Transforming Smart Vehicles and Smart Homes into Private Diagnostic Spaces

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ABSTRACT

The aging societies require disruptive technologies and digitization of health is one of these. Similar to the controller area network bus of (smart) cars we have developed a bus-based system for smart homes. We consider both, vehicles and homes as private spaces, which, in contrast to smart wearables or smart clothes, provide sufficient power supply, computer, and storage hardware. Today's homes and cars are already equipped with a variety of sensors that deliver data relevant with respect to health. The daily delay between opening of bedroom and bathroom doors, or the time between opening the car's door and starting its engine indicates mobility. We further empower eHealth if private spaces are equipped with medical sensors (Step I of the required transforms). However, unobtrusive continuous monitoring of vital signs and biosignals is no yet explored clinically, and data to train artificial intelligence is missing. We propose steering wheel integrated electrocardiography (ECG) recording in smart vehicles and capacitive ECG recording in the chair and bed of the smart home for stroke prevention due to early detection of latent atrial fibrillation. Furthermore, the processing unit needs data warehousing and analytics (Step II). The communication interface needs semantic operability and secure channels, which we propose to establish using the international standard accident number (ISAN) (Step III). Finally, the combination with a medical application such as stroke prevention (Step IV) turns smart environments into private diagnostic spaces.

CCS Concepts

•Information systems→Data management systems→Database design and models • Human-centered computing→Ubiquitous and mobile computing→Ubiquitous and mobile computing systems and tools • Applied computing→Life and medical sciences→Health informatics

Keywords

Smart home; Smart car; eHealth; mHealth; Health-enabling technology; Stroke prevention

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1. INTRODUCTION

There is a paradigm change for computing machinery in healthcare. In the 1968, Peter l. Reichertz founded at Hannover Medical School the first scientific institute for Medical Informatics in Germany. He worded the paradigm: "The right information at the right time at the right place" [1].

Fifty years later in 2018, we have updated this paradigm: "An accurate forecast for a specific individual longest before the predicted event" [2]. In other words, medical informatics is changing from computer-aided diagnosis towards continuous health monitoring and maintenance to predict adverse events and to take according actions in order to prevent the foreseen event.

While todays medicine is based on highly expensive and high-precision data generators such as computed tomography (CT), magnetic resonance imaging (MRI), or four-dimensional ultrasound systems (US), we now have inexpensive low-quality data generators such as motion and activity trackers, respiration and pulse frequency measuring devices, or skin temperature recorders. While CT, MRI, US etc. are taken only after symptoms occur and in public spaces like a hospital, the novel devices record data continuously in rather private spaces (Fig. 1).

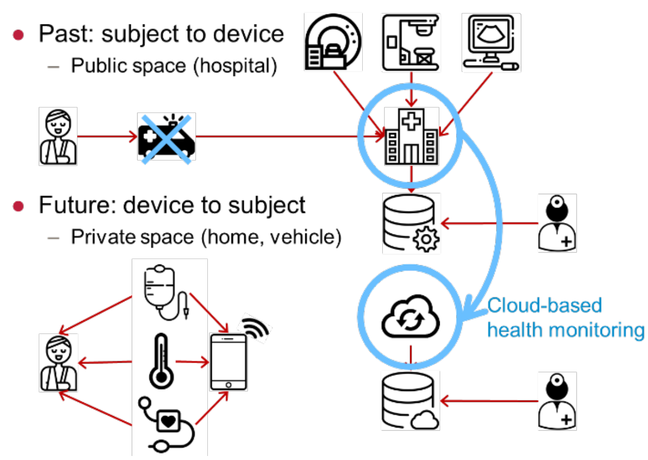

Figure 1. Public and private spaces for health data recording

Today, the patients still need to be transported to the hospital (Fig. 1, top line). In future, we will install the recording devices close to the subjects, which are not yet patients (Fig. , bottom line). Medical decision making still is based on data, but picture archiving and communication systems (PACS) data storage in the hospital will be replaced by cloud-based data repositories (Fig. 1, blue color).

Smart clothes, smart wearables, smart vehicles, or smart homes form such private spaces. The latter two have advantages with respect to individual power supply, computing and storage capacities, and battery-free communication interfaces. In other words, smart cars and smart homes have the potential to replace diagnostic devices in public hospitals with individual data recorders for continuous health monitoring [3].

In this paper, we briefly overview the state-of-the-art in smart environments (Section 2) and analyze the four steps which are required to transform from smart cars and smart homes into private diagnostic spaces (Section 3). In Section 4, we refer to stroke prevention as exemplarity application. The discussion of the paper follows in Section 5, and a conclusion with take-home messages is given in Section 6.

2. STATE-OF-THE-ART

Since the early 1990th, ubiquitous computing has been analyzed in many applications. According to the general definition, smart devices are integrated in smart environments that support smart interaction [4]. Hence, any smart environment necessarily requires all three components: (i) sensing devices for data recording, (ii) processing units for data analytics and (iii) communication interfaces for interoperation with other smart environments, computing machineries, or digital services.

Today, novel vehicles as well as smart homes are equipped with a lot of sensing devices as well as a central processing unit (computer). They both have an independent power supply and can easily integrate data storage capacities. In smart cars, the controller area network (CAN) bus system connects all sensing and acting devices. In smart homes, Schwartze et al. have developed a similar bus-based approach for building automation by a scalable intelligent system (BASIS) [5,6]. The bus knots link sensors and actors, which are grouped by segment controllers. The segment controllers are connected to the building manager, which also interconnects to the Internet (Fig. 2).

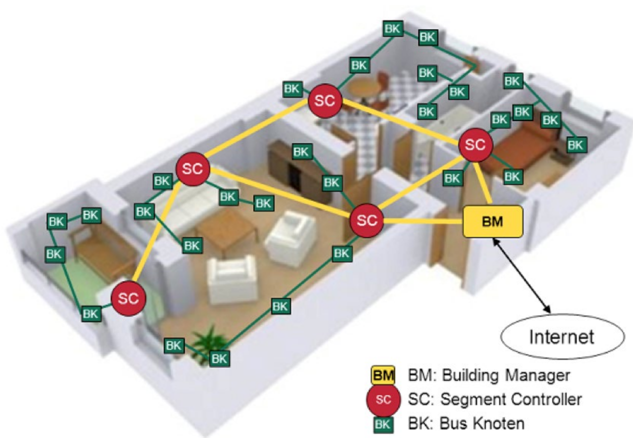

Figure 2. The BASIS system for home automation [4]

As a result, smart cars and smart apartments are of similar technological nature and can likewise form private diagnostic spaces. However, medical meaningful use of the sensors is not yet explored, as they are used exclusively for driving assistance and climate / energy control.

In the following, we will therefore not differ both smart environments anymore. Instead, we will consider the sensing devices that are integrated in these spaces, computers, interfaces, and applications. These sensors and their use do the stepwise transformation of smart homes and smart cars into private diagnostic spaces.

3. DESIGNING DIAGNOSTIC SPACES

We have identified in total 4 steps that are required to transform smart vehicles and smart homes into private diagnostic spaces.

3.1 Transforming the Sensing Devices

In this subsection, we exclusively focus on medical use of the smart environments. The aim is unobtrusive measurement of medical meaningful data.

3.1.1 Secondary Use of Environmental Sensors

To reach this goal, the first step is using the data that is already recorded. For instance, the seat belt control system in the car detects occupied seats by an integrated scale. Such data can be used to monitor the body weight of a driver or passenger, who is, for instance, daily commuting by car and suffering from heart insufficiency. Another example are steering wheel and pedals, which record smallest motions that may indicate for special risk group morbus parkinson in early stages.

Similarly in smart homes, existing sensors can be used medical meaningfully. Today, we consider a home as smart if we are able to control heating / air condition, light systems and windows wireless via apps to save energy and to deliver personalized room climate (although a smart home should do that all automatically). To achieve this aim, the smart home tracks all doors and windows for opening and closing. Additionally, it may monitor hot- and cold-water consumption as well as all the power outlets.

Fig. 3 shows smart-home tracked events, which are recorded continuously. A circle spans 24 hours and each circle represents a full day, stacked from inner to outer rings. The colors indicate different sensors, but it is irrelevant which color indicates which sensor. On the left hand side of Fig. 3, we can see morning and evening periods (maybe, the red color indicates the use of hot water in the bathroom), nights with only a few events, and also a resting periods at noon. The most important feature, however, is that all days are likewise, as elderly tend to have a very structured and regulated day flow.

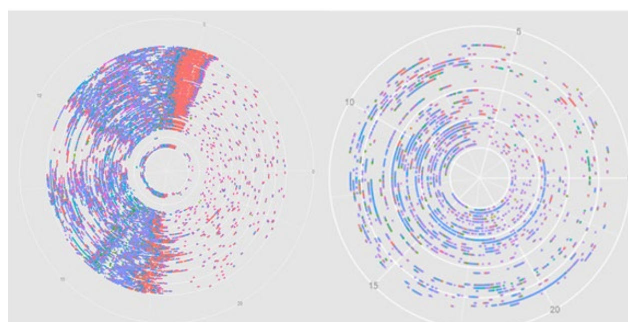

Figure 3. Regular and irregular use of a smart home

The diagram on the right hand side of Fig. 3, contrarily, does not show any such regularity. A pattern change from one to the other obviously indicates medical problems at early stages such that according action can be taken long before a serious adverse event actually occur [2].

Furthermore, both, smart homes as well as smart cars can monitor mobility. Simply taking the time it takes the elderly from opening the sleeping room door in the morning until she crosses the hallway and opens the bathroom door indicates any trend in gaining or loosing mobility. Same, for instance, from opening the driver's door of the car until starting the engine. Of course, there will by strong outliers (e.g., if the phone rings during the procedure), but trends will be detected robustly and at early stages, i.e. "longest before the predicted event" [2].

3.1.2 *Integrating Additional Medical Sensors*

The advantage of the CAN and BASIS bus systems is that additional sensors and actors can be integrated easily. So, we can equip the smart environments additionally with medical sensors, exclusively designed to monitor vital signs and biosignals.

Usually, there are four primary vital signs, which are standard in most medical settings: (i) body temperature, (ii) heart rate or pulse, (iii) respiratory rate, and (iv) blood pressure. Oxygen saturation (as measured by pulse oximetry) and end-tidal CO_2 are often referred to as fifths [7] and sixed [8] vital sign, respectively.

Leonhardt et al. recently reviewed unobtrusive vital sign monitoring in automotive environments [9]. Based on cardiorespiratory and thermoregulatory couplings, we obtain bioelectrical, mechanical, and thermal effects (Fig. 4). Sensors, such as electrocardiography (ECG), capacitive ECG (cECG), radar, ballistocardiography (BCG) and seismocardiography (SCG), video imaging, photoplethysmography (PPG) and PPG imaging (PPGI), magnetic induction (MI), and thermography capture body surface potentials, displacements and temperatures, the superficial perfusion, and the intrathoracic impedance.

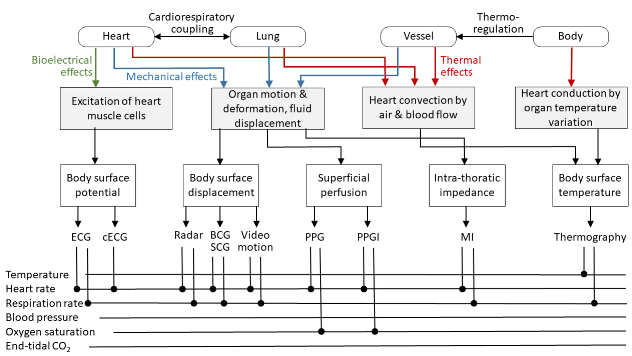

Figure 4. Unobtrusive vital sign monitoring [8]

In the following, we are focusing on video cameras, accelerometers, and electrical electrodes as sensing devices.

With increased computational power, camera-based vital sign monitoring is becoming more evident [10]. Not only for motion analysis but also for color measures, such as with PPGI, video forms an inexpensive sensing technology. Zaunseder et al. recently reviewed cardiovascular assessment by PPGI. Beside the mean heart rate, video-imaging data can be further processed and analyzed for heart rate variability (HRV), pulse oximetry, morphology effects related to vasculature, and pulse transit time (PTT) [11]. However, being continuously video-controlled, in particular at home, has not adopted sufficient compliance so far. Hence, we see the lack of user acceptance as main limiting factor of this bio-monitoring technology.

BCG and SCG technology is likewise inexpensive. However, robustness of acceleration-based body-motion assessment becomes crucial in cars when driving (on bumpy roads). Surprisingly, it seems possible to measure seatbelt-integrated BCG, if we place the data sensor near the buckle lock [12] and use a second sensor to capture noise only [13]. Fig. 5 illustrates in-car BCG sensor placement for noise cancelling.

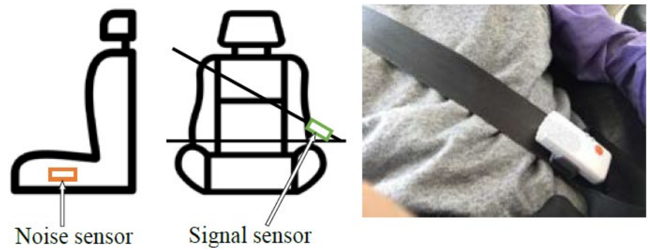

Figure 5. In-car BCG with noise-cancelling [13]

On a first glance, unobtrusive sensors and contacting electrodes yield a contradiction. However, in cars as well as homes, there are places where the hands rest regularly, e.g. the steering wheel or gearshift as well as the television-chair's armrest, respectively. Hence, electrodes for ECG or skin impedance can be integrated here and deliver signal only when hands are placed appropriately. The same holds for PPG sensing devices. In all these cases, the technical challenge is to differ robustly the noisy signal-recording periods from noisy non-recording periods.

The top-left panel in Fig. 6 shows an experimental setup for ECG in-car measurement. In addition, cECG can be integrated to cars and homes. Here, one electrode and the subject's skin from a capacitor that injects the ECG-driven electric potential to a signal amplifier. Textile electrodes allow convenient integration of the sensing device into the car seat (Fig. 6, top right, © Ford motor company), an armchair (Fig. 6, bottom left) or a bed as a mattress topper (Fig. 6, bottom right).

Figure 6. ECG and cECG recording in smart environments

Luo et al. recently determined blood pressure in a contactless manner using a camera-based technology called transdermal optical imaging (TDOI). This technology processes imperceptible facial blood flow changes from videos and uses advanced machine learning to determine blood pressure from the captured signal [14]. The authors enrolled 1328 normotensive adults and used 70%, 15%, and 15% of the data to train and test the model, and to validate the model performance, respectively. The predicted blood pressure had a bias of 0.39, -0.20, and 0.52 mm Hg for systolic, diastolic, and pulse pressure, respectively.

We picked the work of Lou et al. exemplarily to emphasize that novel machine learning algorithms – in particular when combining different sensors – will close the gaps for unobtrusive vital-sign monitoring towards all vitals. It is beyond the scope of this paper to list all recent work aiming at completely delivering the vital sings from a distant, i.e., unobtrusively (Tab. 1).

Table 1. Unobtrusive vital sign monitoring

No	Vital Sign	Sensing Device
1	Body temperature	Camera, Machine learning
2	Heart rate	Accelerometer, ECG, cECG, PPG
3	Respiratory rate	Accelerometer, ECG, Camera
4	Blood pressure	Camera, Machine learning
5	Oxygen saturation	PPG, Camera
6	End-tidal CO2	Camera, Machine learning

3.2 Transforming the Central Processing Unit

We consider the central processing unit as the core of a smart environment. Like the sensing devices, this core needs to transform into a diagnostic space with respect to its hardware and software for data warehousing and analytics.

3.2.1 Hardware

According to the BASIS concept, the smart homes has a central processing unit, which is integrated in the fuse box. This location is advantageous with respect to the bus connection, but also for security reasons [5].

Fig. 7 illustrates that server, storage devices, and connection interfaces are available to be mounted into the fuse box.

Figure 7. PC components integrated in the fuse box

Designing diagnostic spaces, we need sufficient computational power and storage for all data continuously monitored over at least one year, wireless local area network (WLAN), and Bluetooth (low energy) interfaces.

3.2.2 Data Warehousing

According to Dimitrov, for instance, we also suggest a data warehouse approach for the data delivered by all the sensing devices and mappings between structured concepts such as the Logical Observation Identifiers Names and Codes (LOINC) codes or the International Classification of Diseases-9 (ICD9) and ICD10 codes. However, we also need integration of the environmental sensors [15]. Schwartze et al. already introduced a Health Level Seven (HL7) Fast Healthcare Interoperability Resources (FHIR)-based object model for a home-centered data warehouse in ambient-assisted living environments [16].

3.2.3 Data Analytics

In near future, health-related alerts will be generated autonomously from the private diagnostic spaces. Therefore, the smart environments must extract the appropriate information form the data warehouse. Dimitrov and others consider artificial intelligence (AI) algorithms as key technology here [15]. In particular, the aggregated warehouse data forms the basis of effective data analytics. In addition, such AI technology is also fast (e.g., Google is retrieving suggestions from billions of record options instantaneously as-you-type in a search bar).

3.3 Transforming the Communication Interface

So far, we considered our smart environment as stand-alone system. For data security reasons, we built the data warehouse as a silo that does not allow access from outside the closed environment. To transform such a system into a diagnostic space, the communication interface must be opened securely not only to request information from other sources (such as a cloud-based electronic health record) but also to initiate interaction with other systems (such as that of the medical rescue services).

3.3.1 Semantic Interoperability

Communication of medical information has a syntactical as well as a semantical level. Using the HL7-FHIR-based object model by Schwartze et al., we obtain semantic interoperability. The smart environment can then collect data from many different sources, normalize it into a consistent structure in the data warehouse, and resolve it around unique patient identifiers (PID) with a particular medical history. Only then, the data becomes truly useful [16].

3.3.2 The ISAN Project

A technical approach to establish secure data exchange from smart homes and smart cars is the International Standard Accident Number (ISAN).[1] When we buy books, the International Standard Book Number (ISBN) is a valuable resource, since it provides a unique identifier disregarding different publishers or editions. Accordingly, the ISAN aims at establishing a unique identifier for adverse events such as accidents, medical events, and emergencies.

The ISAN is generated from global positioning system (GPS) coordinates of the event, date and time stamps as well as an identifier of the creating system. The alerting system, e.g., a smart home that detected the fall of an elderly resident, communicates the token to a trustee for encryption and passes it to the alert receiver. Furthermore, the trustee may generate a quick response (QR) code (Fig. 8).

Figure 8. Quick response (QR) ISAN code

[1] https://aei.plri.de/de/projects/the-isan-project

Thereafter, for instance, the emergency rescue team can contact the smart home via the trustee using the ISAN as credentials for access from outside, and request a floor plan indicating the room of happening as well as the best way to get there. It can inform the smart home on arrival electronically, such that the door opens automatically, or the smart home sends the key-code back to the rescue team and they manually open the door.

3.4 Adding Context for an Application

As a last step of the transform, we add context information in terms of particular applications. The diagnostic space need to know about the individual it is observing, her weaknesses and her medical record. For instance, an altered mobility pattern needs different understanding according to the age and health status, or depending on illnesses and the medical history.

4. EXAMPLE APPLICATION: STROKE

We now present a future scenario of transforming smart homes and smart vehicles into private diagnostic spaces. As we pointed out already in the previous subsection, an application domain needs to be identified such that the diagnostic spaces can be adjusted appropriately with respect to sensitivity and specificity of automatically generated alerts.

We now consider stroke as serious adverse event. According to the Centers for Disease Control and Prevention (CDC) in the United States (US) of America, stroke

- Is the fifth leading cause of death, killing about 140,000 Americans each year; one every four minutes;
- Reduces mobility in more than half of its survivors aged 65 and over;
- Costs the American nation $34 billion annually [17].

Fig. 9 indicates that in the southeast of North America, up to 200 strokes occur annually per 100,000 inhabitants aged 35 years and above – one out of 500 adulted individuals is affected.

In this example application, we do not aim at alerting a stroke that already happens but at forecasting strokes before they happen to allow their prevention. We also know that atrial fibrillation (AF) is a reliable indicator of forthcoming strokes [18]. Unfortunately, humans cannot feel irregularities on their heart beets and hence, most AF patients remain undetected until the stroke hits.

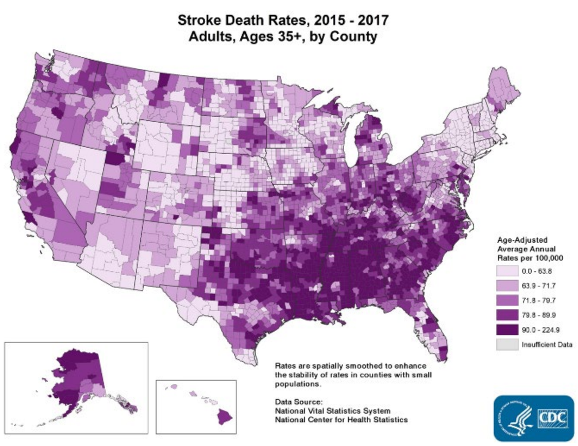

Figure 9. CDC stroke map.[2]

[2] https://www.cdc.gov/dhdsp/maps/national_maps/stroke_all.htm

However, not effective pulsation of blood may yield clots in the left ventricle. When a latent AF period ends, the heart pumps the clots into the large arteries, where they may block the blood supply of the brain: the stroke has happened. ECG, heart rate, and HRV are valuable signs to predict individually increased stroke risk.

In our vision, private diagnostic spaces such as smart vehicles and smart homes will robustly identify first signs of stroke – "longest before the adverse event" [2], and enable comprehensive diagnostics and preventive treatment of the subject keeping them in a healthy and regular way of life. While contact electrodes or ECG patches are not tolerated more than 2 or 14 days [18], the combination of smart homes and smart cars allows continuous everyday monitoring, although limited to certain periods within a day.

5. DISCUSSION

In this paper, we shared a vision of future health care [2], where paradigms are changing (i) from symptom-driven diagnostics towards continuous health monitoring and prevention; and (ii) from expensive recording devices in public spaces towards inexpensive recorders installed in private spaces, such as smart vehicles or smart homes.

In order to enable continuous health monitoring as well as to serve the growing healthcare needs, affordable, non-invasive and easy-to-use healthcare solutions are critical. As such, we are in line with Majumder & Deen [19]. However, as they see the ever-increasing penetration of smartphones, coupled with embedded sensors and modern communication technologies making it attractive for continuous and remote monitoring of an individual's health, we are promoting smart homes and smart cars over smart clothes and smart wearables, as such private environments offer unobtrusive health monitoring.

With recent information and communication technologies and biosensors, the access to continuing health monitoring is becoming real [20]. We agree with Gruson & Gouget that the development of efficient, accurate, and interactive solutions for continuing health monitoring will contribute to an improved care of chronic diseases like hypertension, diabetes or heart failure.

However, as we see AI-based analytics as the core component for data understanding, we need large sets of appropriately labeled data (so-called ground truth) for training and testing. With respect to heart failure and other chronic diseases, such data does not exist. Still, computational algorithms are validated using small sets of highly accurate measures rather than large sets of continuous data recorded with low-cost and low-quality devices [21].

Bai et al. [22] further pointed out that available reference data annotates records rather than events. For instance, ECG recordings of several minutes are labeled as AF vs. non-AF, but it is not indicated when exactly the AF period occurs within the measurement.

In future, unobtrusive monitoring may also include skin-mounted devices [23]. Skin is the largest organ of the human body, and it offers a diagnostic interface rich with vital biological signals from the inner organs, blood vessels, muscles, and dermis/epidermis. As such, soft, flexible, and stretchable electronic devices may provide a novel platform to interface with soft tissues for continuous health monitoring [23].

The Medical Informatics Initiative Germany (MII)[3] is fostering another change in computing-machinery paradigms: In future, we will distribute algorithms rather than building data warehouses (Fig. 10). This avoids handling of pseudonyms but allows complete de-identification at time of the data-evaluation request. The ISAN may play an important role for building data integration centers that connects the data silos from private diagnostic spaces.

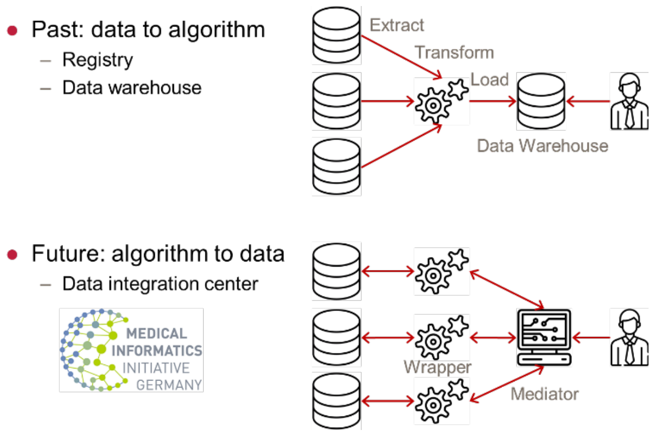

Figure 10. Distributed queries replace the data warehouse [2]

6. CONCLUSION

In conclusion, we word the following take-home messages:

- Private environments such as smart cars and smart homes transform into diagnostic spaces by (i) meaningful use of existing sensors; (ii) integrating additional sensors for unobtrusive vital-sign monitoring; (iii) transforming data storage into warehouses; (iv) adding semantic interoperability and analytics; and (v) opening communication channels.
- If a smart environment records private or medical data, the ISAN concept supports secure communication of that data with external IT systems, e.g., those the rescue chain is operating.
- Annotated reference data of vital signs continuously recorded with low-cost devices still is unavailable, and hence, AI lacks appropriate training.
- Designing private diagnostic spaces for stroke prevention, we may avoid 70,000 deaths in the US (50%) and hence, save $17 billion annually only in the US.

7. ACKNOWLEDGMENTS

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