses the challenges of designing a secure system and offeres recommendations,

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solutions and guidelines for identified pre-6G and 6G security and privacy issues.

**Keywords:** Wearable sensors, eHealth, healthcare, 6G, internet of things, internet of medical things, electronic health record, EHR.

#### 1 Introduction

Fitness tracker is an electronic wearable device (usually a wristband) with embedded sensors that monitors various health-related metrics, such as heart rate, oxygen saturation, steps taken, or distance walked. The popularity of fitness trackers is continuously on the rise, especially in the era of Coronavirus disease 2019 (COVID-19) [1]. Fortune Business Insights reported the global market size for fitness trackers amounted to USD 30 billion in 2019 and is estimated to reach USD 92 billion by 2027 [2]. Utilizing health-related data collected via fitness trackers would prompt massive improvements to fields of medicine [3–5], telemedicine [6, 7], and personal well-being [7–9], as it would lead to an improved, personalized healthcare approach since it would enable the physicians continuous comprehensive insight into the patient's state of health. Thus, integrating the personal health data, collected by various sensors within a fitness tracker into the formal Electronic Health Record (EHR) shall provide tailored medical services in compliance with standards and regulations, and offer the patients a more personalized and consistent care while helping physicians to make better and more informed decisions. Smart healthcare:

- Creates well-connected healthcare system
- Allows use of smart biomedical devices
- Offers more personalized healthcare
- Provides better access to healthcare
- Allows improved patient monitoring
- Enables easier tracking of chronic illnesses, as well as early detection and prevention of some diseases
- Improves efficiency and is cost-effective because of preventive care it provides.

However, in order to achieve this, several requirements must be met. Challenges are:

- System needs to handle large volumes of sensor-collected data
- Data quality of the data generated by the sensors

**Table 1** 6G and 5G performance comparison

| T                           |              |                     |
|-----------------------------|--------------|---------------------|
|                             | 5G           | 6G                  |
| Peak data rate              | 10 Gb/s      | 1 Tb/s              |
| End-to-end (E2E) latency    | 10 ms        | 1 ms                |
| Maximum spectral efficiency | 30 (b/s)/Hz  | 100 (b/s)/Hz        |
| Maximum frequency           | 90 GHz       | 10 THz              |
| Mobility support            | 500 km/h     | 1000 km/h           |
| Architecture                | Massive MIMO | Intelligent surface |
| Satellite integration       | No           | Yes                 |
| AI                          | Limited      | Yes                 |
| Autonomous vehicles         | Limited      | Yes                 |
| Haptic communication        | Limited      | Yes                 |
| THz communication           | Limited      | Yes                 |

- Data interpretation
- Scalability
- Software complexity
- Compliance to standards and regulations
- Security and privacy

Main challenges identified are guaranteeing data quality, ensuring security, and maintaining privacy and compliance to the applicable standards and regulations. The way data is being used is changing, with once ordinary devices becoming more and more useful (e.g., smart watch or smart glasses). This will result in massive growth in the rate of information exchanged, and, in the future, might pose a problem to capacity of 5G system. Six-generation (6G) communications is expected to begin in the 2030s [10]. The 6G system has higher capacity and data rates, with lower latency, as shown in Table 1. It also offers superior security and improved quality of service (QoS) compared to the 5G system. Future 6G system is said to revolutionize Internet of Things (IoT) applications in multiple domains, such as:

- Internet of Medical Things (IoMT),
- Vehicular Internet of Things and Autonomous Driving,
- Unmanned Aerial Vehicles (UAV),
- Satellite Internet of Things,
- Industrial Internet of Things.

Thus, (IoT), including IoMT, is identified as one of the key candidate technologies and application scenarios [11]. Finally, [12] presents a comprehensive survey on enabling massive IoT via 6G.

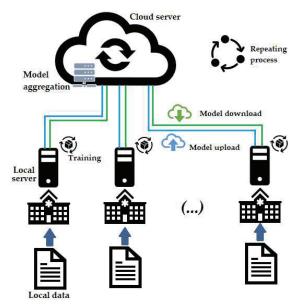


Figure 1 COVID-19 data analytics.

Figure 1 illustrates a potential process of using 6G technologies to analyze COVID-19. Each hospital server has generative adversarial network (GAN), which consists of a generator and discriminator which uses convolutional neural network (CNN, or ConvNet) to learn COVID-19 data distribution from its own dataset. Afterwards, multiple GANs synchronize, and exchange learned information. Model parameters are aggregated in cloud server and form a global model. Global model is propagated to the servers by the cloud server for another round. This process is repeated several times, each time increasing the accuracy [13].

In Section 2, relevant related research is given, including summarized past work by the authors pertinent to the topic. Section 3 provides comprehensive overview of potential security risks and privacy concerns relevant to data collection and communication of information to and within e-Health system, while Section 4 offers threat analysis. Finally, conclusion offers security recommendations and proposition of future work.

## 2 Related Research

Systematic review [14] and summary of 67 studies [15] concluded wearable devices meet acceptable accuracy and offer high reliability. However, several

studies [16–19] point out the need to clean data collected via wireless sensors, as imprecise data can easily lead to erroneous data analytics and ill-informed decisions. Thus, our previous work [20] compared various data-driven models for cleaning health-related sensor data with the goal of providing accurate and relevant data that could be used in formal EHR. The paper identified multiple linear regression and neural network as the best models for data imputation which were further optimized and resulted in 10-17% improvement in accuracy, depending on the person monitored.

Compliance to standards and regulations was addressed in depth in previous work [21]. Semantic constraints for healthcare datatypes were defined and a process of semantic verification and Schematron-based validation was proposed. The process was then verified using datasets containing various health-related datatypes. The medical information was communicated to healthcare service providers through Health Level 7 Fast Healthcare Interoperability Resources (HL7 FHIR), a standard for health care data exchange, published by HL7, for exchanging healthcare information electronically.

Data collected via wearable sensors are vulnerable to data security breaches [22] offers security analysis of a various fitness trackers available on the market, focusing on the possibility of malicious injection of false data by the user into the tracker's cloud-based services [23] importance of secure pairing mechanisms to avoid eavesdropping attacks as the data is wirelessly transmitted from tracker to smartphone using Bluetooth LE (low energy). SecuWear [24], a multi-domain wearable testbed platform, expedites security research of wearables by conducting attacks in order to identify vulnerabilities of hardware and software. Unencrypted communication between the application and cloud-based server is identified as the biggest risk to data privacy in [25]. [26] proposes a filter system that would balance the security and sharing of health data and [27] presents SensCrypt, a secure protocol for managing Bluetooth fitness trackers. [28] uses the AES algorithm for data encryption and decryption as it prevents the data to be manipulated with. Privacy is another issue as [29] reports many health applications compatible with popular fitness trackers communicate with "unexpected" third parties, such as social networks or advertisement services.

Even though this information must be disclosed in the app's privacy policy, most users never read it [30] and are thus unaware their data is being shared. Finally, patients' adoption of new healthcare technologies is crucial for achieving improved, personalized, and more cost-effective healthcare. However, evidence suggests some patients resist it as they perceive it as a threat to their privacy. [31] examines the impact of privacy concerns have

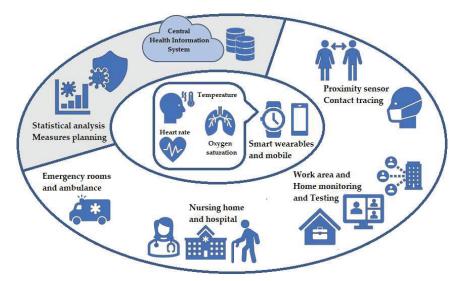


Figure 2 Use-case scenarios for sensing wearable devices and telemedicine.

on the decision whether to accept e-Health technologies. The results show the strongest predictor to the use of digital health technologies is the perception of benefits. Similarly, [32] shows high correlation between individuals' on-going health condition and their healthcare technology acceptance decisions.

Whatever the challenges, the potential and benefits of such a system are gaining more interest than ever, especially because of the current coronavirus (COVID-19). On Figure 2, possible use-case scenarios for wearable devices and telehealth systems during COVID-19 pandemic are illustrated. This includes measuring and tracking personal health data using smart wearables, proximity sensor and contact tracing, work area and home monitoring and testing, aiding staff in caring for patients in nursing homes, hospitals and emergency rooms as well as statistical analysis which allows for more informed measures planning. For example, [34] proposes a BloCoV6, a blockchain-assisted unmanned aerial vehicles (UAV) contact tracing scheme for identifying potential COVID-19 patients.

# 3 Security and Privacy Threats

Data security protects digital information from being accessed by unauthorized individuals, modified in a destructive manner (corruption), or

stolen. Three major threats to the security of medical data [29] are the following:

- integrity data must not be tampered with,
- availability data must be readily accessed when desired,
- confidentiality data must not be disclosed to unauthorized parties.

Data security must be robust and properly implemented. It needs to protect the information from external malicious parties but also internal threats and human error.

On the other hand, privacy ensures data is handled in a correct manner, including asking for users' consent, giving necessary notice, and following regulatory obligations. Specifically, concerns in context of data privacy are:

- sharing data with third parties,
- how data is collected and stored,
- regulatory restrictions (e.g., GDPR or HIPAA).

General Data Protection Regulation (GDPR) is a single law that unifies data protection within the European Union. In the United States, medical data protection is legislated by Health Insurance Portability and Accountability Act (HIPAA). Comparison of GDPR and HIPAA is given in the Table 2 below. As there are some clear differences, in order for full EHR interoperability, ultimate solution needs to consider all relevant laws and regulations.

In this paper, we focus on European Union and, thus, GDPR. General principles of GDPR are:

- consent patient must be unambiguously informed and agree to processing of data,
- purpose limitation must have clearly meaningful purpose,
- data minimization only required data,

Table 2 GDPR and HIPAA comparison

|                        | GDPR   | HIPAA   |
|------------------------|--|---|
| Data protected         | Any information related to   | Protected Health Information                  |
|                        | identifiable individual  | (PHI)   |
| Accountability         | Data controller  | Covered entity (health provider)              |
| Breach<br>notification | Must report breach within 72 hours;<br>must inform users affected by the<br>breach | Covered entity required to notify the patient |
| Third parties          | Written safeguards   | User must be informed                         |
| Sanctions              | Depends on the country   | Criminal and money penalties                  |

- transparent to the user,
- accuracy of collected data,
- privacy by design (default) consideration of privacy in design and implementation process,
- data subject right patient has the right to access data and request data be deleted,
- retention period data should not be stored indefinitely,
- security measures ensuring data integrity, availability, and confidentiality.

"Health data" is defined in GDPR by Article 4 paragraph 15, as "personal data related to the physical or mental health of a person, including the provision of health care services, which reveal information about his or her health status". However, some types of data, such as fitness tracker data aren't strictly defined as belonging to this category. Therefore, health data is further specified as:

- strictly medical data data in a formal medical setting, such as EHR data.
- raw data e.g., collected by fitness tracker's sensors only when it's used to assess person's health. While data as heartbeat rate, oxygen saturation or blood pressure are straightforwardly labeled as health data, step count may or may not be, depending if it is being used in medical context or not.

Thus, when using raw data from a tracker, it is crucial to rigidly define types of data being collected, as different types of data may have divergent legal implications.

Privacy Impact Assessment (PIA) is a crucial step when handling confidential data. PIA's goal is to identify and assess privacy implications when collecting, storing, managing, and sharing data, and, thus, to mitigate information risks [35]. The assessment must be made before starting the development of any system which is planned to collect or manage personal data of individuals. Privacy issues found during this process must be documented so the risks can be further analyzed. Then, compulsory actions are set depending on determined impact and probability of occurrence.

## 4 Threat Analysis

Figure 3 gives an overview of identified security and privacy threats in eHealth system which uses patient-side collected personal health data, i.e.,

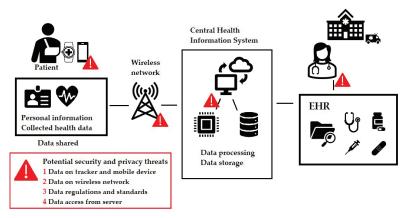


Figure 3 Overview of security and privacy issues in mHealth system.

data collected by a fitness tracker. As illustrated in Figure 3, security and privacy threats when handling personal health data may occur at the following stages:

- while collecting data (sensors) and communicating to mobile device,
- while transmitting data via wireless networks,
- while processing and storing information on healthcare servers, i.e., complying to standards and regulations,
- while accessing stored information (e.g., physician viewing patient's EHR).

### 4.1 Data on Tracker and Mobile Devices

Identified vulnerabilities of fitness trackers in the past years include:

- use of third-party analytics,
- lack of privacy policy,
- internal (device-side) or external (cloud-side) poor encryption,
- poor protection at transport layer, i.e., using HTTP instead of HTTPS protocol,
- poor security at application implementation, enabling client-side injection, e.g., SQL injection,
- lack of authentication and authorization (password-protected access),
- improper session handling.

These can be avoided but manufacturers need to ensure privacy and security when developing fitness tracker. Likewise, any mHealth mobile

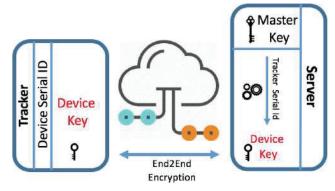


Figure 4 End-to-end encryption.

application must be insusceptible to tampering and capable of protecting itself by detecting threats at runtime.

### 4.2 Data on Wireless Network

During its transmission from mobile device to cloud server, data is susceptible to being manipulated, e.g., Man-in-the-middle attack, (MITM). In order to prevent this from happening, end-to-end encryption (E2EE), illustrated in Figure 4, with a device-specific key is necessary.

## 4.3 Data Regulations and Standards

Data must be stored in such a form that it is compliant with applicable standards and regulations, which includes following semantic constraints for healthcare datatypes. This can be achieved with aforementioned process of data verification and validation using Schematron-based validation process [21]. Furthermore, legislative regulations must be obeyed. In case of GDPR this entails privacy policy where patient is explicitly informed what data will be collected, how it will be used, and whether it will be shared to third parties. Patient must give their consent in order data to be used. Patient may revoke their consent at any point in time.

## 4.4 Data Access From Server

The Electronic Health Record proves to be an important tool in providing medical care as it is implemented in many Central Health Information systems around the world. In order to prevent unauthorized personnel accessing it, security policy must be implemented within the hospital (or other access point). The policy must have role-based access control to ensure patient privacy and guarantee confidentiality of data within the EHR.

Finally, Table 3 shows possible both security and privacy risks and solutions for how to mitigate them. This should be viewed as general solution ideas and guidelines for future model designs and implementations of systems that handle IoMT health data (e.g., data collected via wearable sensors) within Central Health Information System, i.e., EHR.

Number of such devices is increasing exponentially, and with introduction of new technologies, such as 5G and, in the future, the approaching 6G which envisions Internet of Everything (IoE), new opportunities arise. However, along with higher capacity and data rates, lower latency, and better quality of service, new challenges arise as well. Following section covers security and privacy issues in such future systems.

# 5 6G: Security and Privacy

In terms of 6G, analysis of security and privacy threats is shown in Figure 5. Billions of interconnected devices will form the Internet of Everything in era of 6G. Device security model of subscriber identification module (SIM) is not viable for such devices, considering their small form factor. This is especially true when talking about Internet of Medical Things (IoMT) and on-body and in-body sensors. [36] reports key distribution and management to be inefficient in a network of such scale. Furthermore, these devices are operating with limited resources and cannot support cryptography necessary to ensure high security level [37]. This leads to them being the primary target to malicious parties. Once compromised, the device can them be used to propagate attacks in the network. Finally, exploiting the same vulerabilities could lead to data theft which in turns compromises privacy.

6G systems will inherit some 5G technologies, and with it, related security, and privacy issues. Best examples of this are:

- attacks targeting Software-Defined Networking controller, interfaces, and deployment platform vulenrabilities [38],
- attacks on virtual machines, hypervisor, and Network Function Virtualization (NFV) related attacks [39],
- Multi-access Edge Computing (MEC) security and privacy threats, such as information theft using compromised slices [40] or man-in-themiddle (MitM) and Distributed denial os service (DDoS) attacks [41].

 Table 3
 List of possible risks and solutions

| Table 3                             | List of possible risks and solutions                        |           |
|-------------------------------------|---|-----------|
| Risk                                | Solution  | Result    |
| The purpose of collecting the       | The purpose of collecting data                              | Mitigated |
| patient's data has not been         | must be stated explicitly in the                            |           |
| precisely explained to the patient  | privacy policy or consent form,                             |           |
| before data has been collected      | e.g., COVID-19 symptoms or                                  |           |
|                                     | chronic illness tracking                                    |           |
| The nature of data collected, i.e., | The nature of the medical data                              | Mitigated |
| exact data types, is not made       | being collected must be                                     |           |
| clear to the patient                | explicitly stated in the privacy policy/consent form, e.g., |           |
|                                     | heartbeat rate, oxygen saturation,                          |           |
|                                     | body temperature, etc.                                      |           |
| Privacy policy or consent form      | Before medical data collection of                           | Mitigated |
| does not explicitly specify to      | any kind, patient must be                                   | managatea |
| what extent and in which way        | explicitly informed via privacy                             |           |
| the data will be used               | policy/consent form, which he                               |           |
|                                     | must consent to   |           |
| Privacy policy or consent form      | If the data is to be shared with                            | Mitigated |
| does not address whether the        | third parties (e.g., anonymized                             |           |
| data will be shared with third      | data for statistical purposes), this                        |           |
| parties and for what purpose        | must be explicitly stated in the                            |           |
|                                     | privacy policy/consent form                                 |           |
| No option for withdrawing           | Patients can, at any given                                  | Mitigated |
| consent and deleting all the data   | moment, withdraw their consent.                             |           |
| collected is given to the patient   | If this is to happen, all their data must be deleted        |           |
| Patients are not able to request    | Patients must be able to inform                             | Mitigated |
| revision or modification of         | of errors in data, or ask for a                             | Miligated |
| potentially incorrect data          | revision, via secure channel                                |           |
| Data is not anonymized              | Data must be anonymized, i.e.,                              | Mitigated |
| Data is not anonymized              | data must be processed in such a                            | Miligatea |
|                                     | way it is impossible to identify a                          |           |
|                                     | specific patient  |           |
| Data is being stored for a longer   | Data is retained only temporarily                           | Mitigated |
| period of time than necessary for   | until it is has not finished being                          |           |
| it to be processed                  | uploaded to the cloud                                       |           |
| Data is being stored in an          | Medical data must be stored                                 | Mitigated |
| insecure manner (e.g.,              | encrypted and cannot be                                     |           |
| unencrypted or publicly             | accessible via external storage                             |           |
| accessible)                         | devices or other applications                               |           |
|                                     | present on the same hardware or                             |           |
|                                     | device  |           |

(Continued)

| Table 3 | Continue |  |
|---------|----------|--|
|         |          |  |

| Table 3   Continued  |   |                     |
|--|---|---------------------|
| Risk   | Solution  | Result              |
| Password and/or encryption keys are kept in plain text   | Secure hash algorithm (SHA) is used to store encryption keys  | Mitigated           |
| Points of data-input are not<br>secure; validation of input data is<br>needed in order to prevent<br>client-side attacks or tampering<br>with data (e.g., SQL injection) | Client-side attacks are prevented<br>by input sanitization  | Mitigated           |
| Insecure data communications channel for transmission of data  | Secure data transmission via<br>Secure Sockets Layer (SSL)<br>protocol                                      | Mitigated           |
| Poor logging practices, i.e.,<br>writing collected sensitive data<br>into logs   | No data classified as health data, i.e., confidential, is being written into log files                      | Mitigated           |
| Lack of encryption process when backing up data  | Data backup is stored after encryption process  | Mitigated           |
| Possibility of data being accessed by unauthorized parties (data breach)   | Processes of authentication and<br>authorization follow AuthO2<br>standard. Access control is<br>role-based | Mitigated           |
| Possibility of data modification<br>by unauthorized parties (data<br>tampering)  | All data is encrypted, and keys are hidden securely   | Mitigated           |
| Possibility of exploits by<br>malicious software, i.e., taking<br>advantage of bugs or<br>vulnerabilities to cause harm  | Software, if possible, should be sandboxed (in an isolated virtual)   | Partially mitigated |

As Terahertz (THz) communications are seen as major part of future 6G technology [42], small cells (5G) will be replaced with tiny cells, leading to ultra-dense networks and mesh connectivity. However, this leads to threat increase as malicious attackers can now potentially target large amount of vulnerable multi-connected devices and compromise the network.

6G will make use of artificial intelligence and blockchain which provide network autonomy and decentralized resource management, respectively. However, this will cause potential security threats to arise. Machine learning systems can potentially be compromised using logic corruption, input inference (model inversion), data manipulation, or poisoning attacks [43]. Similarly, blockchain can potentially be destabilized by attacks using quantum computers.

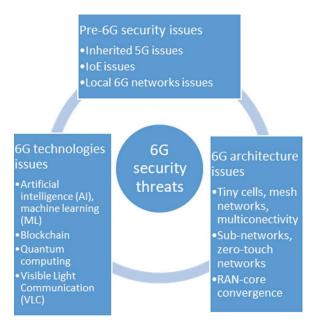


Figure 5 Security and privacy threats in the context of 6G.

In terms of EHR and sensitive IoMT data, possible security issues include:

- Attacks on weak cryptographic systems by the use of quantum computers,
- Compromised or rogue IoT devices,
- Data theft from IoT devices,
- Eavesdropping of communication channels,
- Signal jamming.

## 6 Discussion: Solutions, and Future Work

General security concerns regarding 6G era are an active research area. In an attempt to mitigate these risks, artificial intelligence is suggested as the main tool [33] to create resilient and robust systems. Table 4 shows how security risks can be mitigated by using AI and machine learning. New design challenge arises, which is to balance the defense improvements with performance degradation due to the increase of resources necessary for the implementation of additional defense mechanisms.

**Table 4** Security risk mitigation using machine learning

| Security Threat                      | ML Defense Mechanism                                    |
|--------------------------------------|---|
| Poisoning attacks                    | Input validation  |
|                                      | Robust learning   |
| Evasion attacks                      | Adversarial training                                    |
|                                      | Defensive distillation                                  |
| API-based attacks                    | Differential privacy                                    |
|                                      | Homomorphic   |
|                                      | Encryption  |
| Present cryptography solutions       | ML-based algorithms that detect malicious traffic, e.g. |
| vulnerable against quantum computers | ML Multilayered intrusion detection and prevention [44] |
| Use of AI for attacking, making      | Advanced defense techniques are necessary, e.g., using  |
| rule-based detection systems         | distributed intelligence, moving target [45] or use of  |
| ineffective                          | quantum computers [46]                                  |

Furthermore, present authentication and authorization systems using key management will become inadquate when dealing with large scale mesh networks consisting of huge number of heterogeneous devices. Thus, new security mechanisms should be developed in the future. [33] suggests a hierarchical security mechanism that would distinguish sub-network level sub-network to wide area network security. Other open questions are preserving privacy in automated 6G networks and implementing automated machine ethics.

### 7 Conclusions

Advanced monitoring which IoT device offer, i.e., continuously track patient's vital signs or activities of daily living can positively influence the quality of healthcare they receive. Continuous real-time monitoring of persons health and well-being includes tracking vital signs. For this, sensorequipped wearable electronic devices are required. Considering the quantity of data and the necessary quality of service (QoS), 6G technology could prove itself to be the key solution for such a healthcare system as it promises greater connectivity, low latency, and high speeds. Security and privacy, however, are major impediments when designing and implementing smart healthcare system. Any applications providing or facilitating medical services must comply with local regulations and legislation concerning data protection, in this case, GDPR. Healthcare data must not be susceptible to unauthorized access or tampering. Privacy can be ensured by guaranteeing confidentiality, integrity, and authentication. The work presents comprehensive security and privacy threat identification and analysis when integrating IoMT health data into EHR, both in pre-6G and future 6G era. Solutions associated with the identified threats are provided for pre-6G, while general solution ideas for 6G are discussed, with some open questions being highlighted.

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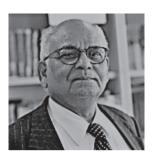
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Ana Koren completed undergraduate studies in 2012, and graduate studies in 2014 at the Faculty of Electrical Engineering and Computing, University of Zagreb and is currently enrolled in a PhD programme at University of Zagreb. She has been a visiting researcher at TU Graz (Austria), Universidad de Zaragoza (Spain) and Universidad Nacional de Colombia (in Bogotá, Colombia). Main areas of interest include e-Health and wireless personal communications. She worked on implementing Croatia's Central Health Information System.



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