

**Introduction to the Cognitive Hospital Conceptual Framework
and Validation in Two Use Cases**

Jordi Rovira Simón

ADVERTIMENT. L'accés als continguts d'aquesta tesi queda condicionat a l'acceptació de les condicions d'ús establertes per la següent llicència Creative Commons:  <https://creativecommons.org/licenses/?lang=ca>

ADVERTENCIA. El acceso a los contenidos de esta tesis queda condicionado a la aceptación de las condiciones de uso establecidas por la siguiente licencia Creative Commons:  <https://creativecommons.org/licenses/?lang=es>

WARNING. The access to the contents of this doctoral thesis it is limited to the acceptance of the use conditions set by the following Creative Commons license:  <https://creativecommons.org/licenses/?lang=en>



Introduction to the Cognitive Hospital

Conceptual Framework and Validation in Two Use Cases

Jordi Rovira Simón

Introduction to the Cognitive Hospital

Conceptual framework and validation in two
use cases

Jordi Rovira Simón

Tesi doctoral

Directora: Dra. Patricia Pozo Rosich

Tutor: Dr. José Álvarez Sabín

Programa de Doctorat en Medicina
Departament de Medicina
Universitat Autònoma de Barcelona
Barcelona, 2025

ACKNOWLEDGEMENTS

En primer lloc, vull expressar el meu més sincer agraïment al meu director de tesi, **Dr. José Álvarez Sabín** i la meva tutora **Dra. Patricia Pozo Rosich**, per la confiança i el suport que han dipositat en mi al llarg d'aquesta etapa. En especial, vull donar les gràcies a la **Dra. Patricia Pozo** no només per guiar-me amb rigor científic, sinó també per inspirar-me i motivar-me fins al final. El seu lideratge i la seva visió han estat una font constant d'estímul.

També vull agrair profundament a la meva **família**, i molt especialment a la meva dona, per acompanyar-me i donar-me suport durant tots aquests anys de doctorat, un període durant el qual han nascut els nostres tres fills. Compaginar la recerca amb la vida familiar ha estat un repte, però també una de les experiències més significatives de la meva vida. Agraïxo també als **meus pares**, Antonio i Pilar, per ser-hi sempre, en els bons i en els mals moments, i als meus fills **Nicolau, Domènec i Caterina**, que han estat una font inesgotable de motivació i alegria.

Finalment, vull donar les gràcies a tots els **companys de MYSPHERA** i al **personal del bloc quirúrgic de l'hospital**, que van desenvolupar i implementar una solució intel·ligent sense precedents. Em sento realment privilegiat d'haver compartit aquesta aventura amb persones tan compromeses i talentoses. La seva feina en equip i dedicació han estat essencials per fer realitat aquest projecte.

ABBREVIATION

AI – Artificial intelligence

AIOT – Artificial intelligence of Things

BLE – Bluetooth Low Energy

ECS – Energy Control System

EMR – Electronic Medical Record

EHDS – European Health Data Space

EU AI ACT – European Artificial Intelligence Act

FHIR – Fast Healthcare Interoperability Resources

GDPR – General Data Protection Regulation

HVAC – Heating, Ventilation and Air Conditioning

ICU – Intensive Care Unit

ICT – Information and Communication Technology

IoT – Internet of Things

KPI – Key Performance Indicator

LED – Light Emitting Diode

MQTT – Messge Queuing Telemetry Transport (protocol)

NHS – National Health Service (UK)

OPC UA – Open Platform Communications Unified Architecture

OR – Operating Room

OT – Operating Theatre

PLC – Programmable Logic Controller

RFID –Radio Frequency Identification

RTLS – Real Time Location System

UWB – Ultra Wide Band

WOT – Waste per Operating Theatre

WSB – Waste per Surgical Block Consumption

TABLE INDEX

Table 1 – Patient flow automation endpoint monitoring	57
Table 2 - Data sampling	58
Table 3 – Training groups	58
Table 4 – Operating theatre climate variables	61
Table 6 – HVAC automation endpoints	62
Table 7 - Results table of surgical key performance indicators.....	68
Table 8 - Results table of energy savings indicators.....	69
Table 9 - Study formulas.....	110

FIGURE INDEX

Figure 1 – Evolution of hospital concepts	18
Figure 2 – The rise of the cognitive hospital	25
Figure 3 – The surgical process.....	32
Figure 4 – High energy consumption in surgical blocks	34
Figure 5 – Federative learning across hospital domains	37
Figure 6 - Federation of specific health data spaces	40
Figure 7 – Research approach for this thesis	52
Figure 8 – Concept of surgical pathway automation through RTLS solution	54
Figure 10 – Used RTLS hardware.....	55
Figure 11 - Phases of the study	56
Figure 12 - Average pathway steps and times	57
Figure 13 -Automatic climate control of OTs	61
Figure 14 - Dashboard dedicated to improving OT climate control staff experience	62
Figure 15 - Publications by 5-year interval searching for "smart" and "intelligent hospital"	66
Figure 16 - Publications by 5-year intervals searching for "green hospital"	67
Figure 17 - Comparing the human nervous system with the cognitive hospital.....	76

TABLE OF CONTENT

SUMMARY.....	11
RESUM	12
1. INTRODUCTION.....	14
1.1. Approaching the Cognitive Hospital (CH) Concept	16
1.2. Evolution of Smart Hospital Concepts: Literature Review	18
1.2.1. Smart vs Intelligent Hospital	18
1.2.2. Green Hospital	21
1.2.3. Liquid Hospital	22
1.2.4. The Rise of the Cognitive Hospital	22
1.3. State of the art of the CH key technologies enablers	24
1.3.1. Technological Introduction	24
1.3.2. IoT as the Sensory and Motor System	26
1.3.3. AI as the Cognitive Core.....	27
1.3.4. AI & IoT Convergence: The Cognitive Loop.....	28
1.3.5. Impacted Areas in the Hospital.....	29
1.3.6. Technical Challenges of the Cognitive Hospital	30
1.3.7. Studying two use cases for Vall d’Hebron hospital.....	31
1.3.7.1. Patient flow automation in the surgical block.....	32
1.3.7.2. Dynamic control of HVAC’s	33
1.4. Cognition beyond the hospital.....	35
1.4.1. Extending Cognitive Intelligence to the Continuum of Care	36
1.4.2. Federated Intelligence and Data Spaces.....	36
1.4.3. Cognitive Assistants across Care Settings	38
1.4.4. Integration with Public Health and Research Infrastructures	39

2. HIPOTHESI	42
3. OBJECTIVES.....	46
4. METHODOLOGY	50
4.1. Literature Survey for first study	53
4.2. Retrospective Design for First Use Case	53
4.2.1. The New Intervention	53
4.2.2. The Solution Design Aspects.....	54
4.2.3. Intervention Roll-out Strategy	56
4.2.4. Patient Pathway	56
4.2.5. Endpoint Monitoring.....	57
4.2.6. Data Collection.....	58
4.2.7. Staff Training.....	58
4.2.8. Solution Deployment	59
4.2.9. Solution Running.....	60
4.3. Retrospective design for Second Use Case	60
4.3.1. The Setting	60
4.3.2. The Solution	60
4.3.3. Solution Deployment	62
4.3.4. Endpoint Monitoring.....	62
5. RESULTS.....	64
5.1. Cognitive Hospital Literature Review Study	66
5.2. Patient Flow Automation Study.....	68
5.2.1. Cost Assessment	68
5.3. HVAC Automation Study	69
5.3.1. Cost Assessment	70
6. DISCUSSION	72
6.1. The Need of an Overarching Concept.....	74
6.1.1. Defining the Cognitive Hospital Model.....	74

6.1.2.	The Hospital's Central and Peripheral Nervous System	76
6.1.3.	The Hospital's Somatic and Autonomous System	77
6.1.4.	The Hospital's Sensitive and Motor System	77
6.1.5.	Capacities of the Cognitive Hospital	78
6.1.6.	A Proposed Definition for the Cognitive Hospital.....	81
6.1.7.	Early Implementations of the Cognitive Hospital	81
6.1.7.1.	Alder Hey Cognitive Hospital, Liverpool.....	82
6.1.7.2.	Vall d'Hebron Hospital, Barcelona	82
6.1.7.3.	Sant Joan de Déu Hospital, Barcelona.....	83
6.1.7.4.	The Royal Marsden NHS Foundation Trust, London	83
6.1.7.5.	The Seattle Children's Hospital, Seattle	84
6.2.	Discussion of the Patient Flow Automation Study	85
6.3.	Discussion of the HVAC Automation Study.....	86
7.	CONCLUSIONS.....	88
8.	FUTURE LINES OF RESEARCH	92
9.	BIBLIOGRAPHY	96
10.	ANNEXES	105
10.1.	Study Formulas.....	107

SUMMARY

This thesis explores and develops the concept of the *Cognitive Hospital (CH)*, a new paradigm that reimagines the hospital as a dynamic, intelligent, and adaptive system. The work began with a conceptual investigation that led to the publication of *“Introduction to the Cognitive Hospital”* (Future Healthc J, 2022), which coined and defined this term for the first time in the scientific literature. This conceptual framework is inspired by the distributed functioning of the nervous system: sensors and IoT devices perceive and collect data, AI models interpret it, and actions are triggered to support decision-making and optimise both clinical and operational processes in real time.

Building upon this conceptual foundation, the research continued with the **validation of two real-world use cases** within the surgical block of the Vall d’Hebron University Hospital. The **first use case** evaluated how real-time coordination tools and RTLS-based patient flow management systems improved workflow execution and surgical performance. The **second use case** focused on energy efficiency, demonstrating how the integration of real-time patient flow data with an automated Health, Ventilation and Air Conditioning (**HVAC**) system improved environmental stability and energy savings without compromising patient safety or quality of care.

Together, these studies show that the Cognitive Hospital is not just a theoretical model but a practical and measurable approach to transforming hospital operations. By combining AI, IoT, and automation, hospitals can evolve into adaptive, sustainable, and intelligent systems capable of responding dynamically to clinical and environmental needs. This thesis lays the groundwork for future research on the large-scale deployment of cognitive architectures in healthcare settings, ultimately paving the way toward more efficient, sustainable, and patient-centred hospitals.

RESUM

Aquesta tesi explora i desenvolupa el concepte d'**Hospital Cognitiu (CH)**, un nou paradigma que reimagina l'hospital com un sistema dinàmic, intel·ligent i adaptatiu. El treball va començar amb una investigació conceptual que va conduir a la publicació "*Introduction to the Cognitive Hospital*" (*Future Healthc J*, 2022), que va encunyar i definir aquest terme per primera vegada en la literatura científica. Aquest marc conceptual s'inspira en el funcionament distribuït del sistema nerviós: els sensors i dispositius IoT perceben i recullen dades, els models d'IA les interpreten, i s'activen accions per donar suport a la presa de decisions i optimitzar tant els processos clínics com els operatius en temps real.

Partint d'aquesta base conceptual, la recerca va continuar amb la validació de **dos casos d'ús reals** dins del bloc quirúrgic de l'Hospital General del Vall d'Hebron. El primer cas d'ús va avaluar com les eines de coordinació en temps real i els sistemes de gestió del flux de pacients basats en RTLS milloraven l'execució dels fluxos de treball i el rendiment quirúrgic. El segon cas d'ús es va centrar en **l'eficiència energètica**, demostrant com la integració de dades de flux de pacients en temps real amb un sistema automatitzat de **climatització i ventilació (HVAC)** millorava l'estabilitat ambiental i l'estalvi energètic sense comprometre la seguretat del pacient ni la qualitat assistencial.

En conjunt, aquests estudis mostren que l'Hospital Cognitiu no és només un model teòric, sinó un **enfocament pràctic i mesurable** per transformar les operacions hospitalàries. En combinar IA, IoT i automatització, els hospitals poden evolucionar cap a **sistemes adaptatius, sostenibles i intel·ligents**, capaços de respondre dinàmicament a les necessitats clíniques i ambientals. Aquesta tesi estableix les bases per a futures investigacions sobre el **desplegament a gran escala d'arquitectures cognitives en entorns sanitaris**, obrint així el camí cap a hospitals més eficients, sostenibles i centrats en el pacient.

1. INTRODUCTION



1.1. Approaching the Cognitive Hospital (CH) Concept

Digitalisation is driving an increase of hospital capacity by overcoming the inherent constraints of such large and complex organisations. These include poor communication and coordination across big, fragmented premises and numerous teams; limited access to updated, timely clinical and operational information in data systems; and, especially, fragmented siloed data.¹

In recent decades, the increasing adoption of digital technology, including a wide take-up of key enabling electronic medical record (EMR) solutions, advanced medical devices and equipment to improve diagnostics and treatments, as well as other key information systems, has radically expanded the limits of healthcare and our understanding about the role of hospitals.²

The recent explosion of the internet-of-things (IoT) technologies has only accelerated the exponential growth of data in clinical facilities as a result of the rapid uptake of a multitude of sensors and devices and the integration of their data streams, together with those provided by the expanding myriad of systems and solutions in the hospital.³ In turn, this has paved the way for the start of Artificial Intelligence (AI) solutions in this sensitive domain, which promise to enable a proactive healthcare based on predictive and, later, prescriptive algorithms.⁴ While the first step is for predictive analytics to provide forecast capabilities, the next step is for prescriptive algorithms to generate automated recommendations.⁵ Likewise, this transformation will drive greater personalisation of care and precision medicine by the addition of genomics medicine data and technology, while also embracing the increasing social call to achieve greener and accessible hospitals.⁶

Every new technological development in recent decades has helped spur the terms ‘smart hospital’ and ‘intelligent hospital’ to portray a more futuristic image of these facilities. Nevertheless, in practice, these terms have, so far, been focused on presenting specific applications that address local problems and challenges, rather than viewing the hospital as a global entity.^{7,8} The rocketing growth of data and the increasing capacity to integrate and quickly process large volumes of information through big data and AI techniques takes us to the beginning of a new era that needs new paradigms to help express what is to come, which has been named ‘Society 5.0’.⁹

This thesis aims to introduce the **Cognitive Hospital (CH)** concept, first by analysing the evolution of key terms that preceded it, such as “*smart hospital*”, “*intelligent hospital*”, “*green hospital*” and “*liquid hospital*”, which progressively shaped a futuristic vision of healthcare environments. By studying how these terms have been used and evolved over time, this research reflects on the need to move beyond fragmented approaches toward a unified model that conceives the hospital as a **complex, intelligent system**.

Drawing inspiration from the organisation of the brain and nervous system, the **Cognitive Hospital** is envisioned as a distributed, adaptive and self-optimising environment where sensors, data and AI interact in real time to perceive, reason and act. Within this conceptual framework, two real-world **use cases** have been developed to demonstrate the feasibility and impact of cognitive principles applied in surgical settings.

The **first use case** focuses on **real-time coordination of patient flows**. By deploying an IoT-based Real-Time Location System (RTLS) and task-oriented coordination tools, the surgical block was transformed into a data-driven environment. This enabled the precise monitoring of every step of the perioperative pathway, improved synchronisation between teams, reduced idle times and increased surgical performance metrics.

The **second use case** explores how cognitive infrastructures can also drive **sustainability and operational efficiency**. Here, patient flow data were integrated with an automated HVAC system to dynamically adapt environmental conditions in operating theatres. This approach achieved significant energy savings and ensured stable temperature and airflow conditions without compromising surgical safety or quality standards.

Together, these studies illustrate how the **Cognitive Hospital** concept can be operationalised through IoT, automation and AI. They provide an early blueprint for standardising cognitive maturity levels in healthcare facilities, paving the way for the **fourth industrial revolution in hospitals**, where intelligent infrastructures will play a critical role in improving patient outcomes, efficiency and sustainability.

1.2. Evolution of Smart Hospital Concepts: Literature Review

The evolution from *smart* and *intelligent hospitals* to the *cognitive hospital* mirrors the progressive digitalisation of healthcare. In the 1990s and 2000s, *smart* and *intelligent* hospitals focused on automation, sensors, and information systems that improved operational efficiency and data management. The following decade introduced the *green hospital*, highlighting sustainability and energy efficiency through intelligent HVAC systems, renewable energy, and eco-design. More recently, the *liquid hospital* extended care beyond the hospital's physical walls, enabled by IoT, mobile technologies, and remote monitoring. Together, these ideas converge in the *cognitive hospital*, a new paradigm that integrates AI, IoT, and robotics into an adaptive ecosystem capable of perceiving, reasoning, and acting in real time to enhance patient outcomes, operational performance, and environmental sustainability.

Evolution of Hospital Concepts: From Smart to Cognitive

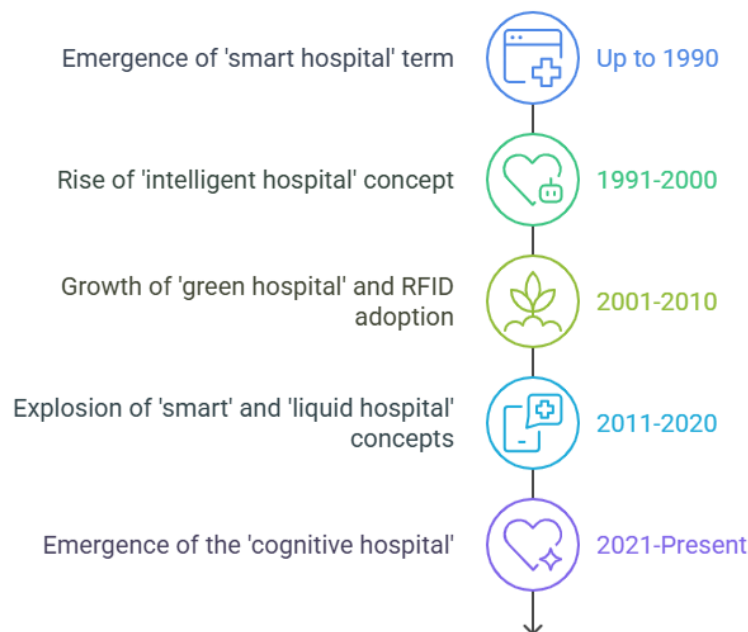


Figure 1 – Evolution of hospital concepts

1.2.1. Smart vs Intelligent Hospital

'Smart hospital' and 'intelligent hospital' are terms that have been used in recent decades to refer to the increasing cleverness shown by hospitals through the adoption of new technologies.

Up to 1990

Over the last few decades, as life has undergone a continuous process of digitalisation, first with the arrival of electronics and personal computers, then with the appearance of smartphones and now with the emergence of the IoT, all areas of society have been constantly transforming. The healthcare system has traditionally been a slow adopter of digital innovations as its critical role in public health tends towards conservative behaviour. However, this has not stopped new concepts from transforming hospitals over time. As informatics started to be widely adopted by the general public in the late 1980s, the first publications using the term ‘smart hospital’ began to appear.^{[10](#)}

1991-2000

Interestingly, the expression ‘intelligent hospital’ appeared a few years later in the early 1990s as, predominantly, researchers in Japan started to understand the power of medical informatics for transforming the healthcare system by piloting the very first EMR solutions.^{[11,12](#)} From then on, the term ‘intelligent hospital’ appeared to gain traction as more publications used it (i.e. 44 references compared with 21 mentioning ‘smart hospital’ from 1991–2000). This leading position was driven by the link with soft technological areas (such as ‘information systems’, ‘messaging solutions’, ‘knowledge-based solutions’, ‘middleware’ and ‘agent software components’) versus the association with a more hardware-based perception and the term ‘smart’, which in its early days was strongly linked to location technologies and sensors.^{[13](#)}

2001-2010

Over the following decade (2001–2010), the same dynamic can be observed in the first 5 years (i.e. 66 new references compared with 42 using ‘smart hospital’), both terms maintaining their initial links with software and more technological–hardware inventions. Without a doubt, this was the decade of the internet and the onset of the world wide web (WWW). Therefore, concepts related to data accessibility (such as ‘unified modelling language (UML)’, ‘ontology’, ‘semantics’ and ‘ubiquitous computing’) started to be more popular and were also connected to the ‘intelligent hospital’ concept.

On the contrary, ‘smart’ was still linked to advanced hardware and physical innovations involving ‘sensor networks’, ‘embedded systems’ and ‘smart spaces’. Interestingly, a publication mentioning both terms (‘The intelligent hospital: patient smart card’) reinforces

our perception that 'smart' was reserved for a more technical innovation while 'intelligent' was used as a broader concept, referring to a hospital that embraces technical innovations.¹⁴

Over the last 5 years of that decade, however, the strong adoption of radio-frequency identification (RFID) and mobile technologies started to boost the appearance of the 'smart' concept with references to 'advanced location', 'tracking' and 'activity monitoring' solutions, surpassing the intelligent hospital by 294 vs 173 citations.¹⁵ The use of 'intelligence' in the period 2006–2010 intensifies the mixture of emerging terms (including 'business process', 'semantic management', 'information exchange' and 'context awareness') as the Google revolution truly transforms access to vast amounts of data and these concepts start to be applied in the digitalisation of patients' clinical records.¹⁶

2011-2020

The start of the new decade confirms the explosion of the 'smart' concept and the standstill of the 'intelligent hospital' as broadband and mobile technologies conquer all areas of life and are mostly associated with the term 'smart'. In the years 2011–2015, 'smart' surpasses 'intelligent' by 561 references to 247.¹⁷ This confirmed lead is driven by the emergence of remote monitoring pilots, their sensors and wearables. However, in the same period, 'intelligent' begins to be more associated with the first applications flourishing in healthcare (with names such as 'intelligent operating room', 'intelligent appointment', 'automated pharmacy' and 'mHealth') and appears to be a term used to denote a more ethereal concept that goes beyond technology.¹⁸

Over the following 5 years, 'smart' carries on growing exponentially in use through the disruption driven by the IoT concept, surpassing the use of 'intelligent hospital' by 2,040 references to 277, through the decisive launch of the use of sensors.¹⁹ This last push appears to reformulate the links with the word 'smart' that has also come to encompass software concepts (such as new AI, cloud, blockchain and augmented reality (AR) technologies) and even final solutions (such as scheduling, security and telehealth services). Nevertheless, the use of 'intelligent' decelerates as 'smart' takes over its original associations, although it still retains a special link with big data and data-driven concepts.

Today, more general media uses 'smart' as the most common term that embraces concepts referring to an advanced futuristic hospital.

1.2.2. Green Hospital

‘Green hospital’ is the term used to refer to a hospital that is eco-friendly. This concept has been driven by the adoption of new technologies in recent decades.

Up to 1990

This term was completely unknown in literature.

1991 – 2000

With less intensity than the previous concepts, this term introduces the physical dimension of the hospital, its architecture, use of clean energies, reduction of water use and management of waste (such as anaesthetic gasses, which have a significant impact on the greenhouse effect). The utilisation of the concept ‘green hospital’ appears following the Kyoto Protocol in 1997, and the first references can be found from then on.[20,21](#)

2001-2010

The term starts to take off between 2001–2005, with four publications focused on green architecture with a strong lead in the USA, which saw the first hospital calculating its ecological footprint.[22](#) From 2006–2010, after the Montreal Action Plan focused on the extension of the Kyoto Protocol, continued interest increased in the topic, with 27 references adding new subjects (such as energy control systems, and heating, ventilating and air conditioning solutions (HVAC)) driven by the significant contribution of Asian countries and the construction of the first green hospital in the USA.[23](#)

2011-2020

The term seems to reach peak growth during the period 2011–2015, with 59 references which now include works all around the globe (ie USA, China, Japan, Taiwan, European countries, India, Iran etc). At this time, it reaches global acceptance and gains more emphasis in relation to engineering aspects, such as the installation of light-emitting diode (LED) lighting and more efficient HVAC solutions, which lends a considerable technological aspect to the concept. From 2016–2020, the term reaches 67 references, driven by the Paris Climate Agreement, yet its growth appears to slow. These references include more sophisticated connotations, added to by IoT technologies, such as intelligent energy and HVAC systems.[24](#) Interestingly, the renewed hopes of the new decade seems to be an acceleration of the number of works using the term ‘green hospital’ due to greater social

awareness of the topic highlighted by the campaigning of Greta Thunberg and the increasing pressure on public authorities to stop climate change. This is symbolised by new policies such as the European Green Deal or UK's 25-year plan to improve the environment.^{25,26} Likewise, the appearance of AI in this topic becomes a reality.²⁷

The green hospital is at the brink of exponential growth due to an increase of climate change awareness and AI technologies.

1.2.3. Liquid Hospital

‘Liquid hospital’ is a term that refers to the accessibility of care that goes beyond the hospital's walls to reach a patient's home. It was coined by Sant Joan de Déu hospital in Barcelona and has become prevalent in general media, with thousands of articles in search engines. However, it has still not thrived in the scientific domain with barely five publications from 2015–2020.²⁸ Nevertheless, we felt that it is was important to include it in this article as it adds another dimension related to plasticity that will enrich the future definition of the cognitive hospital.

The term clearly leverages the ideas of ‘liquid modernity’ proposed by Zygmunt Bauman, where the philosopher establishes that current society does not have rigid boundaries anymore and that public and private domains are in a constant blend.²⁹ As a result of the increased improvement of communications and availability sensors and applications, this term moved to portray hospitals as an extended seamless and invisible network of applications able to overcome the hospital's physical boundaries, enabling some care at home.

The liquid hospital will extend care outside the walls of a traditional hospital, engaging patients anywhere.

1.2.4. The Rise of the Cognitive Hospital

“The decade we are facing signals the start of real artificial intelligence solutions. This will majorly transform all applications and interactions in hospitals, for patients, professionals and anyone interacting with the hospital.”

The current decade marks a turning point in hospital transformation. The convergence of AI, IoT, robotics and the appearance of data spaces is enabling hospitals to evolve from static, service-oriented structures into **dynamic and intelligent environments**.³⁰ This requires moving beyond the concepts of *smart* or *intelligent hospitals* toward a new framework that captures the pervasive and adaptive nature of emerging technologies.

The **Cognitive Hospital** embodies this shift. It is not merely a collection of digital tools but an **adaptive ecosystem** capable of perceiving, reasoning and acting in real time to support patients, professionals and infrastructure. By combining continuous data flows from IoT sensors with advanced AI models, cognitive hospitals can anticipate needs, optimise workflows and coordinate complex clinical and operational processes.

1.3. State of the art of the CH key technologies enablers

1.3.1. Technological Introduction

Much like the **human nervous system**, the concept of the **Cognitive Hospital (CH)** requires a clear distinction between its **sensory–motor substrate**, responsible for perceiving and acting upon the environment, and its **cognitive core**, responsible for interpreting, reasoning, planning and learning. Just as sensory organs capture signals, the brain processes them and motor pathways generate responses, the hospital relies on a distributed digital infrastructure that mirrors this structure.

In contemporary digital health, the **Internet of Things (IoT)** provides this sensory and motor foundation. A dense ecosystem of ambient, biomedical and asset-tracking sensors, combined with actuators controlling infrastructures such as HVAC systems, lighting, logistics and patient flows, enables continuous monitoring and real-time action. **Recent work shows that healthcare IoT has evolved from fragmented pilot ecosystems to integrated platforms capable of autonomously closing feedback loops**, enhancing patient safety, operational efficiency and environmental performance.³¹

This sensory–motor layer depends critically on **semantic interoperability**, which transforms heterogeneous signals into actionable data. The adoption of HL7 FHIR as a backbone for real-time data exchange, coupled with standardised clinical data models, has emerged as a key enabler for hospital-wide orchestration, for example, integrating occupancy sensors with automated HVAC control. Recent studies underline FHIR’s role as the “connective tissue” between clinical IoT and hospital information systems.³²

Above this substrate lies **Artificial Intelligence (AI)** as the cognitive core. AI technologies transform data streams into **contextual perception**, inference, and **prescriptive planning**. Over the past five years, hospitals have moved from descriptive analytics to **predictive** (e.g., forecasting demand and clinical risk) and **prescriptive intelligence** (e.g., scheduling and resource optimisation). More recently, **Generative AI (GenAI)** and multimodal models have emerged to support clinical and operational decision-making, enabling **closed cognitive loops**: perceiving through IoT, reasoning with AI, acting through IoT, and learning through feedback.³³

The **convergence of AI and IoT (AloT)** is therefore the operational mechanism of the CH. This architectural pattern typically combines **edge AI** (for real-time sensing, local pre-processing, and event detection) with **core AI** (on-premises or in the cloud) for predictive and prescriptive intelligence. Interoperable APIs, often through FHIR, allow these layers to integrate with transactional systems and decision-support interfaces. This **AloT loop** enables autonomous and semi-autonomous assistants capable of orchestrating patient flows, optimising energy use, and tailoring interventions dynamically.³⁴

Finally, this technological evolution unfolds under a **new regulatory framework**. The EU Artificial Intelligence Act (**EU AI Act**) establishes strict requirements for **risk management**, **data governance**, **traceability**, **human oversight**, and **model robustness** for high-risk applications, including healthcare.³⁵ This reinforces the need for **secure-by-design** and **explainable-by-design** architectures that connect IoT (data and actuation) with AI (models and decisions) under strong ethical, legal, and safety controls.

In short, **IoT provides the “senses and muscles” of the CH**, while **AI provides its “brain”**, its capacity to perceive, learn, reason, and act. Their convergence, mediated through interoperability standards and regulatory governance, is a prerequisite for evolving from **fragmented local intelligence** to **integrated organisational cognition** capable of optimising clinical safety, operational performance, and environmental sustainability in real time.

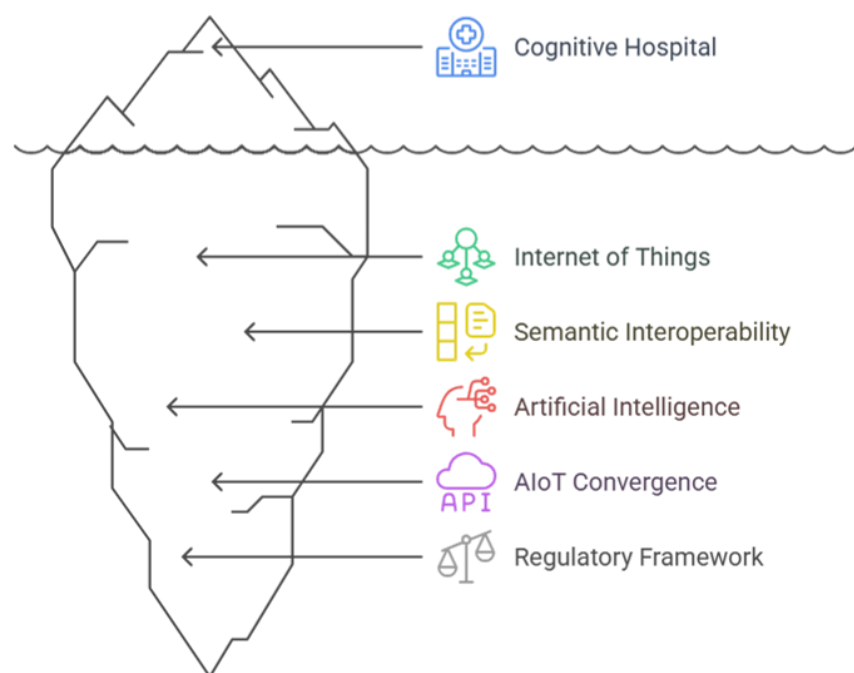


Figure 2 – The rise of the cognitive hospital

1.3.2. IoT as the Sensory and Motor System

Within the Cognitive Hospital, IoT constitutes the substrate that senses the environment, patients, assets, and infrastructure, then executes context-aware actions upon them. In technical terms, hospital IoT spans dense, heterogeneous sensor networks for environmental, biomedical, and logistical monitoring, together with actuators embedded in building management and clinical operations, for example HVAC dampers and set points, lighting, access control, automated transport, and infusion or bed systems.³⁶ A key component within this ecosystem is **Real-Time Location Systems (RTLS)**, which provide continuous, high-resolution spatial awareness of patients, staff, equipment, and critical assets. RTLS functions as the “*proprioception*” of the hospital, enabling precise tracking and coordination that underpins both operational efficiency and patient safety.³⁷ Recent systematic reviews document a transition from isolated pilots to increasingly integrated platforms that support continuous telemetry, device identity and provisioning, quality-of-service aware communications, and closed feedback loops that improve safety and efficiency in real time.³⁸

Modern hospital IoT stacks are layered. At the acquisition layer, low-power devices and gateways collect multimodal signals, including temperature, pressure, occupancy, vibration, air quality, **location**, and vital signs. At the transport layer, constrained and broadband links coexist, from BLE and IEEE 802.15.4 to Wi-Fi and 5G, with protocol translation at edge gateways.³⁹ At the processing layer, edge computing has become central, since on-premises inference near devices reduces latency, bandwidth, and privacy exposure, while allowing graceful degradation when wide-area links are unavailable. Recent surveys show edge AI in healthcare enabling local filtering, anomaly detection, and event recognition that trigger immediate actuation, for example switching an operating theatre from at-rest to surgical mode based on verified occupancy or throttling air changes per hour to meet particle thresholds before incision.

Actuation demands robust **integration with Building Management Systems**, which in hospitals must coordinate HVAC regimes, pressure differentials, filtration states, and thermal set points with clinical schedules and infection control constraints. Cross-domain interoperability remains difficult, since building automation ecosystems use industrial protocols such as BACnet and OPC UA, while clinical systems speak HL7 v2 and FHIR.⁴⁰

However, there is growing evidence that model-driven OPC UA information models and standard connectors can bridge HVAC and plant telemetry to IoT data lakes and control APIs, enabling consistent read-write semantics for supervisory control at scale. In parallel, **FHIR** has matured as the **clinical interoperability “spine”**, carrying near real-time context such as patient location, procedure status, and device observations, which can be consumed by orchestration services that drive actuators responsibly.

Communications capacity and reliability are critical to the sensory–motor metaphor. 5G brings deterministic latency profiles, network slicing, and uplink enhancements that benefit mobile assets and high-density device fleets in complex campuses, supporting continuous monitoring and control within strict timing budgets.⁴¹ Recent reviews describe architectures where 5G backhauls edge gateways, supports telemetry bursts from wearables and movable clinical equipment, and provides resilient paths for command signals to safety-critical actuators. Beyond transport, digital twins of critical subsystems, for example the surgical block’s air handling, are emerging as mediators between sensed state and control intent, allowing what-if simulation and optimal control, infection, and energy constraints.

1.3.3. AI as the Cognitive Core

If IoT represents the sensory and motor system of the Cognitive Hospital, Artificial Intelligence constitutes its **cognitive core**, transforming continuous data streams into perception, reasoning, and decision-making. Over the past decade, AI has progressively evolved from descriptive analytics to **predictive intelligence**, capable of forecasting events such as emergency demand, surgical delays, or risk of clinical deterioration. More recently, **prescriptive algorithms** and **reinforcement learning** approaches are enabling real-time optimisation of complex hospital processes, for example surgical scheduling, patient flow, and energy use.⁴²

In operational domains, AI supports **real-time decision-making** by integrating multimodal data from sensors, electronic health records, and hospital information systems. Machine learning models detect anomalies, anticipate bottlenecks, and suggest proactive interventions, while optimisation algorithms allocate resources dynamically. In clinical applications, deep learning methods already equal or surpass expert-level performance in imaging **diagnostics** and physiological **signal interpretation**, opening the path to context-aware clinical decision support systems that learn continuously from local and federated datasets.⁴³

Recent developments in **generative and multimodal AI** represent a further leap. Large language models, combined with structured data and sensor streams, can provide conversational interfaces, automated reporting, and decision support integrated with hospital workflows. These models are increasingly explainable, allowing clinical staff to interrogate the reasoning behind AI outputs.⁴⁴ Their deployment, however, requires strong **governance and alignment with the EU AI Act**, which classifies most clinical and operational AI as high-risk systems subject to traceability, and human oversight obligations.⁴⁵

Ultimately, the AI cognitive layer provides the hospital with **situational awareness, learning capacity, and planning ability**. By integrating predictions with prescriptive optimisation, AI acts as the hospital's "brain," continuously interpreting what is sensed and coordinating how to act. Its maturity and integration with IoT are decisive for advancing from fragmented intelligence to a truly cognitive hospital.

1.3.4. AI & IoT Convergence: The Cognitive Loop

The convergence of Artificial Intelligence and the Internet of Things establish the operational foundation of the Cognitive Hospital. While IoT provides real-time sensory input and the capacity to act upon the environment, AI interprets these inputs, generates predictions and plans, and issues decisions that close the loop. This **cognitive loop** consists of four essential stages: sensing, interpreting, deciding, and acting. When properly orchestrated, it allows hospitals to respond adaptively to clinical and operational conditions in real time.

In this architecture, **IoT devices and edge nodes** continuously collect multimodal data, for example patient location, occupancy, climate conditions, and clinical parameters. **AI models**, running locally or centrally, process these signals to detect patterns, predict future states, and prescribe optimal actions. These outputs are then transmitted back to IoT actuators, which modify physical or digital environments, for example adjusting HVAC parameters, reallocating resources, or triggering alerts to clinical staff.

Recent research demonstrates how **edge–cloud collaboration** enhances this loop, reducing latency, improving scalability, and preserving data privacy.⁴⁶ Edge AI performs rapid pre-processing, anomaly detection, and event recognition, while more complex models at the core handle forecasting, optimisation, and global orchestration. This layered design is already proving effective in areas such as operating theatre climate control, patient flow automation, and predictive maintenance of critical assets.

The **interoperability layer** is critical for ensuring that the cognitive loop functions seamlessly across heterogeneous systems. Standards such as FHIR for clinical data, OPC UA for building management, and secure MQTT or AMQP protocols for messaging enable data and commands to flow across domains with traceability and control. This technical integration is reinforced by emerging governance frameworks that ensure accountability, auditability, and compliance with the EU AI Act.

In essence, AIoT transforms hospitals from reactive, manually coordinated environments into **adaptive, learning systems**. By continuously cycling between perception, reasoning, and action, the cognitive loop supports safer, more efficient, and more sustainable healthcare delivery, laying the foundation for the fully operational Cognitive Hospital.

1.3.5. Impacted Areas in the Hospital

The integration of AI and IoT technologies has the potential to transform virtually every functional domain of the hospital. By combining pervasive sensing, advanced analytics, and intelligent automation, Cognitive Hospitals can achieve more accurate diagnostics, more efficient and personalised treatment pathways, and smarter operational coordination. These impacts go beyond isolated use cases, influencing both clinical care and the underlying infrastructure that sustains it.

The **diagnostic process** is one of the hospital's most data-intensive domains. AI and IoT are enabling earlier and more accurate diagnosis by combining multimodal inputs such as imaging, laboratory data, physiological monitoring, and real-time patient tracking. Deep learning systems for radiology and pathology have achieved expert-level performance in image classification and anomaly detection, while IoT sensors provide continuous vital sign streams that allow early detection of deterioration and sepsis. When these data are integrated in interoperable architectures, clinicians can access contextualised diagnostic information at the point of care, accelerating decision-making and improving outcomes.⁴⁶

The **treatment domain** benefits from AI-assisted decision support, process automation, and patient-specific optimisation. Predictive models can guide treatment selection and timing, for example recommending personalised therapeutic strategies based on patient profiles, procedural history, and resource availability.⁴⁸ IoT devices enable continuous monitoring during and after interventions, improving safety and supporting early discharge when appropriate.

Robotics and adaptive operating environments, driven by sensor data and AI orchestration, are enhancing precision, safety, and efficiency in surgical interventions. This combination is particularly valuable in critical care, perioperative settings, and high-acuity wards, where real-time adaptation can significantly improve patient outcomes.

Beyond direct clinical care, AI and IoT enable major improvements in **operational coordination**. Emergency departments can use predictive analytics to anticipate demand peaks, optimise triage, and coordinate patient routing. Surgical blocks benefit from real-time location systems that synchronise patient flow, theatre preparation, and HVAC conditions, increasing throughput and reducing delays.^{49,50} Logistics and supply chain operations are increasingly automated, with smart asset tracking and autonomous transport reducing manual workload and waste. These capabilities support the hospital as an integrated, adaptive system, improving responsiveness and resilience in both routine and surge situations.

1.3.6. Technical Challenges of the Cognitive Hospital

Although the convergence of AI and IoT is unlocking unprecedented opportunities for more intelligent, adaptive, and efficient hospitals, the full realisation of the Cognitive Hospital vision is still constrained by several critical **technical challenges including interoperability, data quality and governance, scalability and trust and ethical aspects**. These challenges span multiple layers of infrastructure, data, algorithms, and governance. Understanding and addressing them is essential to move from fragmented pilot implementations to large-scale, safe, and reliable cognitive systems.

Hospitals are traditionally composed of a complex mixture of legacy systems, proprietary protocols, and isolated information silos. IoT devices often use industrial standards such as BACnet or OPC UA, while clinical information systems rely on HL7 v2 or FHIR, and building automation follows entirely different paradigms. The lack of seamless interoperability between these layers is a major barrier to implementing real-time, cross-domain orchestration. Standardisation is progressing but remains uneven, and legacy systems frequently lack APIs or modern security models.⁵¹

The cognitive loop depends on data that are timely, **accurate, and trustworthy**. However, clinical data are often fragmented, incomplete, or non-standardised, while sensor data can be noisy or unreliable if not properly maintained and calibrated. In addition, health data are

subject to strict privacy and security requirements under the GDPR and the EU AI Act. This makes secure data governance, provenance tracking, and privacy-preserving computation critical. Breaches or misconfigurations could directly compromise clinical safety.

Most AIoT deployments in healthcare remain limited to single units or pilot projects. **Scaling to the entire hospital requires robust infrastructure**, sustainable maintenance, and reliable fail-safe modes. Edge intelligence and hybrid architectures mitigate some constraints, but deployment complexity, bandwidth management, and computational requirements still limit widespread adoption.⁵² Moreover, system resilience must be ensured under high demand or partial failure conditions, especially in critical areas such as emergency care and surgical blocks.

Because many AI applications in hospitals are considered high-risk under the EU AI Act, they must meet strict requirements for transparency, explainability, human oversight, and continuous post-market monitoring. A lack of trust in algorithmic decision-making, or insufficient explainability, can lead to clinical resistance and limit adoption. To ensure safe and ethical deployment, Cognitive Hospitals need robust model validation pipelines, auditing mechanisms, and clear lines of accountability between automated systems and clinical teams.⁵³

Only through coordinated advances in these domains can hospitals move from isolated digital systems to truly **cognitive entities** that safely integrate sensing, reasoning, and action at scale.

1.3.7. Studying two use cases for Vall d’Hebron hospital

The transition toward the Cognitive Hospital requires grounding technological innovation in real clinical and operational needs. In this context, Vall d’Hebron University Hospital has served as a **living laboratory to validate two early use cases** in one of its surgical blocks, a critical environment where efficiency, safety, and sustainability intersect. The first need addressed is the automation of patient flow, aiming to reduce delays, improve coordination among surgical teams, and enhance the patient and family experience through real-time visibility of the surgical pathway. The second need focuses on the dynamic control of HVAC systems, which are responsible for most of the hospital’s energy consumption, to adapt environmental conditions according to surgical activity without compromising safety or comfort.

Together, these two use cases reflect how AI and IoT can respond to operational pain points, increasing resilience, efficiency, and environmental sustainability while supporting clinical excellence.

1.3.7.1. Patient flow automation in the surgical block

The surgical process is complex and involves many different professionals and relatives, each with specific roles and tasks, as well as intervention-specific materials and equipment that must be ready to enable each phase of the surgical pathway (for example, type of anaesthesia, consumables, medications, surgical instruments, and medical devices). In general, the surgical process begins when the patient is transferred from the hospital ward to the pre-operative area, where they are prepared and anaesthetised while waiting for an available operating room. After the intervention, the patient is transferred to the Post Anaesthesia Care Unit (PACU), commonly referred to as the recovery room, where immediate postoperative care is provided. Finally, patients are returned to the appropriate specialised units in the hospital. This sequence is repeated with hundreds of patients every day.

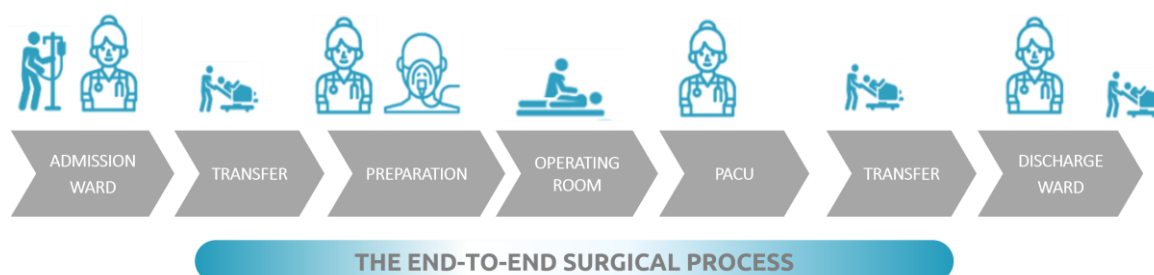


Figure 3 – The surgical process

Team coordination problems in surgical blocks that directly undermine quality of service, safety, and performance. These problems occur at the interfaces between professional groups, at hand-off moments, and in information flow. The main issues are: ⁵⁴

- **Poor real-time communication:** Teams often rely on informal communication (phone calls, corridor conversations, or delayed EMR updates). This leads to **information asymmetries** between surgeons, anaesthetists, nurses, porters, and cleaning staff. When one team is not aware of patient status, case progress, or delays, turnover times increase and unnecessary idle time accumulates.

- **Scheduling conflicts:** Surgeons, anaesthesiologists, and nursing teams often work on separate schedules and information systems. Misalignment between planned and actual case durations, late starts, and last-minute changes create cascading delays and reduced theatre utilisation.
- **Lack of standardised workflows:** In many hospitals, each surgical team follows slightly different routines for preparation, turnover, and postoperative processes. The **variability in practice** makes coordination more difficult, increases error rates, and reduces efficiency.
- **Missing feedback loops:** Delays and incidents often go unreported in real time, meaning teams cannot correct problems during the same shift. A lack of structured **feedback mechanisms** undermines learning and continuous improvement.
- **Resistance to digital coordination tools:** Even when RTLS, scheduling dashboards, or communication platforms are introduced, **lack of adoption** or poor user engagement can neutralise their benefits. Common causes include perceived surveillance, poor interface design, or inadequate training.

1.3.7.2. Dynamic control of HVAC's

Environmental impact of surgical units: In high-income countries, the carbon footprint of health-care systems has been estimated to be 3–10% of the total national greenhouse gas (GHG) emissions.⁵⁵ A recent report revealed that the NHS produces 5.4% of the UK's GHG emissions. This represents 25% of total public sector emissions, equivalent to the greenhouse gas emissions of 11 coal-fired power stations, which is not much lower than those for aviation, agriculture, forestry and land use in the UK (each 6,5%). Hospitals are the major GHG contributor in healthcare, with more than 50%, which is increased by other indirect factors such as patient and healthcare worker transport. In turn, the largest GHG contributor in hospitals is energy consumed by HVAC systems (i.e. heating, ventilation and air conditioning) amounting 57% according to some studies.⁵⁶ It is well known that these heavyweight infrastructures are poorly managed in hospitals, resulting in a chronic squandering of energy.⁵⁷

- **Environmental impact:** Surgical blocks are the most energy demanding unit in a hospital, consuming around 20-40% of the total energy expenditure.⁵⁸ Strict temperature, air pressure and humidity control are required over 24 hours in these units to contain

microbial contamination, which results in significant energy expenditure for the hospital. Intensive care units (ICUs) are the second largest consumers of energy in a hospital, accounting all together (ICUs + ORs) for approximately 70% of the total energy consumption. Although the reliability of HVAC systems -the main contributors- has improved a lot over the years, many hospitals still rely on legacy infrastructure that operates non-stop for fear that it won't start up again, which would negatively affect intervention cancellation. On the contrary, the new appliances are so complex to operate that if they shut down unexpectedly specialist support would be needed. Furthermore, fixation on maintaining over-optimal conditions to prevent air contamination leads to overspending, which current evidence suggests is completely unnecessary.⁵⁹ The range of proposed ideas to affect energy efficiency includes upgrading HVAC systems by adding smart control to regulate heating and cooling as required and to control temperature locally.

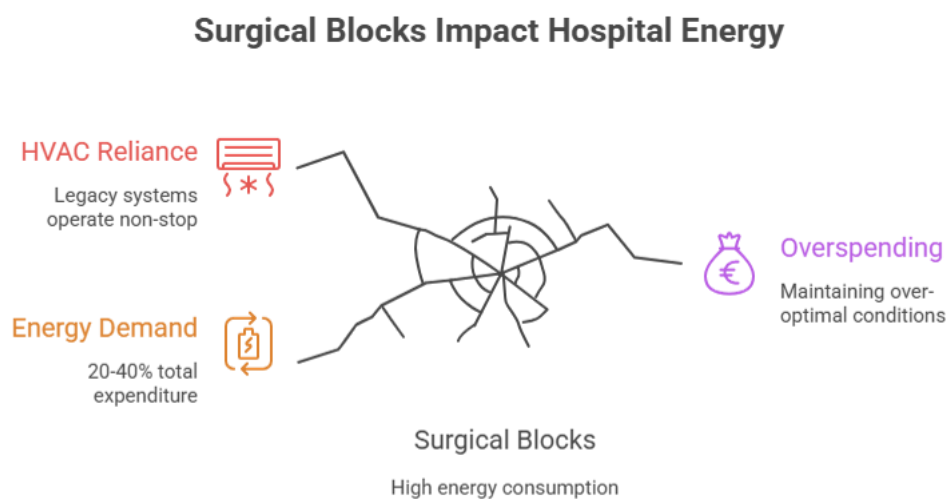


Figure 4 – High energy consumption in surgical blocks

- **Opportunities for energy saving:** Studies have concluded that shutting down operating room (OR) ventilation during off-duty periods, especially at night, does not appear to result in a significant particle count or microbial contamination. It has been proven that if HVACs are restarted 30 minutes before the scheduled operation, a high level of air quality is maintained.⁶⁰ That is why Vall d’Hebron hospital aimed to demonstrate this concept in one of its surgical wings. The current problem is that most hospitals in the western world use a manual notification system that allows surgical staff to modify the climate status.

However, this is far from optimal, as it is rare that ORs are set to “rest” while patients are not in the operating room. The surgery services manager prioritises surgical performance over any procedure cancellation due to suboptimal OR climate conditions. At the same time, not all interventions require the highest standards of air cleanliness (i.e. a non-invasive surgery is not as demanding as open-heart surgery). Therefore, the automated adjustment of OR temperature, based on surgical planning and real time occupancy, represents a huge opportunity for saving energy in surgery units.

- **Technology challenges:** Climate control in hospitals is a complex business. The main reasons why HVAC is still operated manually, causing huge inefficiencies, are: first, when these appliances have some level of intelligence, they are poorly used and tend to be cumbersome; second, and most importantly, they are complex to set up and integrate with other software in the hospital. This is the main reason why hospital technicians avoid dealing with these systems, as they usually rely on external technical support which limits their autonomy and harness hospital innovation potential. These heavyweight climate systems work with PLC technologies, which fall into the electro-mechanical field of technology with low level and fragmented means of integration with other software. However, some means of integration are given, although solutions that aim to manage these systems must innovate in their connective power to link the highly fragmented market of HVAC solutions. Furthermore, limitations for data collection and exploitation are still noteworthy and a long way from the possibilities offered by current IoT cloud ecosystems, including end-user applications. Current IoT middleware technologies open new horizons to solve this challenge by enabling connection and data exploitation with the isolated world of the HVAC.

1.4. Cognition beyond the hospital

The vision of the cognitive hospital extends far beyond its physical walls. Its true potential lies in projecting cognitive intelligence across the entire continuum of care. Through this expanded perspective, the hospital becomes part of a distributed, learning health ecosystem capable of continuous adaptation, collaboration, and personalised care delivery. This distributed intelligence relies on **federated learning** and **health data spaces**, which enable secure, collaborative AI development without compromising privacy.

1.4.1. Extending Cognitive Intelligence to the Continuum of Care

The concept of the cognitive hospital does not end at the hospital's physical boundaries. To fully realise its potential, cognitive intelligence must extend across the **continuum of care**, connecting hospital infrastructures with primary care, community health services, and patients' daily environments. This evolution aligns with the idea of the **liquid hospital**, in which traditional rigid boundaries between hospital and community dissolve, allowing care processes to flow seamlessly across settings.

Extending cognition beyond the hospital relies on combining **real-time sensing**, **federated intelligence**, and **generative AI** to support both clinical decision-making and patient self-management. Remote monitoring technologies, including wearable and ambient sensors, allow continuous assessment of physiological and behavioural markers in real-world conditions.⁶¹ These data streams, securely federated and processed by adaptive AI models, provide early warning signals for clinical deterioration, relapse, or exacerbation of chronic diseases, enabling timely interventions outside the hospital walls.

This distributed cognitive model also allows for **better coordination between levels of care**. Primary care physicians, specialists, hospitals, and home care teams can access contextualised, patient-centred intelligence that reflects both medical records and real-time status. This breaks down traditional care silos, improving transitions between hospital discharge, rehabilitation, and community follow-up. For patients with neurological or chronic conditions, this capability is particularly relevant, since early signs of decline often occur outside hospital settings.⁶²

Moreover, cognitive systems integrated across care settings support **personalised and preventive approaches**.⁶³ Rather than waiting for patients to present at the emergency department, cognitive infrastructures can detect deviations, suggest interventions, and guide patients or carers to the most appropriate setting. In this way, extending cognitive intelligence to the continuum of care aligns with current European strategies such as the **European Health Data Space (EHDS)** and regional data infrastructures, which promote secure, interoperable, patient-centred health ecosystems.

1.4.2. Federated Intelligence and Data Spaces

A core enabler of cognitive healthcare beyond the hospital is the concept of **federated intelligence**, which allows multiple health institutions to learn collectively without centralising sensitive data. At

the heart of this approach lies **federated learning**, a machine learning paradigm in which algorithms are trained locally at each institution and only **model parameters or gradients**, not raw data, are securely shared with a central aggregator.⁶⁴ This preserves institutional and patient-level privacy, ensures that personal health information never crosses organisational boundaries, and facilitates compliance with strict legal frameworks such as the **GDPR** and the **EU AI Act**.

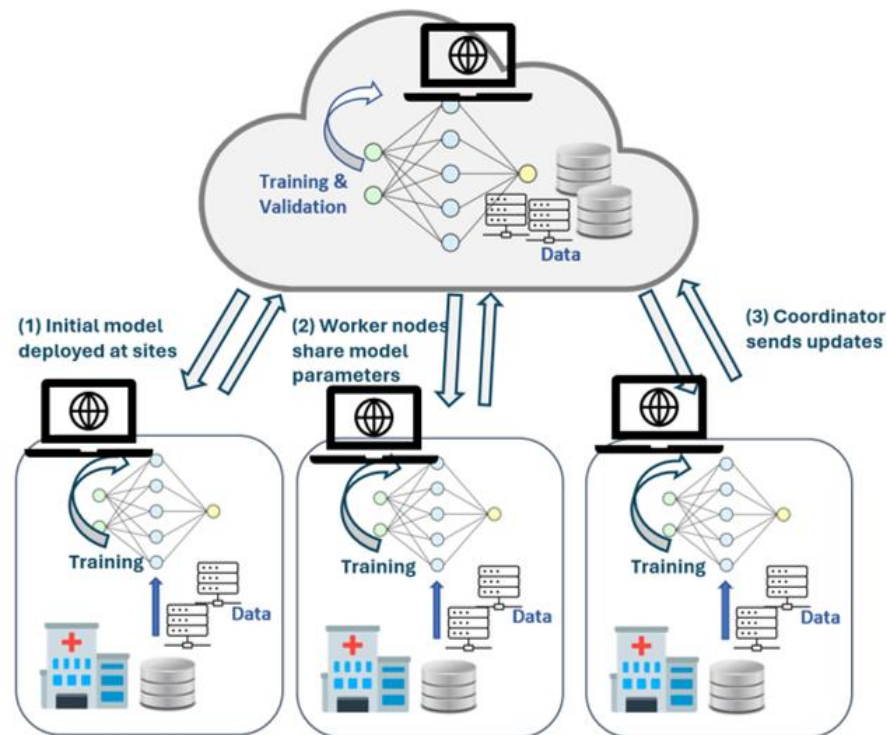


Figure 5 – Federative learning across hospital domains

Federated learning directly addresses one of the most persistent barriers to scaling cognitive systems: the **fragmentation of healthcare data** across hospitals, primary care centres, research institutions, and personal devices. Instead of moving data to a single repository, intelligence is **brought to the data**, allowing hospitals to build **robust and generalisable AI models** for tasks such as early diagnosis, patient flow optimisation, and personalised treatment planning. For modelling any clinical conditions, federated learning enables integration of clinical, imaging, omics, and sensor-derived data from multiple centres without breaching privacy boundaries.

In addition, the concept of **data spaces** complements federated learning by providing the **governance and interoperability** layer required to operate this distributed ecosystem. European health data spaces define common semantic standards, access control policies, trust frameworks, and auditability mechanisms that guarantee responsible data use.⁶⁵ They create a structured environment in which institutions can participate in collaborative

intelligence without losing control of their data. This model is fully aligned with European data strategy and regulatory frameworks, making it scalable and sustainable.⁶⁶

Operationally, **federated intelligence** and **data spaces** could enable **cross-border collaboration** in both clinical care and research. Institutions participating in these networks train shared models across heterogeneous populations, improving generalisability and robustness, while retaining the ability to **specialise models locally** to reflect their patient demographics, care protocols, or epidemiological context. This distributed learning approach strengthens resilience and will create a **pan-European cognitive layer** capable of continuous adaptation and improvement.

Extending cognitive intelligence through federated data spaces and federated learning marks a decisive step from isolated smart hospitals to **networked learning health systems**. Intelligence becomes a **shared, co-created resource**, operating across institutions and jurisdictions, while respecting privacy, security, and trust boundaries.

1.4.3. Cognitive Assistants across Care Settings

The extension of cognitive intelligence beyond the hospital also depends on the deployment of **cognitive assistants** that support patients, clinicians, and care teams across multiple care settings.⁶⁷ These assistants, powered by generative AI (**GenAI**) models, act as **intelligent mediators** between human actors and complex health information systems, enabling more efficient, personalised, and coordinated care throughout the patient journey.

Cognitive assistants operate at different levels. For clinicians, they provide **context-aware decision support**, integrating multimodal data such as clinical records, sensor streams, imaging, laboratory results, and patient-reported outcomes. By interpreting data in real time and surfacing relevant insights, cognitive assistants could support early diagnosis, risk stratification, treatment recommendations, and workflow automation. For example, in perioperative care, they could alert teams to preoperative delays, predict resource constraints, or recommend discharge planning based on recovery trajectories.

For patients and caregivers, cognitive assistants could offer **continuous engagement and guidance** outside the hospital walls. **Conversational AI agents** and multimodal monitoring platforms could explain treatment plans, remind patients of medications, provide personalised education, and detect deviations from expected recovery paths.⁶⁸ These systems could also trigger alerts to clinical teams or recommend appropriate self-

management actions, reducing avoidable admissions and improving adherence to treatment. In chronic diseases, where long-term monitoring is critical, cognitive assistants could play a key role in detecting subtle changes early and facilitating proactive intervention.

A key advantage of cognitive assistants is their ability to **operate consistently across care settings**. When integrated with federated data spaces and hospital infrastructures, they could maintain situational awareness whether the patient is at home, in primary care, or within a specialised hospital unit. This continuity would allow for smoother transitions of care, fewer gaps in communication, and more timely clinical decisions. Unlike static decision support systems, cognitive assistants are adaptive, learning from real-world data and adjusting recommendations over time.

Their deployment, however, must address several **challenges** including transparency, explainability, trust, and clinical responsibility. The EU AI Act classifies many clinical AI applications as high-risk, requiring robust oversight, performance monitoring, and human-in-the-loop mechanisms.⁶⁹ Well-designed governance frameworks ensure that cognitive assistants enhance, rather than replace, human expertise and maintain patient trust.

1.4.4. Integration with Public Health and Research Infrastructures

A key step in extending the cognitive hospital beyond its physical boundaries is its **integration with public health and research infrastructures**. Hospitals are not isolated entities, but nodes in larger health, scientific, and regulatory ecosystems.

Their ability to share intelligence, align data models, and participate in collaborative research networks determines how effectively cognitive health systems can contribute to population health, clinical innovation, and system resilience.

In the wide field of chronic conditions with multifactorial, and highly variability between individuals, this integration is especially critical. The creation of a **dedicated data spaces** would allow hospitals, research centres, and public health authorities to securely share and analyse clinical, omics, imaging, sensor, and behavioural data from large and diverse populations. Such a data space would support early detection of specific disorders, precision medicine strategies, and longitudinal research on disease trajectories. By combining clinical data with real-world evidence and population-level indicators, it would also enable more efficient public health planning and more targeted prevention programmes.

This vision aligns with broader **European initiatives** such as the **European Health Data Space (EHDS)**, **EBRAINS**, and other research infrastructures that aim to build a trusted, interoperable ecosystem for data-driven healthcare and scientific discovery.⁷⁰ Cognitive hospitals can connect to these infrastructures through federated learning frameworks and interoperability standards, contributing local intelligence while preserving privacy and data sovereignty. This model strengthens the feedback loop between clinical practice and research, accelerating the translation of discoveries into care pathways.

Public health agencies would also benefit from this integration. Cognitive hospitals can act as **sentinel nodes**, generating aggregated insights on disease trends, hospital activity, and population health indicators in near real time. This capacity enhances early warning systems, improves surge planning, and supports evidence-based policy making. It also enables health authorities to allocate resources more effectively, particularly in domains with high societal burden such as stroke, dementia, Parkinson’s disease, and multiple sclerosis.

Importantly, integration with research infrastructures facilitates the **continuous validation and improvement of AI models**. Instead of static algorithms, cognitive systems can evolve with new clinical evidence, changing epidemiological conditions, and emerging scientific knowledge. Governance structures based on shared ethical frameworks, transparent consent models, and secure digital infrastructures are essential to make this possible at scale.

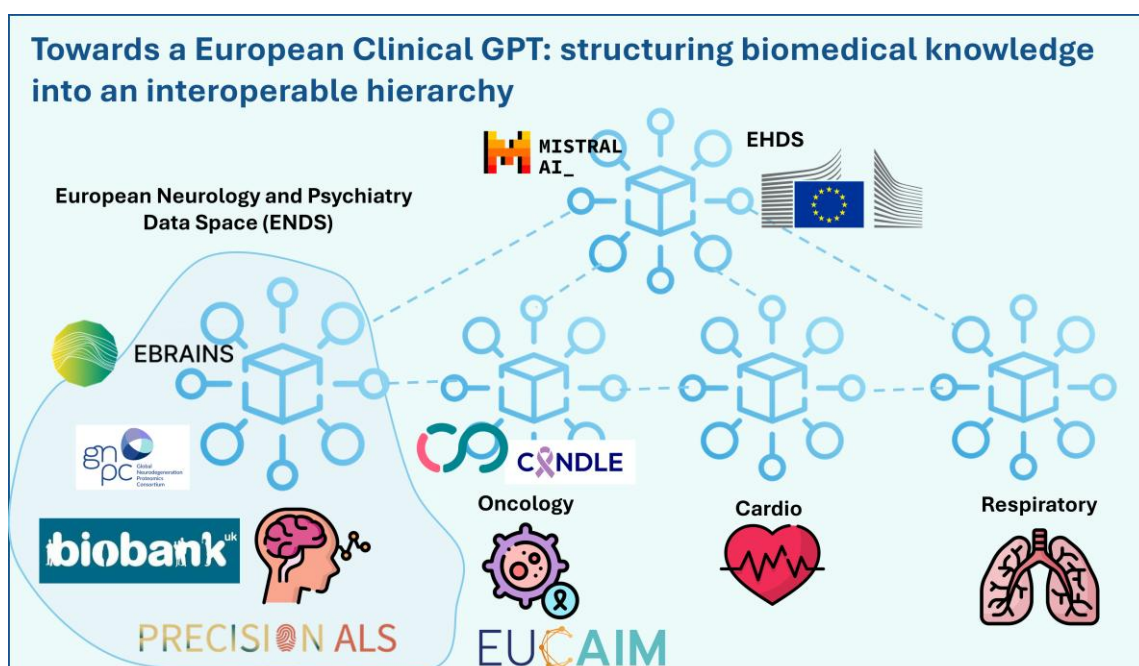


Figure 6 - Federation of specific health data spaces

2. HIPOTESI



As outlined in the introduction, the concept of the **cognitive hospital** proposes a model in which the integration of digital technologies such as IoT and AI enables real-time perception, reasoning, and action within the care environment. This approach allows for a more efficient orchestration of clinical and operational processes, with the aim of improving resource use, reducing inefficiencies, and enhancing the quality of care. In this context, the surgical block represents a particularly relevant scenario, as it is a high-complexity environment where multiple clinical teams, patient flows, and infrastructural systems, such as HVAC, converge and have a direct impact on surgical performance and overall hospital efficiency.

Our hypothesis is that, in a cognitive hospital, **(1)** the implementation of real-time digital coordination applications for different clinical teams **improves** the execution and synchronisation of patient flows, operating room utilisation, and ultimately, surgical performance; and **(2)** the integration of these real-time patient flow data with an automated HVAC system optimises energy efficiency and ensures optimal environmental conditions, without compromising patient safety or the quality of the surgical process.

To test this hypothesis, two sequential studies were designed, both focused on the surgical block. The first study analyses the impact of digital coordination on surgical performance and process management, while the second evaluates the effect of HVAC integration on energy efficiency and the maintenance of real-time environmental conditions. This approach could **lay the foundation for a new model of intelligent hospital process optimisation**, demonstrating that operational cognition can improve both efficiency and sustainability within healthcare systems.

3. OBJECTIVES



The **main objective** of this thesis is:

- To investigate and define the concept of the *cognitive hospital* as a new operational and technological model for healthcare systems, based on the integration of real-time data, Internet of Things (IoT) and AI technologies, and intelligent decision-support systems.

The **secondary objectives** derived from the main objective are:

1. To assess the impact of implementing IoT-enabled, real-time coordination applications to support surgical workflows, improve patient flow execution, and enhance operating room performance in the surgical block.
2. To evaluate the impact of integrating IoT-based real-time patient flow data with an automated HVAC system on energy efficiency and environmental conditions in surgical rooms, ensuring that sustainability gains do not compromise patient safety or quality of care.

4. METHODOLOGY



For the development of this thesis, the **research approach** was structured in three consecutive phases designed to explore, define, and validate the concept of the *cognitive hospital* in two use cases.

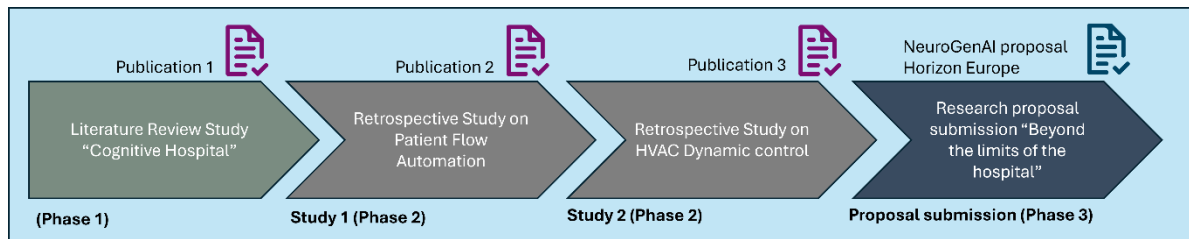


Figure 7 – Research approach for this thesis

The **first phase** focused on carrying out a structured literature review to identify and characterise the conceptual and technological foundations of the cognitive hospital. This phase aimed to establish a clear theoretical framework, defining its key components and their relationship with emerging IoT and AI technologies. The results of this work were published between 2020 and 2022 and described in section 1.2.

The **second phase** aimed to validate the concept through practical implementation in a real hospital setting. In this stage, two retrospective studies were carried out. The first study evaluated the impact of a real-time patient flow coordination solution on **surgical performance** (2021–2022). The second study assessed how the integration of real-time patient flow data with an automated HVAC system could improve **energy efficiency** in surgical rooms without compromising safety or quality of care (2022–2023).

Finally, the **third phase** consisted of establishing a broader research line to consolidate and expand this emerging field. This has led to the design and leadership of the European project **NeuroGenAI** (2024–2025), which aims to explore the application of *generative AI* and cognitive technologies to neurological care and hospital management.

4.1. Literature Survey for first study

We conducted a structured scoping review to trace the evolution of terminology describing the hospital as an advanced entity, focusing on “smart hospital”, “intelligent hospital”, “green hospital”, and “liquid hospital”. We searched Google Scholar, PubMed, Scopus, and Web of Science for records published between 1990 and 2020, since preliminary scoping showed negligible usage before 1990. Search strings used exact-phrase queries in English within title, abstract, or keywords, for example "smart hospital", "intelligent hospital", "green hospital", "liquid hospital", combined with NOT filters to reduce homonyms, for example "green hospital" NOT "Hither Green" NOT "Green Lane". We excluded citations, patents, conference agendas without full text, non-scholarly news, and items lacking bibliographic metadata.

Screening proceeded in two stages, first, automated de-duplication across databases, second, manual relevance screening of titles and abstracts. For “green hospital” and “liquid hospital”, where semantic ambiguity was higher, we limited manual screening to the top 100 most relevant results per five-year period, ranked by database relevance, and verified context to ensure conceptual alignment with hospital models rather than place names or unrelated interventions. For each retained record, we extracted year, document type, and conceptual focus, then aggregated counts by five-year periods to compare terminology trajectories.

Outputs included time-series plots of term prevalence, absolute appearances, and qualitative summaries of definitional shifts that informed the framing of the “cognitive hospital”. Limitations comprised language restriction to English, potential database coverage bias, and residual ambiguity despite disambiguation rules.

4.2. Retrospective Design for First Use Case

The main objective of this study was to assess the progress of the surgical block key performance indicators between 2017 (roll-out) and 2019. 2020 was not included as surgical activity was dramatically affected by COVID-19.

4.2.1. The New Intervention

The digital process intervention was piloted in the new general surgery block with 19 theatres and 20 beds for both patient preparation and the post anaesthetic care unit (PACU). The following elements were included:

- automatic registering of all the steps and timestamps of the surgical process relieving professionals from manual entering of data into their information system, with the aim of improving data quality;
- new digital intervention based on tailored apps that leverage the generated live data by the RTLS solution to smooth collaboration and communication between frontline staff teams across the surgical process (i.e., admission, preparation, theatres, recovery, discharge, porters and cleaners), as well as communications with families;
- aggregation of accurate real times to enable the monitoring of key surgical performance indicators (i.e., theatre utilisation, late starts, early finishes, downtimes between cases, turnaround times, etc).



Figure 8 – Concept of surgical pathway automation through RTLS solution

4.2.2. The Solution Design Aspects

The novel digital approach was designed in collaboration with MYSPHERA S.L., which developed and deployed a bespoke technological solution for the surgical process.

An important design decision taken by the company was to use Bluetooth Low Energy (**BLE**) instead of other active RTLS. The main reason was to obtain a solution that could solve the real time location problem for the specific use case in the hospital cost-effectively, i.e. patient flow at the surgical setting. While technologies like Ultra-Wide Band (**UWB**) can provide greater accuracy, the cost is increased by having more expensive hardware and more complex solution architecture, which might be justified in industrial applications where high precision is needed or for very specific cases in the hospital. This results in much higher installation and operational costs. The same arguments apply for ultrasound technology. In the case of RFID real time technology, applications are limited by the need of having a by-hand operation and prices for its hardware tend to be very expensive too. On the contrary, Wi-Fi could have been a good candidate for RTLS in the hospital as it is already implemented in most facilities with its network of access points.

The main problem of Wi-Fi is the fact that it has not been designed to enable accurate real time location solutions but rather to provide internet. Costly Wi-Fi access points antennas tend to have very poor radiation diagrams and are spread as far as possible to optimise cost vs internet access. The result is a density of access points and a coverage that does not allow the kind of application presented in this work. Finally, Bluetooth technology is massively adopted across sectors, which enables low prices for electronics compared to any other technology. This is key for the mass adoption of RTLS solutions in hospitals. While not as accurate as UWB, Bluetooth can provide accuracy of around one meter, which is enough to solve the problem and optimise the cost-effectiveness of the presented use case.

The Bluetooth solution consisted of two main hardware elements, a patient tag, and a series of gateways.



Figure 9 – Used RTLS hardware

These gateways were installed strategically across the surgical ceiling to record the patient journey in real time. In turn, this generated the live data and location events to automate the intervention. The next step was to develop a platform that was able to leverage the real time data and to orchestrate the process automatically while engaging each of the teams with tailored applications. These applications provided patient-flow live data, notifications and tasks as patients moved concurrently across each step of the surgical process. Patient and operating theatre flows were visualised showing the current status.

Most remarkably, it was decided that automated notifications would be sent to:

- PACU to improve bed management with seamless communication with admissions and theatres areas;
- PACU and porters to speed up patient transfer to theatre as soon as it was ready (i.e., that was generated by detecting that theatre is in status “clean” and patient is ready to be transfer to the PACU area);
- cleaners to reduce times between cases, activating faster theatre cleaning.

Applications were presented as agreed with the team specifications (i.e., large screen panels as well as the use of their PC/laptops in PACU and admission areas, touchable screens in theatres, handhelds for porters and cleaners to support jobs reception in mobility scenarios, panels and handhelds for relatives).

4.2.3. Intervention Roll-out Strategy

The new intervention was structured in two main phases:

- Phase 1 (2017), only the RTLS solution was installed to set the performance baseline and standardise pathways with real and undisputable times. As a result, the real surgical block behaviour could be monitored, enabling the identification of inefficiencies, bottlenecks and improvements.
- Phase 2 (2018 and 2019 onwards) building upon the RTLS solution, the new digital intervention was released adding the tailored applications for each team.



Figure 10 - Phases of the study

4.2.4. Patient Pathway

During the first 3 months of the implementation of phase 1, a monitoring study was carried out on the first patients in the surgical slots. A total of 52 patients were counted, giving a standard pathway (i.e., 1. Admission at Pre-Operation (PreOp); 2. Anaesthesia start; 3. Operating theatre start, 4. Recovery at PACU). The gathered average process time is shown below:

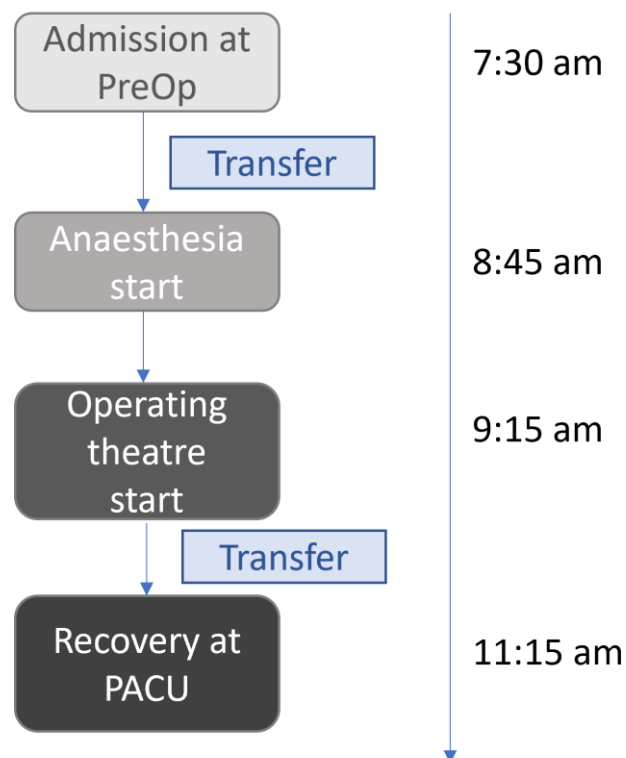


Figure 11 - Average pathway steps and times

Across many different interventions, the average surgical process time had a duration of 4 hours.

4.2.5. Endpoint Monitoring

To assess the surgical block performance, the following endpoints were monitored over several years. A more detailed table has been attached in the annex:

	Endpoint	Description
1	Theatre utilisation	Time when theatres is occupied with a patient
2	Late starts	Surgical sessions when the start of surgery is delayed
3	Early finishes	Sessions when the end of the last surgery is too early, wasting time effective time of theatre.
4	Turnaround time (TAT)	Time in which no surgery is in place
6	Downtime between cases (DBC)	Idle time after the operating theatre has been emptied
7	Surgical activity	Number of operations per year.
8	Cancellations on the day	Percentage of operations cancelled or reprogrammed in surgical session
9	Economic gains	Yearly gains generated by the new approach

Table 1 – Patient flow automation endpoint monitoring

4.2.6. Data Collection

This is an observational pilot study done in one centre with the goal of evaluating the implementation of a new RTLS patient-tracking system. There was no direct patient data involved. In fact, the patient Bluetooth tag does not transmit any sensitive data, but an anonymised ID. Thus, patient consent was not required by the hospital. Data collection was based on the real times captured by the new RTLS solution, which were automatically registered in the hospital's Electronic Medical Record (EMR) system based on SAP technology. While times were registered on a regular basis, outcomes based on those times were aggregated and calculated on a yearly basis as shown in the table.

	Baseline (Phase 1)	12 months (Phase 2)	24 months (Phase 2)
Outcome's aggregation	x	x	x

Table 2 - Data sampling

4.2.7. Staff Training

As the staff was involved in the co-creation process, final apps were highly tailored according to clinical feedback to ensure a high level of usability. As the use of the new apps was meant to be very straightforward, only two hours maximum of training for the new service was required. The idea was to replace the old ways of working, which consisted of manually operated boards in combination with continuous phone calling, by having screens with updated real time information. A training plan was implemented targeting specific groups within the surgical teams. To optimise engagement, training sessions were planned a week before the Go-Live, following this group distribution:

Profiles	Training time
Nurses PACU	1 – 2 hours
Theatre managers	1 – 2 hours
Theatre staff	1 – 2 hours
Porters and cleaning teams	1 – 2 hours
Administrative clinical staff	2 - 3 hours

Table 3 – Training groups

Administrative clinical staff was given a bit more time as they received training in patient tag assignment and un-assignment, which included the use of specific hardware and a standard cleaning process for the reuse of tags for other patients. During the two first weeks after the Go-Live, a more intensive on-site support to solve issues that arose and to help staff with questions was provided.

4.2.8. Solution Deployment

Phase 1 deployment involved MYSPHERA in the installation and adaptation of the RTLS system in the General Surgery area. This included two design sessions with key surgical stakeholders to understand patient flow in the surgical block and the installation of the Bluetooth gateways in the right locations. Several check-ups were carried out to verify that patient flows were captured without any black spots.

As Wi-Fi and Bluetooth share the same frequency band, MYSPHERA's Bluetooth gateways use a special channel within its radiofrequency band to avoid any interference with the Wi-Fi access points already in place in all hospitals. Furthermore, this solution passed the CE mark, which involves being compliant with electromagnetic medical equipment compatibility tests specified in the European directive EMC 2004/108 / CE. These tests verify each device from two aspects: emission and electromagnetic immunity.

Another critical aspect of deploying a RTLS was the integration with the hospital Electronic Medical Record (EMR) system, a powerful integration software tool that allowed a fast interoperability with Vall d'Hebron's EMR was used. This allowed to adapt timestamp location data generated by the new solution to Health Level Seven (HL7) standard messages used by the hospital to register them into its EMR. Another essential integration was with the Theatre Management System, which passed the surgical list of patients in a daily basis so that the solution could orchestrate the workflow in real time.

Phase 2 was focused on deploying the new automated workflow platform and tuning the possible patient pathways. A remarkable aspect of Vall d'Hebron was the fact that the PACU area suffers a lot of pressure as it receives patients for preparation but also those in recovery. Thus, flows are mixed in this area and the new solution had to be flexible enough to model patients in the same physical space but in a different step in the surgical process in real time. Phase 2 was refined gradually as it did not involve any RTLS hardware, already installed in phase 1.

4.2.9. Solution Running

As with any new digital service, a technical support needed to be in place establishing a flow chart to escalate incidences according to the level of severity. MYSPHERA provided a list of potential risks and response times accordingly as part of the Service Level Agreement (SLA) between the hospital and the company. Thus, IT technical support level 0 and 1 was provided by the hospital, while for more in-depth technical support MYSPHERA was involved. A ticketing platform based on Jira was used to coordinate the incidents. In general, the new service has been very stable. Most of the issues reported were due to refinements in the information shown by the apps and corrections in gateways location at early stages. For rare situations such as databases running out of space or any problem with the server, MYSPHERA provided a continuous monitoring system which allowed the prevention of downtime situations and the correction of any technical problem in advance. A back-up system was not necessary, as this was not seen as a critical service by the hospital and the technical support provided by MYSPHERA guaranteed the required quality of service. In the whole phase 2, 156 minor events were recorded, which most of them could be sorted out quickly and remotely. No downtimes were observed caused by the RTLS solution.

4.3. Retrospective design for Second Use Case

The main objective of this study was to assess the impact on energy key performance indicators with the implementation of the new green RTLS solution that dynamically adjusts the right climate conditions of each operating theatre as interventions move along surgical sessions.

4.3.1. The Setting

The new solution was implemented in the new surgical block of the General Hospital with the latest technologies designed to carry out highly complex operations. The new surgical block required an investment of €21 million in construction and €16 million more in equipment. In 10,000 square metres of hospital space there are 700 professionals serving 19 operating theatres, carrying out more than 9,000 interventions every year.

4.3.2. The Solution

The novel digital approach was built in collaboration with MYSPHERA S.L., which developed a bespoke RTLS solution for the surgical process. While this innovation was originally intended to optimise OT utilisation and increase the block performance, eventually it was also used to enable the smart energy control of the OTs. The technological solution had two main purposes. First, it automatically adjusted the climate level of the operating theatres according to different states generated by the real-time location system (RTLS):

Theatre Energy Status	Mode of working	Activation
Active	Perimeter lighting = 100% Temperature = Basal(21°C) (+0,5°C) Ventilation Flow = High	As soon as the RTLS system moves to status "Theatre Ready"
Active with low ventilation	Perimeter lighting = 60% Temperature = Basal(21°C) (+0,5°C) Ventilation Flow = Low	As soon as the RTLS system moves to status "Theatre Dirty"
Sleep	Perimeter lighting = 10% Temperature = Basal (+-4°C) Ventilation Flow = Low	As soon as the RTLS system moves to status "Theatre Dirty" and there are not more patients on the list.

Table 4 – Operating theatre climate variables

Thus, the new solution activates the HVAC in theatre when it detects that a patient has been transferred to the preparation area and is ready for their operation (i.e., activation at least 30 minutes earlier). Whenever there is a patient transfer in the operating theatre, the solution sets the climate to rest, consuming far less energy, until the next patient to be operated is in the preparation area. As soon as the last patient on the daily schedule leaves the operating theatre, regardless of the time, the HVAC is turned off. Likewise, at the weekends, the HVACs are shut down.

All this is possible because patients are localised in real time by means of Bluetooth tags. In specific cases such as professional training sessions, this approach is not used unless a real patient with a tag is part of the session.

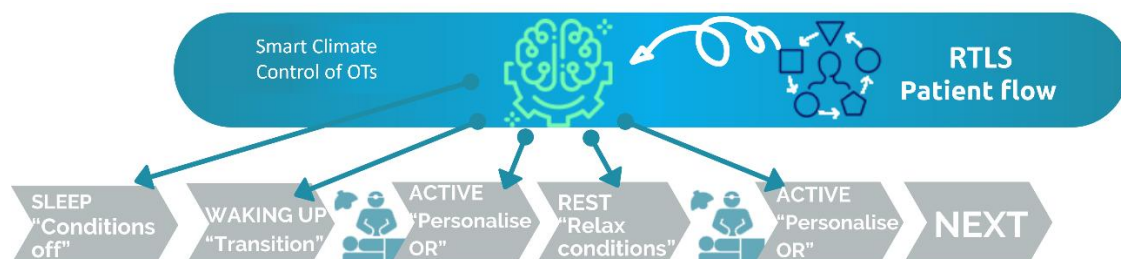


Figure 12 -Automatic climate control of OTs

Secondly, in order to improve theatre staff experience, the new RTLS patient flow solution provided a theatre screen that, as well as showing patient flow and theatre status to optimise process management, also provided the information and direct control of the following climate parameters:

- perimeter light control in 20% steps
- temperature control between 19°C – 23°C
- humidity display
- air pressure display
- operating theatre status control (i.e., active, active in low ventilation, sleep)
- operating theatre timer control



Figure 13 - Dashboard dedicated to improving OT climate control staff experience

4.3.3. Solution Deployment

The new RTLS patient flow solution was first implemented to monitor and automate surgical clinical pathways in 2017. As soon as this new approach was consolidated, the same solution was integrated with operating theatres' energy control system (ECS), based on a solution from Controlli Delta.

4.3.4. Endpoint Monitoring

To assess the surgical block energy performance, the following endpoints were monitored:

	Endpoint	Description
1	SBC	Surgical Block consumption per year
2	OTC	Operating Theatre consumption per year
3	WSB	Waste per surgical block year
4	WOT	Waste per theatre year
5	ES	Economic savings

Table 5 – HVAC automation endpoints

5. RESULTS



5.1. Cognitive Hospital Literature Review Study

The **literature review analysis** revealed a clear evolution of the terminology associated with the digital transformation of hospitals over the last three decades. The **‘smart hospital’** concept has grown exponentially, particularly since 2015, with over 2.000 indexed publications between 2015 and 2020. This surge is largely driven by the widespread deployment of Internet of Things (IoT) technologies, the integration of real-time monitoring systems, and the increasing role of artificial intelligence (AI) in clinical and operational processes. In contrast, the term **‘intelligent hospital’**, which had been dominant in the 1990s and early 2000s, stabilised at a much lower level, with only 277 references during the same period. This reflects a shift from early software- and informatics-focused innovations to a broader ecosystem of interconnected physical and digital solutions.

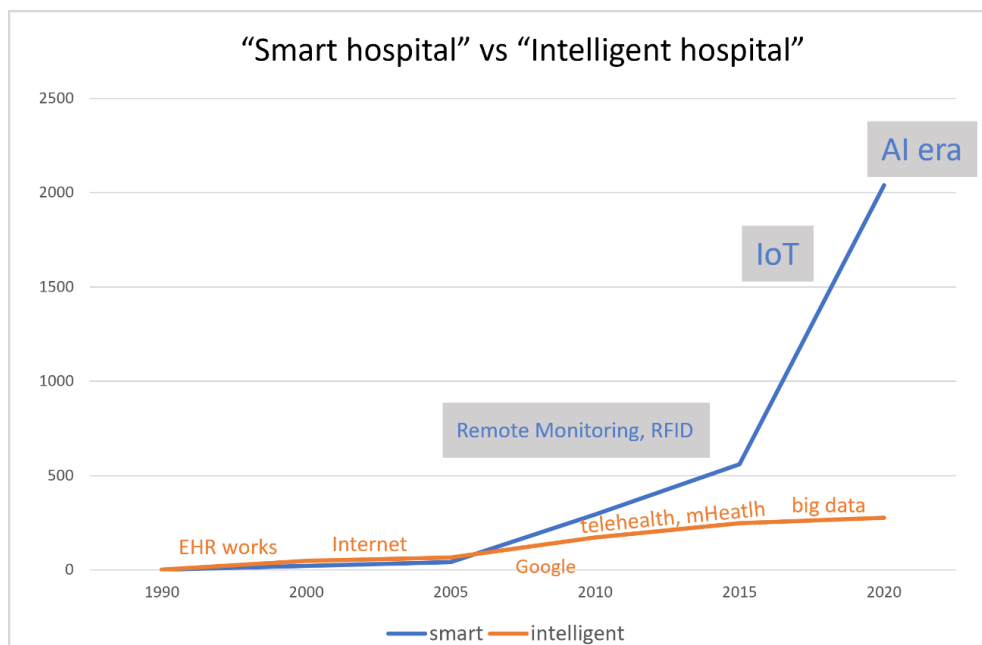


Figure 14 - Number of publications by 5-year interval searching for "smart" and "intelligent hospital"

The **‘green hospital’** concept followed a different trajectory. Initially emerging after the Kyoto Protocol in the late 1990s, it gained momentum with the Montreal Action Plan and later the Paris Agreement, supported by improvements in energy management systems and environmentally sustainable infrastructure. Its peak growth occurred between 2011 and 2015, with around 60 references globally. While its pace slowed between 2016 and 2020, this coincided with growing public environmental awareness and the first applications of AI in energy management, especially in **HVAC** and lighting optimisation. These trends suggest a renewed potential for growth as climate policies and sustainability goals intensify.

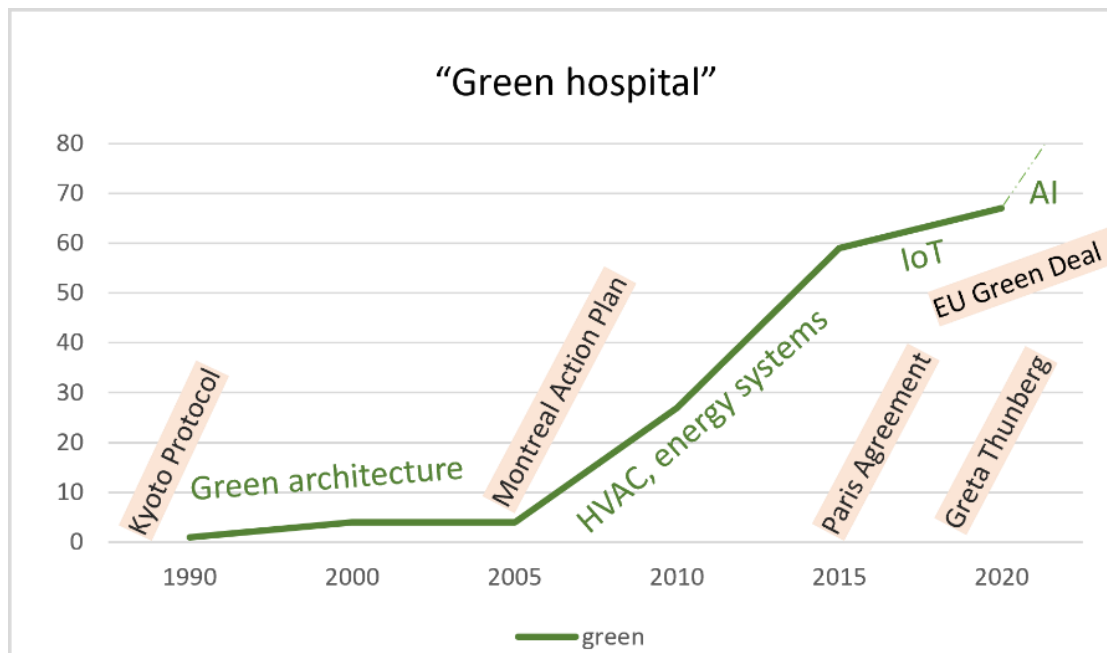


Figure 15 - Number of publications by 5-year intervals searching for "green hospital"

The **'liquid hospital'** concept, though still limited in scientific publications (only five between 2015 and 2020), plays a complementary role. It represents the dissolution of traditional hospital boundaries through the extension of care into patients' homes, supported by mobile technologies, telehealth, remote monitoring, and wearable devices. This concept adds an essential dimension of *plasticity and permeability* to the hospital of the future.

Overall, these findings indicate that **IoT and AI are the dominant technological forces** reshaping hospital models, with sustainability and care continuity increasingly embedded as transversal priorities. The dominance of the 'smart hospital' concept reflects the consolidation of digitalisation, while the emergence of the 'green' and 'liquid' perspectives highlights the transition toward more **adaptive, sustainable and boundaryless hospital ecosystems**.

5.2. Patient Flow Automation Study

The aggregated theatre utilisation in 2017 was 70.02%, far from the optimal goal of 85%. By the end of 2019, the general surgery block was close to the optimal performance, reaching 82.5%. That increase propelled surgical activity from 8.154 operations in 2017 to 9235 in 2019. These improvements in theatre productivity were possible for the combined breakthroughs on key performance indicators such as late starts, early finishes, turnaround times and downtimes between cases. Furthermore, the new way of working drove global process gains and saved nurse-time as a result of better coordination between teams and automating activity registering into the hospital's EMR. Interestingly, the access to accurate times and real time applications allowed better scheduling and activity management, which seems to have had an impact by reducing the number of operations that need to be extended and, in turn, producing fewer cancellations on the day.

	Variables	2017 (Phase 1)	2018 (Phase 2)	2019 (Phase 2)
1	Theatre utilisation	70.02%	80.15%	82.5%
2	Late starts	35min (97%)	22min (85%)	16min (71%)
3	Early finishes	43%	24%	21%
4	Turnaround time (TAT)	23min	16min	15min
6	Downtime between cases (average cleaning time of 12 minutes)	11min	4min	3min
7	Surgical activity	8154	8731	9200
8	Cancellations on the day	23%	14%	9%
9	Economic gains	-	3% (1.88M€/year)	8% (2.31M€/year)

Table 6 - Results table of surgical key performance indicators

5.2.1. Cost Assessment

The increase of surgical activity enabled the addition of 577 new operations in the block in 2018, which at an average cost of 3.258€ per surgical intervention represented an economic gain of 1.88M€ just. On the other hand, the cost of a RTLS project varies depending on the rooms, corridors, and size of the area to

cover. It is also important to consider the types of surgery and other aspects such as screens and smartphones for professionals, apps adaptations according to staff needs and number of integrations to be performed with the hospital system. According to MYSPHERA and taking in consideration the scope of this project, i.e. size, 19 operating theatres and other rooms, integrations and adaptations; the market price of this project is about €425.000, which gives a return of investment (ROI) the very first year of implementation of 342%.

5.3. HVAC Automation Study

According to MYSPHERA and taking in consideration the scope of this project, i.e. size, 19 operating theatres and other rooms, integrations and adaptations; the market price of this project is about €425.000, which gives a return of investment (ROI) the very first year of implementation of 342%. By connecting the HVAC systems to MYSPHERA's solution, the hospital was able to obtain a staggering saving of 1.445 MWh in 2018, moving from a baseline spending of 4.817 MWh in 2017, to a final consumption of 3.372 MWh in 2018, representing a cost reduction of 150.000 € per year. This is a reduction of about 30% of the total energy spending in that surgery unit alone and a waste per OT of 76 MWh/year.

	Endpoint	2017	2018
1	SBC	4.817 MWh/year	3.372 MWh/year
2	OTC	253,52 MWh/year	177,47 MWh/year
3	WSB	-	1.445,08 MWh/year
4	WOT	-	76 MWh/year
5	ES	-	150.000 €/year

Table 7 - Results table of energy savings indicators

Overall, the whole hospital campus employs more than 9000 professionals and comprises 22 buildings in an area of 132.695 m² including the General, Maternity and Trauma Hospitals. This campus generated a total consumption of electricity of 22.431,6 MWh by the end of 2016 with a total cost of 2,33 million euros. The new surgical area in the General Hospital is taking 10.000 m² out of that, representing only 7,5% of the total area of the hospital campus, but consumes the significant 21,46% of the campus electricity. After the implementation of the innovation, the contribution of this surgical block was reduced to a contribution of about 15%.

Taking into account the years **2018, 2019, 2020 and 2021**, the total accumulated eliminated waste was 5,78 GWh/year with savings of 600.000 euros and a reduction on GHG of 1.227,27 tCO₂e.

5.3.1. Cost Assessment

The freed waste achieved by the innovation has led to savings of 150.000 euros per year in that surgery unit with 19 operating theatres, which represents 7.895 euros per year and operating theatre. On the other hand, according to MYSPHERA and taking into consideration the scope of this solution, which was originally designed to optimise surgical performance, i.e., amount of area, number of theatres and other rooms, integrations, and application adaptations, the market price of this project is about 425.000 euros, which gives a return of investment (ROI) of 64,7% in the very first year of implementation. However, it is important to note that the original purpose of the RTLS patient flow solution was to increase surgical performance, and this was achieved with a ROI of 342%.⁴⁹ Therefore, the combined ROI, including increase of surgical and energy performance, would correspond to a total ROI of 406,7%.

6. DISCUSSION



6.1. The Need of an Overarching Concept

There is a need of a new overall term to face the future of the artificially intelligent, green and boundaryless hospital. The last 2 decades have been heavily dominated by the adoption of EMR solutions, which is one of the key enablers in the hospital digitalisation journey that spurs the use of the terms ‘smart’ and ‘intelligent’. AI policy in medicine and its application has advanced at pace over the past 5 years alongside a global commitment to a greener planet. This means that a hospital of the future now needs to be cognisant of autonomous capabilities that provide healthcare in a responsible and sustainable way, to benefit all of society. Cognitive studies could help develop a robust new model for the upcoming AI era by leveraging a neuroscience background.³⁰

6.1.1. Defining the Cognitive Hospital Model

Cognition is the ability to process information from perception and senses, acquired knowledge (experience) and the subjective characteristics that allow the information to be assessed.⁷¹ It consists of processes such as learning, reasoning, attention, memory, problem solving, decision making, feelings, all of which are optimised by the nervous system to obtain results with the minimum expense of energy. All of this is smart, green and probably liquid, amongst other adjectives; a cognitive hospital though is also one that learns, adapts and connects with professionals.

We could imagine the hospital of the future as an entity, able to learn from the environment, integrating staff talent, interacting with patients and professionals to personalise care on a daily basis. How then can a hospital, a complex rigid physical structure with hundreds of healthcare professionals, transform into an intelligent adaptive entity in the broader sense of the word?

Similar to the nervous system, the cognitive hospital would be distributed across functional levels and physical areas to enable a wide range of applications that are still connected to a common “being”, the hospital “brain”. This intelligence could follow an organisation similar to the human body, going from the smallest component, the cell, to the tissue, then the organ, the system and finally the organism, in this case the human body. This might resemble the hospital organisation going from the professional to the team, then the service, department and finally the hospital as whole. Every single level is vital and autonomous. It develops local intelligence and is coordinated with its peers and upper structures with the leading role of the brain as shown in [Figure 17](#). This hierarchisation is also found in several approaches that interpret the human brain and nervous system as a whole.

These approaches can be used to shape the cognitive hospital concept, which might also help devise its architectural design on a physical and functional level from varying perspectives:

- placing emphasis on physical cognitive distribution: **central and peripheral**;
- focusing on level of awareness to execute actions: **somatic and autonomous**;
- dividing the nervous system between receptors and actuators: **sensitive and motor**.

These ways of representing the nervous system can be extrapolated to depict the cognitive hospital concept. This could be roughly defined as an artificial body that will seamlessly orchestrate healthcare provision by resembling the cognitive capacities of the human brain and the rest of the nervous system. As such, this involves the integration of a multitude of local activities (e.g., processes and pathways in A&E, ITU, wards, theatre suites, hospitalisation, outpatient clinics, administration, logistics, procurement) and intelligences (e.g., individual expertise and decisions by staff, AI provided by medical devices and monitoring systems) to generate overall meanings and insights to control global processes in the hospital, in real time. Likewise, this global awareness will support healthcare staff in their specific, local, operational tasks by providing the big picture at all times to enable the best decision making possible to optimise healthcare outcomes, including patient and staff satisfaction.

This way of performing mimics the hierarchy of the human body. Staff represent the essential cells of the hospital, working in a coordinated fashion as teams. These teams, symbolised as tissues in the figure below, are highly specialised and implement very specific tasks according to their role in the service (i.e., A&E, surgery, ITU, etc). The best performance of any service or organ requires perfect orchestration and communication between each different layer, which is conducted by the “hospital brain”. A good delivery of care requires a fine coordination of varying services, and, in the same way our body handles the digestive, respiratory and circulatory systems, to mention a few, the cognitive hospital should manage urgent and elective care so that the experience in each department is optimal for patients, families and staff. Patient and families will benefit from a seamless delivery of care, avoiding unexpected disruptions (i.e., waiting times, cancellations) and receiving constant and adequate information. Staff will be helped by real-time applications and devices that provide meaningful insights to support optimal clinical conditions, decision making and communication between teams, services and departments.

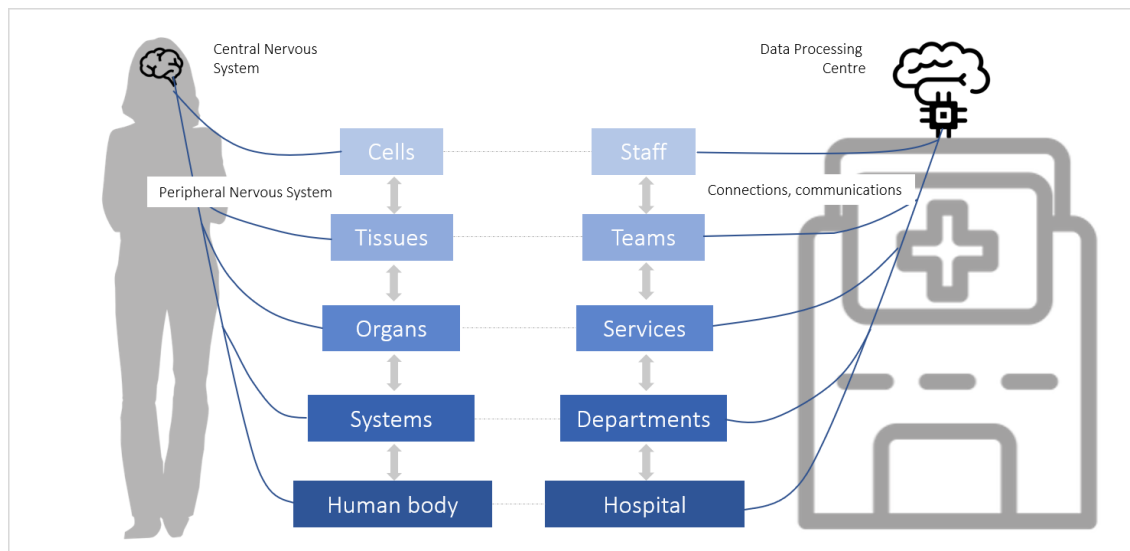


Figure 16 - Comparing the human nervous system with the cognitive hospital

The following subsections propose a brief description about how the anatomic and digital world can be blended by the presented concept.

6.1.2. The Hospital's Central and Peripheral Nervous System

On a higher level, the nervous system's architecture is divided into the central nervous system (CNS), composed of the brain and spinal cord, and the peripheral nervous system (PNS), containing nerves that reach all parts of the body and connections with the CNS.

Interestingly, this anatomical model fits well with the physical distribution of intelligence in a hospital building. In fact, anatomical could be extrapolated to the infrastructure, the physical elements that make up a body. As happens with the human body, the central nervous system is mainly composed of the brain and the spinal cord. Similarly, a hospital's "brain" is located in the data centre, while the spinal cord is the main channel that enables communication with the different peripheral areas that comprise a hospital. Likewise, the peripheral nervous system that is composed of a myriad of nerves, ramified to reach every part of the body, could be modelled as the various communication channels, cables and different networks that reach every single area in a hospital, where digitalisation enables data generation (sensors), information gathering and processing, and, eventually, data-driven actions to close the intelligence loop.

For instance, in a critical, time-sensitive, clinical pathway such as the stroke code, all the healthcare professionals involved, from the paramedics in the ambulance, the A&E team receiving the patient, to the specialist intervention staff, can be represented as vital cells of the hospital body that are connected to its peripheral nervous system by means of different medical devices, sensors, diagnosis tests, communications.

This constant communication should be seamlessly integrated by the hospital CNS to anticipate and streamline the coordination of services to execute a responsive intervention. The stroke pathway coordinator should be empowered by key, real-time clinical and process indicators as the patient moves along the pathway, advising and providing decision support suitably to complete the case and optimising healthcare outcomes.

Another interesting take on this concept, in line with the “liquid hospital”, is how the PNS could be highly distributed within the same hospital and even other centres (e.g., hub/spoke, tertiary and secondary care centres, expert communication/remote surgery, etc.). Furthermore, the PNS could be part of the patient’s home, as an extended tentacle, that allows real-time monitoring, self-management and communication applications to carefully monitor the patient.

6.1.3. The Hospital’s Somatic and Autonomous System

Awareness is a key factor to enable human cognition. While the autonomic system is in charge of processes without any conscious control, for actions such as cardiac function, breathing rate and many activities carried out by smooth muscle and glands, the somatic system is in charge of the actions that require awareness, such as conscious control of muscles and skeleton during physical activity. In the same way, it could be suggested that a cognitive hospital should have these two levels of behaviour. There are many processes in a hospital that are not core for patient care provision, but which are still critically essential and foundational for higher complex functions and applications. For instance, hospital climatization is an important task that has an impact on patient and professional satisfaction and care, in addition to hospital expenditure on electricity due to heavy HVAC solutions. The cognitive hospital should cater for this process smartly, in the background, without the need of a human operator regularly adapting the conditions for each area.

6.1.4. The Hospital’s Sensitive and Motor System

Another way to represent the nervous system is by means of an architecture connected to a large sensory receptor network with the motor system. The human body, like any multicellular animal, must monitor and maintain a constant internal environment, as well as monitor and respond to the external environment. In many animals, these two functions are coordinated by two integrated and coordinated organ systems: the nervous system and the endocrine system. While the nervous system coordinates rapid responses to external stimuli, the endocrine system controls slower, longer lasting responses to internal stimuli.

From a technological perspective, spurred on by the IoT and the AI explosion, hospital will carry on implementing an increasing ubiquitous network of sensors and actuators. Thus, the cognitive hospital should integrate in real time vast amounts of data provided by its pervasive sensory system, digesting relevant datasets to generate highly contextualised responses to the range of applications provided (output), e.g., regulation of oxygen administered according to the level of oxygen in blood detected in patients or automatically allocating healthcare resources according to predicted healthcare demand, to mention two examples that provide staff with insightful and timely information to support the best clinical or operational decision to maximise quality of care for patients.

6.1.5. Capacities of the Cognitive Hospital

Receptors are parts of the nervous system that sense change in internal and external environments. Sensory input can occur in many forms, including pressure, taste, sound, light, blood pH, or hormone levels, which are converted to a signal and sent to the brain or spinal cord. Recalling what has been addressed so far, the new concept of the cognitive hospital goes beyond many other terms formerly used. That is because it places emphasis on the integration of all local intelligences at once, as part of an aware smart being. In this model, the hospital brain would undertake the central processing of artificial intelligence algorithms currently still centralised in the hospital data centre. Increasingly, over the coming years, a more distributed cloud approach is being adopted. In fact, the human body has local “brains” in key areas, such as the heart and digestive system, which also show an amazing level of intelligence distribution.⁷² Interestingly, the invertebrate nervous system in cephalopods sees cognition highly distributed and significantly placed at the tentacles.⁷³ Perhaps advanced edge intelligence enabled by the *Internet of Things* and *AI* in hospitals could resemble that of octopuses rather than humans.

Nevertheless, coming back to the inspiration provided by human intelligence and better understanding how a hospital could resemble the human nervous system, it is even more important to understand what capacities are needed to talk about a fully operational cognitive hospital that mimics those processes in human cognition. The following are the most relevant:

- ✓ **Plasticity.** This is a structural characteristic of the brain that makes it adaptable according to the needs and stimuli being absorbed. Studies reveal that after a stroke a survivor’s brain reorganises its internal structures to find new pathways that shortcut

the damaged area in an attempt to regain its previous capacities.⁷⁴ Similarly, the cognitive hospital should be adaptable, featuring architectonic spaces resembling this brain capacity, which is connected to the idea of the Liquid Hospital.

- ✓ **Learning capacity.** A key capacity of the cognitive hospital is its potential to digest and acquire new knowledge. Although healthcare systems host tens of petabytes of data, this is hardly exploitable.⁷⁵ Currently, it is limited by the significant fragmentation of siloed data, which lacks standardisation and requires human supervision and reinforced learning to train specific algorithms. In the future, as data become both accessible and standardised, automatic unsupervised learning mechanisms will exponentially accelerate the acquisition of new knowledge.
- ✓ **Communication, interpretation (symbolism) and empathy (cognitive flexibility).** Delivering human-like communication in all its applications and interactions is an important part of cognition. This does not only mean verbal communication but also the interpretation of non-verbal and visual communication. The cognitive hospital will implement communication in all its manifestations and touch points where voice, gestures and visual expression are integrated as part of a complex language. A combination of different technologies, including voice assistants, natural language, image processing and even touch, will be blended in miniaturised hardware technology to enable a natural complex interactive system. The hospital's learning capacity will enable it to personalise and interpret higher complex symbols and human behaviour to ultimately develop an understanding of the "other" and implement human empathic mechanisms to boost engaging interactions.
- ✓ **Perception.** All the different applications rendered by the cognitive hospital at every level will be contextually aware, fed by human-like communication and a multitude of sensors and data inputs, both from internal and external data sources (i.e. weather forecast, pollution, traffic, etc). The rise of the *Internet of Things* will enable sensory technological elements that will form the core of the perception system for the cognitive hospital. The integration and comprehension of all these real-time contextual data channels will activate an understanding of the local reality in a hospital at any time.
- ✓ **Memory.** The current understanding of memory in technology is the amount of information that a database is able to store. Developments in this field to date allow

hospitals to store tens of petabytes of information to keep scans, MRI images, electronic health records, lab-tests, clinical trials data, among others. The current storage level is similar to that of the average human brain, which is able to store the equivalent of 2.5 petabytes of information.⁷⁶ However, the viability of the cognitive hospital model depends on whether, like the human brain, all this information can be instantly searched, accessed, discovered and integrated to generate more complex meanings and personalisation when responding in real time to each individual interaction with patients, health professionals and other people in the hospital.

- ✓ **Anticipation, planning and problem-solving capability.** The combination of the different capacities listed above enables another key characteristic of a cognitive body, which is being able to predict, understand, organise and provide solutions to everyday challenges. For instance, the cognitive hospital should be able to predict the instantaneous health demand faced by an A&E department on a particular day and, therefore, all the applications and processes related to A&E will be frequently and automatically updated to improve patient care and health professionals' workload. Similarly, it will produce highly optimised plans and scheduling to reduce waiting lists while maximising patient care. Furthermore, the cognitive hospital will be able to assist professionals and patients by recommending solutions to different problems that arise throughout the healthcare process. As more technical problems are able to be automated, less energy should be for administration tasks and more for patient care-
- ✓ **Superior skills** will be increasingly unlocked as cognitive hospitals champion the previous capacities described so far. This would create the potential for cognitive hospitals to generate self-awareness and reflection. The hospital would evolve into a body that is able to create an artificial sense of self-motivation, that can set and attain its own goals while involving patients and professionals, using its creativity to find engaging and optimal ways of achieving those goals. In this latter stage of cognition, a hospital will be able to behave as a social stakeholder in a community, which in turn will raise ethical questions regarding what is accepted by this awareness. Is it a being or mere technology at the service of society? Could hospitals start making their own decisions, bypassing humans? This is the eternal fear of **Singularity**, where machines' super intelligence becomes uncontrollable and irreversible, resulting in unforeseeable changes to human civilization.⁷⁷

6.1.6. A Proposed Definition for the Cognitive Hospital

At this point, an obvious question would be to ask whether a cognitive hospital is just a facility that implements a series of AI applications. This is the scenario today with an increasing number of fragmented smart applications in the field of diagnostics, treatments and health management and care delivery. While, certainly, the achieved local smartness is already part of the very early stages of the cognitive hospital, the new concept expands exponentially in different dimensions represented by human cognition (i.e., learning capacity, communication / interpretation and empathy, perception, memory, anticipation / planning and problem-solving and superior skills such as self-awareness and reflection).

This opens up the possibility of creating a model based on an entity similar to the human nervous system, inspired by its cognitive skills, hence the analogy in the previous section. This seamless, pervasive body will integrate the distributed vast number of professional talents and capacities as well as the generated real-time data streams provided by all kinds of sensors and applications, to empower staff with the right insightful information, knowledge and decision support, in the right place, at the right time, according to the specific level of patient care, process or pathway. In turn, this resembles how the human body functions, with billions of autonomous body cells cooperating, by means of the brain coordinating a specific organ (i.e., department or process in the hospital) to handle concurrent higher level activity processes .

On a different level, the new concept could enable further developments to model the increase of a hospital's intelligence according to the dimensions of human cognition. As a result, a new scaled structure could be created and subsequently standardised to enable a vision of the cognition level achieved by hospitals globally. This is similar to the process followed to monitor the level of digitalisation of hospitals in the last two decades with the Electronic Medical Record Adoption Model (EMRAM).⁷⁸ The model developed by the Healthcare Information and Management Systems Society (HIMSS) has become a universally recognised maturation model of a hospital's EMR. As more hospitals reach the top digitalisation scale, they will be prepared for the next leap, which is where the concept presented in this article can help them take up the baton for the new era ahead.

6.1.7. Early Implementations of the Cognitive Hospital

The journey towards the cognitive hospital is still long and will surely evolve over the next few years, refining its meaning. It will also give rise to many discussions about societal and ethical challenges but, in the meantime, leading facilities are already implementing specific concepts in the direction described thus far. The following are examples of four leading hospitals that are expanding the intelligence of their facilities.

6.1.7.1. Alder Hey Cognitive Hospital, Liverpool

Alder Hey Children's Hospital is a world-renowned institution and the first to coin the term "cognitive hospital" to imagine the hospital as a living organism with a 'brain' for processing, a 'sensory system' for data collection and a 'heart' to engage with families via an avatar. The cognitive hospital project has a vision to oversee all areas of the hospital, including patient engagement, patient flow, logistics and supply chains, utilising technologies such as the IBM Watson cognitive platform.⁷⁹ Initially, the innovation team launched an app, Alder Play, as a channel to engage with patients and families alongside an AI powered digital assistant called AskOli. As a children's hospital, reducing fear and anxiety and improving patient experience is a central goal. Together, these innovations help to familiarise children and their caregivers with the hospital through 360° tours, guides and interactive games as well as empowering them with knowledge about what to expect during a hospital visit. The system is subsequently able to gather information about questions that matter most to patients and families and identify trends to further personalise and improve their care.

6.1.7.2. Vall d'Hebron Hospital, Barcelona

Vall d'Hebron Barcelona Hospital Campus is a world-leading healthcare complex. In 2016 it decided to undertake the implementation of the Smart Hospital concept in one of the hospital surgery buildings, with 19 operating theatres equipped with state-of-the-art technology distributed across 10,000 m², to carry out highly complex operations. Among other innovations, which include new cutting-edge robotic equipment and asset tracking, the hospital co-created together with MYSPHERA a solution called ORVital that is able to automate the surgical process. It does this by leveraging patient real-time location information and orchestrating the process, engaging surgical staff with tailored applications that provide real-time information and automated tasks as patients move along the surgical process. Similarly, families can monitor the end-to-end process by using an app, which offers them great reassurance. The first-time access to reliable information has revealed logjams and operational problems, while identifying delays in real time leading to finer scheduling. As a result, this revolutionary approach showed an increase of theatre utilisation and surgical activity of more than 10% during the first year of deployment and is still driving further optimisations. Furthermore, the same automated orchestration solution has been integrated with the heat, ventilation and air conditioning system of the hospital, adapting and personalising the climate conditions for each surgical procedure and theatre and, most

importantly, setting the system automatically to “at rest” after each intervention and to “off” at the end of the day and at weekends. This automation has revealed notable energy savings in the surgical wing of around 30%.

6.1.7.3. Sant Joan de Déu Hospital, Barcelona

As part of its continuous innovation strategy, Hospital Sant Joan de Déu started a project, in 2010, called Liquid Hospital (H2O+), with the aim of creating a facility that adapts to the environment and the needs of patients and families by overcoming the physical and structural limitations of the facility. This project coined the term “Liquid Hospital” that was subsequently used by other hospitals and literature. To implement the concept, the hospital worked on making web applications available to patients and families so that they could carry on receiving care at home, which was a radical idea at the time. As a children’s hospital, it was especially important for helping children and their parents confront and reduce feelings of anxiety and worry at home, where possible. As these new digital tentacles were made available, the hospital launched another initiative called CORTEX with the aim of integrating all the data generated by the hospital (i.e. clinical trials, lab-tests, electronic health records) and those generated by patients and families with these new applications and the environment (i.e. social networks). The ultimate goal was to provide higher personalised care and to have the capacity to anticipate potential complications and resource planning. Interestingly, the hospital also adopted the ORVital solution implemented by Vall d’Hebron, which is adding a new level of process automation.

6.1.7.4. The Royal Marsden NHS Foundation Trust, London

The Royal Marsden opened its doors in 1851 as the world’s first hospital devoted to cancer diagnosis, treatment, research and education. Today it operates as a specialist cancer hospital and National Institute for Health Research (NIHR) Biomedical Research Centre for Cancer, working closely with its principal academic partner, the Institute of Cancer Research (ICR). Together the Royal Marsden and the ICR are ranked in the top five cancer centres in the world for the impact of their research, treating over 59,000 NHS and private patients every year. The hospital has embraced the new era of artificial intelligence to promote novel approaches for faster and personalised treatments, such as using Machine Learning algorithms to provide faster diagnosis in patients with Myeloma to improve diagnosis of lung cancer and sarcomas.⁸⁰

As well as being a pioneer of personalised and precision medicine, the hospital has also partnered with IBM Watson to offer its first ever virtual assistant, which will provide key workers immediate access to Covid-19 hospital-related information and policies, as well as updates on hospital and workplace guidance as the country comes out of a series of lockdowns. Therefore, digital transformation in healthcare is not just limited to the clinical environment. Modern technology has incredible potential to change the way a hospital operates for the better and to help revolutionise the care patients receive.

6.1.7.5. The Seattle Children's Hospital, Seattle

Seattle Children's is one of the largest U.S. paediatric health systems in the U.S. and is a world-renowned research and teaching institution. Lean processes, continuous process improvement (CPI), as well as digital innovation, have been part of the DNA of the health system for the last 15 years. Seattle Children's has a long-standing partnership with Autoliv (the Swedish airbag manufacturer at their Ogden, UT plant) to learn how they have applied Lean and CPI to manufacturing. These learned techniques have been applied for the last 10 years to Seattle Children's CPI to break down silos and to remove obstacles and inefficiencies that prevent the health system from providing the highest level of service.

In addition, Seattle Children's has pioneered its move to the cloud with 90 percent of its data centre services in a private cloud versus 10 percent of services in the public cloud (AWS, Azure). Seattle Children's also has a high-performance computing cluster that allows them to provide retrospective and predictive analytics (to HIMSS Analytics stage 7) to overcome capacity and demand management issues, as well as difficulties posed by the current COVID-19 pandemic. Seattle Children's has combined hyperconverged infrastructure with public cloud supported by Nutanix, a global leader in hyperconverged and cloud software, to provide healthcare workers with secure and virtual access to sensitive data anywhere anytime in today's digital world. Seattle Children's digital transformation is built with guidance from and in partnership with a patient and parent advisory council, and is based on easy-to-use apps, digital equity, telehealth, transparent (via OpenNotes) and better patient access to information and services, available anywhere anytime.

6.2. Discussion of the Patient Flow Automation Study

The significant surgical performance improvements obtained in 2018 and 2019 are clear. They are the consequence of a combination of transformations, which were prompted by genuine interest and adequate change in cultural attitude to improve the surgical process. This was part of an overall strategy to optimise the patient pathway using a LEAN approach. Thus, as the hospital was measuring undisputable process times provided by the new solution, this information revealed important opportunities. Specifically, in phase 1, it was revealed that average late starts and theatre downtimes between cases could be improved significantly, especially during surgical session changes, to increase capacity.

As a result, by early 2018 (phase 2), more activity could be scheduled simply by making a better use of the slots in each surgical session. Furthermore, as the optimised and automatised process was launched in phase 2, notable team coordination gains were obtained. “Corridor-shouting” was replaced by straightforward communication between theatres, preparation and recovery areas, porters and cleaners. Casual testimonials from the various stakeholders, including families, suggest an increase of satisfaction as the pathway experience improved. It has been calculated that 5 minutes per operation of nurse-time has been gained by eliminating the manual data entry of activity into the information system. Furthermore, surgical patient journeys have been reduced, on average, by 15-20 as a result of optimised coordination across the process. All in all, the gains in process times and theatre utilisation have allowed an increase in the number of surgical interventions, year after year.

Verbal feedback given by all groups of surgical staff encourages us to think that satisfaction across all staff members has improved significantly. Interestingly, porters are the group who proactively continue to ask for additional features in their smartphone application. It might be that they now feel more engaged, part of the team and recognised as their key role for smooth delivery is now more visible. No problems related to feelings of being spied on have been reported to date. Our impression is that involving all the different stakeholders during the creation of the new apps has helped to integrate different perspectives and needs, and has showed that the change was implemented to support staff, and not to spy on anyone.

Likewise, the feedback given by families is very positive too. Typically, family members would have to waylay health professionals in hospital corridors to find out what was going

on with their loved ones. Now, they can check real time information on the waiting rooms screens and, what's more, they can use the smartphone app at home. As these messages are automated by the platform, messages are delivered as soon as a new status change happens. This system has hardly caused any problems, and in the case that problems occur, personal feedback is always part of the back-up plan. It must be said that professionals have also felt the relief of improving this critical part of the process. As in phase 2, the solution was rolled out on a new site that undertook daily surgery with six theatres. The preliminary results obtained suggest an even greater increase of activity as shorter procedures provide greater opportunity to schedule more operations. A dedicated study for this new site and the covid year will be considered. Although the first attempts to use RTLS technology in the surgery area are emerging, there are no similar developments reported in literature to compare. To our knowledge, this is the first time that the surgical process has been digitalised using this approach. The significant strain that surgery units endure, together with the specialisation of surgical blocks and the idiosyncrasy of each type of surgery, limits the implementation of RCT studies in the same hospital. It is difficult to compare the technology implemented in one block dealing with general surgery with another one, e.g., orthopaedic or daily surgery, that doesn't use the same technology, as operations, times and dynamics are very different. Multi-centric RCT studies in this field are encouraged to overcome these difficulties.

6.3. Discussion of the HVAC Automation Study

Optimising the use of HVAC is relatively straightforward and has a significant impact on energy savings in secondary hospitals in areas with demanding climate conditions. Usually, surgical units tend to be the areas with the highest consumption in a hospital. However, ITU (Intensive Treatment Unit) and A&E are also high energy spenders, and opportunities should be investigated here too.⁸¹

Importantly, the real time factor was key for the fine adjustment of the climate conditions, as this ensured that the operating theatre logic was connected with each patient journey in real time. As these RTLS solutions are increasingly adopted by hospitals, it appears plausible that these kinds of strategies will be implemented in the coming years. Likewise, as RTLS solutions are also expanded to other areas of the hospitals, such as the A&E, outpatients, ITU and more, the same concept could also be implemented in these areas to have a greater impact in the hospital.

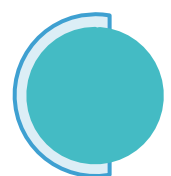
7. CONCLUSIONS



Therefore, the conclusions of this thesis are:

- 1. Cognitive hospital as a new paradigm:** Hospitals are evolving beyond digital and smart concepts toward cognitive systems that can perceive, reason, and act through the integration of IoT, AI, and interoperable data architectures.
- 2. Impact of an intelligent IoT system in surgical settings:** Real-time patient flow automation using RTLS improved theatre utilisation (from 70 % to 82.5 %), reduced delays, and increased surgical capacity, demonstrating measurable operational gains. Digital interventions enable seamless coordination between multidisciplinary teams, reducing manual data entry and improving communication with professionals and patients' families.
- 3. Energy efficiency and sustainability:** Integrating smart building management systems, including automated HVAC, led to significant energy savings in surgical areas (up to 30%), aligning sustainability goals with operational efficiency.
- 4. Extending care beyond hospital walls:** The 'liquid hospital' concept connects hospitals to patients' homes and communities through telehealth and remote monitoring, increasing accessibility and continuity of care.
- 5. Need for systemic interoperability:** Realising the cognitive hospital requires robust data interoperability, governance frameworks, and alignment with regulatory standards to ensure trust, scalability, and clinical impact.

8. FUTURE LINES OF RESEARCH



Building on the findings and technological developments of this thesis, the next step focuses on **connecting cognitive hospitals to a global intelligence layer** through **federated learning**. This strategy enables hospitals to train AI models collaboratively without exchanging sensitive patient data, ensuring privacy and data sovereignty are maintained.

The first line of work is the **creation of the first European and global data space in neurology**, aiming to federate multimodal datasets across leading clinical and research institutions. This federated infrastructure will provide a shared, secure, and interoperable framework to support large-scale research and innovation in neurological and psychiatric diseases.

The second line of research involves the **development of a generative AI layer** on top of this federated data space. This layer will enable the creation of advanced **GenAI research assistants** capable of supporting researchers in tasks such as hypothesis generation, patient stratification, early diagnosis, and personalised treatment design. These assistants will act as intelligent collaborators, leveraging the collective knowledge embedded in distributed hospital networks.

Ultimately, these efforts aim to **transform the cognitive hospital from a local intelligent system into a node of a global, federated brain health intelligence network**, enabling more equitable access to cutting-edge AI capabilities and accelerating discovery in neurology and related fields.

In line with this vision, the research team has submitted the **Horizon Europe proposal NeuroGenAI**, a large-scale international initiative led by Vall d'Hebron, which seeks to make this vision a reality at the European level.

9. BIBLIOGRAPHY

1. Dobrzykowski D, Tarafdar M. Understanding information exchange in healthcare operations: Evidence from hospitals and patients. *Journal of Operations Management* 2015;36:201–14.
2. Sood HS, McNeil K. How is health information technology changing the way we deliver NHS hospital care? *FHJ* 2017;4:117–20.
3. Bolhasania M, Mohsenib M, Rahmanic AM. Deep learning application for IoT in health care: A systematic review. *Informatics in Medicine Unlocked* 2021;23:100550.
4. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. *FHJ* 2019;6:94–8.
5. Lopes J, Guimarães T, Santos M F. Predictive and Prescriptive Analytics in Healthcare: A Survey. *Procedia Computer Science* 2020;170:1029–34.
6. Tennison I, Roschnik S, Ashby B, et al. Health care's response to climate change: a carbon footprint assessment of the NHS in England. *Lancet Planetary Health* 2021;5:e84–92.
7. Guinard PF. Building a smart hospital using RFID technologies. In: Stormer H, Meier A, Schumacher M. (Eds), *European Conference on eHealth. Gesellschaft für Informatik*, 2006:S131–42.
8. Sutherland J, Heuvel W. Towards an intelligent hospital environment: adaptive workflow in the OR of the future. *HICSS'06* 2006:100b.
9. Ioppolo G, Vazquez F, Hennerici MG, et al. Medicine 4.0: new technologies as tools for a society 5.0. *J Clin Med* 2020;9:2198.
10. Pacione G, Vollaro G. The 'smart hospital': the role of technological structures. *J Clin Computing* 1988;17:17–22.
11. Sakuma S, Ishigaki T, Ikeda M. The goal of PACS in Nagoya University Hospital. *Comput Methods Programs Biomed* 1991;36:143–6.
12. Kondoh H, Ikezoe J, Mori Y, et al. PACS in Osaka University Hospital; *Computer Methods and Programs in Biomedicine*. *Comput Methods Programs Biomed* 1994;43:57–63.
13. Beadle H, Maguire G, Smith M. Using location and environment awareness in mobile communications. *Proceedings of ICICS, International Conference on Information, Communications and Signal Processing* 1997;3:1781–5.
14. Fairus H. Intelligent hospital: patient smart card. *Universiti Teknologi Petronas*, 2004; Final Year Project.
15. Fuhrer P, Guinard D. Building a Smart Hospital using RFID technologies: Use Cases and Implementation. *ECEH06* 2006.

16. Kataria P, Juric R, Paurobally S, Madani K. Implementation of Ontology for Intelligent Hospital Wards. *HICSS'08* 2008:253.
17. Gomez-Sacristan A, Rodriguez-Hernandez MA, Sempere V. Evaluation of quality of service in smart-hospital communications. *Journal of Medical Imaging and Health Informatics* 2015;5:1864–9.
18. Frisch P. What Is an Intelligent Hospital? A place where technology and design converge to enhance patient care. *IEEE Pulse J* 2014;5:10–5.
19. Uslu B Ç, Okay E, Dursun E. Analysis of factors affecting IoT-based smart hospital design. *J Cloud Comp* 2020;9:67.
20. Tanner R. A low energy green hospital. *Health Estate J* 1997;51:2,4,6–8.
21. Beadle H, Maguire G, Smith M. Using location and environment awareness in mobile communications. *Proceedings of ICICS, International Conference on Information, Communications and Signal Processing* 1997;3:1781–5.
22. Germain S. The ecological footprint of Lions Gate Hospital. *Hosp Q Winter* 2001–2002;5:61–6.
23. Grazier K. Interview with David P Gehant, FACHE, President and Chief Executive Officer, Boulder Community Hospital. *Journal of Healthcare Management* 2009;54:287–90.
24. Sharma RL, Singh A. Smart energy technologies and building architecture: An overview. *International Journal of Civil Engineering and Technology (IJCIET)* 2019;10:473–84.
25. Breukelaar J. The European Green Deal: opportunities and challenges. *JBDG EFCC*, 2019.
26. Curnow J. Environmental economics in UK environmental policy: Defra's 25 Year Environment Plan. *Journal of Environmental Economics and Policy* 2019;8:353–8.
27. Benzidia S, Makaoui N, Bentahar O. The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change* 2021;165:120557.
28. Aagaard A, Lindgren P. The opportunities and challenges of persuasive technology in creating sustainable innovation and business model innovation. *Wireless Pers Commun* 2015;81:1511–29.
29. Bauman Z. *Liquid modernity*. Wiley, 2013.
30. Rovira-Simón J, Sales-I-Coll M, Pozo-Rosich P, et al. Introduction to the cognitive hospital. *Future Healthc J*. 2022 Mar;9(1):34-40.
31. Chunyan Li, Jiaji Wang, Shuihua Wang, Yudong Zhang, A review of IoT applications in

healthcare, Neurocomputing, Volume 565, 2024, 127017, ISSN 0925-2312.

32. de Mello BH, Rigo SJ, da Costa CA, et al. Semantic interoperability in health records standards: a systematic literature review. *Health Technol (Berl)*. 2022;12(2):255-272.
33. Xie Y, Zhai Y, Lu G. Evolution of artificial intelligence in healthcare: a 30-year bibliometric study. *Front Med (Lausanne)*. 2025 Jan 15;11:1505692.
34. Laxmi Shaw, Hardik A. Gohel, Role of artificial intelligence in health monitoring using IoT based wearable sensors: A survey, *Internet of Things*, Volume 34, 2025, 101761.
35. van Kolfschooten H, van Oirschot J. The EU Artificial Intelligence Act (2024): Implications for healthcare. *Health Policy*. 2024;149:105152.
36. Li C, et al. *A review of IoT applications in healthcare*. *Comput Methods Programs Biomed*. 2024;234:107497.
37. Manso M, García A, et al. *A Survey About Real-Time Location Systems in Healthcare Environments*. *Comput Med Imaging Graph*. 2019;75:101621.
38. Arumugam GRM, et al. *A Survey on Sensors and Smart Devices for IoT Enabled Intelligent Health-care Systems*. *SN Appl Sci*. 2023;5:253.
39. Attiq Ur Rehman, Songfeng Lu, et al. *Internet of Things in Healthcare Research: Trends, Innovations, Security Considerations, Challenges and Future Strategy*. *International Journal of Intelligent Systems*, Wiley, 2025, 8546245, 53 pages.
40. Carrascal L, Gonzalez J, et al. D4.2 Implementation of Local CPS-IoT RSM. *Odin Smart Hospital H2020 project*, 2022.
41. Chinchilla-Romero L, Prados-Garzon J, Ameigeiras P, Muñoz P, Lopez-Soler JM. 5G Infrastructure Network Slicing: E2E Mean Delay Model and Effectiveness Assessment to Reduce Downtimes in Industry 4.0. *Sensors (Basel)*. 2021 Dec 29;22(1):229.
42. Alowais, S.A., Alghamdi, S.S., Alsuhebany, N. *et al*. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Med Educ* **23**, 689 (2023).
43. Aggarwal, R., Sounderajah, V., Martin, G. et al. Diagnostic accuracy of deep learning in medical imaging: a systematic review and meta-analysis. *npj Digit. Med*. 4, 65 (2021).
44. Raza, M.M., Venkatesh, K.P. & Kvedar, J.C. Generative AI and large language models in health care: pathways to implementation. *npj Digit. Med*. **7**, 62 (2024). <https://doi.org/10.1038/s41746-023-00988-4>

45. ABENDROTH DIAS, K., ARIAS CABARCOS, P., BACCO, F.M., et al., Generative AI Outlook Report - Exploring the Intersection of Technology, Society and Policy, Publications Office of the European Union, Luxembourg, 2025.
46. Osama Almurshed, Ashish Kaushal, et al. Enhancing performance of machine learning tasks on edge-cloud infrastructures: A cross-domain Internet of Things based framework, *Future Generation Computer Systems*, Volume 166, 2025, 107696.
47. Jandoubi B, et al. Multimodal Artificial Intelligence in Medical Diagnostics. *Information*. 2025;16(7):591
48. Liu L, Yuan P, Wang X. Predictive models and therapeutic strategies for breast cancer. *Cancer Pathog Ther*. 2024 Jul 1;3(2):85-86. doi: 10.1016/j.cpt.2024.06.008.
49. Rovira-Simón J, Sales-I-Coll M, Pozo-Rosich P, et al. Surgical block 4.0: a digital intervention based on a real-time location patient-flow solution to support the automation of surgical pathways. *Future Healthc J*. 2022 Jul;9(2):194-199.
50. Rovira-Simon J, Sales-I-Coll M, Pozo-Rosich P, et al. The Green Surgical Block 4.0: Automation of the operating theatre's climate conditions through a real-time patient-flow solution. *Future Healthc J*. 2023 Mar;10(1):46-49.
51. Al-Jaroodi J, Mohamed N, Abukhousa E. Health 4.0: On the Way to Realizing the Healthcare of the Future. *IEEE Access*. 2020 Nov 18;8:211189-211210.
52. Han Wang, Kumar Ankur Anurag, Amira Rayane et al. HealthAloT: AloT-driven smart healthcare system for sustainable cloud computing environments, *Internet of Things*, Volume 31, 2025, 101555.
53. Nouis SC, Uren V, Jariwala S. Evaluating accountability, transparency, and bias in AI-assisted healthcare decision- making: a qualitative study of healthcare professionals' perspectives in the UK. *BMC Med Ethics*. 2025 Jul 8;26(1):89.
54. Vladu A, Ghitea TC, Daina LG, Țîrț DP, Daina MD. Enhancing Operating Room Efficiency: The Impact of Computational Algorithms on Surgical Scheduling and Team Dynamics. *Healthcare (Basel)*. 2024 Sep 24;12(19):1906.
55. Wu, Rui. The carbon footprint of the Chinese health-care system: an environmentally extended input–output and structural path analysis study. *The Lancet Planetary Health*, Volume 3, Issue 10, e413 - e419.
56. Chirarattananona S, Chaiwiwatworakula P, Hiena VD. Assessment of energy savings from the revised building energy code of Thailand. *Energy* 2010;35:1741–53.
57. Tekea A, Timur O. Assessing the energy efficiency improvement potentials of HVAC systems considering economic and environmental aspects at the hospitals. *Renew Sust Energ Rev* 2014;33:224–35

58. Schoenmakers I, Zeiler W, Boxem G. KPI's energy consumption of isolation rooms in hospitals. CLIMA REHVA World Congress, 2016.
59. Green Investment Bank . A healthy saving: energy efficiency and the NHS. Green Investment Group, 2014.
60. Zarzycka A, Maassen WH, Zeiler W. Energy saving opportunities in operating theatres: a literature study. Federation of European Heating, Ventilation and Air Conditioning Associations, 2019
61. Mazhar T, Khan S, Shahzad T, Amir Khan M, Saeed MM, Awotunde JB, et al. Generative AI, IoT, and blockchain in healthcare: application, issues, and solutions. *Health Services & Outcomes Research Methodology*. 2025;5(1):5.
62. Balch JA, Ruppert MM, Shickel B, et al. Building an automated, machine learning-enabled platform for predicting post-operative complications. *Physiol Meas*. 2023 Feb 9;44(2):024001.
63. Abid Haleem, Mohd Javaid. Role of cognitive computing in enhancing innovative healthcare solutions, *Advances in Biomarker Sciences and Technology*, Volume 6, 2024, Pages 152-165.
64. Teo ZL, Jin L, Li S, Miao et al. Federated machine learning in healthcare: A systematic review on clinical applications and technical architecture. *Cell Rep Med*. 2024 Feb 20;5(2):101419.
65. Dragana Paparova, Margunn Aanestad, Polyxeni Vassilakopoulou, et al. Data governance spaces: The case of a national digital service for personal health data, *Information and Organization*, Volume 33, Issue 1, 2023,100451.
66. https://health.ec.europa.eu/ehealth-digital-health-and-care/european-health-data-space-regulation-ehds_en
67. Bhuyan SS, Sateesh V, Mukul N, et al. Generative Artificial Intelligence Use in Healthcare: Opportunities for Clinical Excellence and Administrative Efficiency. *J Med Syst*. 2025 Jan 16;49(1):10.
68. Anil Palepu, Valentin Liévin, Wei-Hung Weng et al. Towards Conversational AI for Disease Management. 2025 arXiv:2503.06074
69. https://health.ec.europa.eu/ehealth-digital-health-and-care/artificial-intelligence-healthcare_en
70. <https://www.ebrains.eu/>
71. Baars BJ, Gage NM. Cognition, brain, and consciousness: Introduction to cognitive neuroscience. Elsevier, 2010.
72. Brack K E. The heart's 'little brain' controlling cardiac function in the rabbit. *Experimental Physiology Journal* 2015; Volume 100, Issue 4, Pages 348-353.

73. Budelmann B U. The cephalopod nervous system: What evolution has made of the molluscan design. *The Nervous Systems of Invertebrates: An Evolutionary and Comparative Approach* 1995; Experientia Supplementum, vol 72. Birkhäuser Basel.
74. Alia C, Spalletti C, Lai S *et al.* Neuroplastic Changes Following Brain Ischemia and their Contribution to Stroke Recovery: Novel Approaches in Neurorehabilitation. *Front Cell Neurosci J.* 2017; 11: 76
75. Koutkias V. From Data Silos to Standardized, Linked, and FAIR Data for Pharmacovigilance: Current Advances and Challenges with Observational Healthcare Data. *Drug Saf* 2019; 42, 583–586.
76. Mialhe N, Hodes C. The Third Age of Artificial Intelligence. *Artificial Intelligence and Robotics in the City 2017*; Special Issue 17.
77. Eden A H, Moor J H, Soraker, J.H *et al.* Singularity hypotheses: A Scientific and Philosophical Assessment. *Springer Computational Intelligence and Complexity* 2012.
78. Pettit L. Understanding EMRAM and how it can be used by policy-makers, hospital CIOs and their IT teams. *World Hospitals and Health Services* 2013;49:7–9.
79. Armstrong S. Alder Hey’s “cognitive hospital” aims to turn NHS use of AI on its head; *BMJ* 2018; 362.
80. Blackledge M D, Winfield J M, Miah A *et al.* Supervised Machine-Learning Enables Segmentation and Evaluation of Heterogeneous Post-treatment Changes in Multi-Parametric MRI of Soft-Tissue Sarcoma. *Frontiers in Oncology* 2019; volume 9.
81. Schoenmakers I, Zeiler W, Boxem G. KPI's energy consumption of isolation rooms in hospitals. CLIMA REHVA World Congress, 2016.

10. ANNEXES

10.1. Study Formulas

Variables	Long description	Formula and parameters	How it was measured	Example
Theatre utilisation (TU)	This is the time a theatre is busy with a patient out of the total time available in the surgical session (in the case of Vall d'Hebron: 8:30 am to 3pm).	$TU = \sum_1^{N \text{ Theatres}} \frac{ttwp}{ttss}$ <i>ttwp = time theatre with patient</i> <i>ttss = total time surgical session</i> To build the overall TU of the surgical block, the average TU for all the surgical sessions in that year have to be aggregated.	Theatre time with patient / Theatre time per surgical shift	3 surgical interventions of 1.5 hours in a shift from 8:30h to 15h would be = $3 \times 1,5 \times 60 \text{min} / 6,5 \times 60 \text{min} = 270 / 390 = 69,23\%$
Late starts (LS)	Delays at the start are those situations in which the time the surgery starts is later than the time agreed by the surgical committee (usually 8:30 am in the morning and 3:30 pm in the afternoon when there is no continuous surgery). The minutes of delay with respect to the scheduled time are counted.	1) $LS_1 = \frac{dd}{nwd}$ <i>dd = days with delay</i> <i>nwd = number of working days</i> 2) $LS_2 = \frac{\sum ddm}{nwd}$ <i>ddm = days with delays in minutes in each theatre</i> <i>nwd = number working days</i>	Two indicators: 1) % delay days with respect to the total. 1) In order to measure how much delay, we have in the surgical block the RTLS solution indicates when the patient enters the operating theatre and when the start of surgery is marked. The indicator is per day and operating theatre (yes/no), and the objective is 0 delays in the start. The result is given in % according to the number of days	1) 22 days of activity with 18 delays = 81.81%. 2) in day 1, a surgical block with 8 theatres started 35 minutes late on average. In day 2, average late start across the 8 theatres was 25 minutes. After two days of work, the average late start = $35 + 25 / 2 = 30$ minutes.

			of opening of the operating theatre. 2) average delay in minutes per operating theatre or surgical block. Average number of minutes of delay per day, and average number of minutes over total days worked.	
Early finishes	Early finishes. When the programmed surgical activity ends at a time that would still allow a new surgical intervention to be performed	$EF = \sum \frac{dfot}{nwd}$ <i>dfot = days finished out of time</i> <i>nwd = number working days</i>	To measure how many early finishes in the surgical block, the RTLS solution indicates when the last scheduled patient leaves the operating theatre during the shift. The indicator is per day and operating theatre (yes/no) and the objective is that the last patient in the morning shift finishes the operation between 14:00 and 15:00, or between 20:00 and 21:00 for the afternoon shift. The objective is 0 early finishes.	22 days of activity with 11 days of sessions ending before target times
Turnaround time (TAT)	TAT was defined as the interval in minutes between the end of surgical dressing and knife-to-skin time for the subsequent patient, i.e., time during which no	$TAT = \frac{\sum twns}{npss - 1}$ <i>twns = time with no surgery</i>	Time between surgeries has to be added up and the result divided by the number of patients in that surgical session minus 1.	If we have 3 scheduled patients and the times between surgeries are 25 minutes and 35 minutes, the TAT percentage would be: (25 + 35) / (3 patients -1) = 60/2 = 30 min.

	surgery is taking place	$npss = \text{number of patients surgical session}$ The overall surgical block TAT is the aggregation of all the values for each theatre.	The RTLS system made it possible to record these events automatically by capturing the interactions with the applications.	
Turnover time (TOT)	TOT was defined as the interval in minutes between the patient's departure from the operating theatre and the arrival of the subsequent patient in the operating theatre.	$TOT = \frac{\sum tet}{npss - 1}$ $tnpit = \text{time empty theatre with no patient}$ $tpd = \text{time patient departure}$ The overall surgical block TOT is the aggregation of all the values for each theatre.	The time in which no patient was in the operating theatre was automatically recorded by the RTLS system by subtracting the time the new patient enters the operating theatre by the time the previous patient left it.	If we have 3 scheduled patients and the times of empty theatre are 15 and 25 minutes, $TOU = (15 + 25) / (3 \text{ patients} - 1) = 20 \text{ min}$.
Downtime between cases (DBC)	Inactive time once the operating theatre has been cleared of the first patient until the next patient arrives.	$DBC = TOT - ct$ $ct = \text{Average cleaning time was 12 min}$	DBC= TOT – cleaning time	If the TOT is 25 min and the cleaning time is 12 minutes, the DBC is 13 min.
Surgical activity	Number of operations	$SA = \sum_1^{nwdy} ndo$ $nwdy = \text{number working days year}$ $ndo = \text{number daily operations}$	Number of operations carried out in a year.	9200 operations were carried out in 2019.

Cancellations on the day	Number of surgical interventions scheduled for the day that have had to be cancelled or rescheduled for various reasons	$COD = \frac{\sum nc}{noss}$ <i>nc = number of cancellations</i> <i>noss = number operations in surgical sessions</i>	No. of cancellations or rescheduling of patients compared to total number of scheduled patients (%)	If there are 10 programmed operations in a day and 5 have been reprogrammed, then COD = 50%.
Economic gains	Two indicators. 1) Extra turnover due to increased activity due to the time recovered by process improvements + cost reductions. 2) Average gain of 9.750€ per each 1% of improvement of theatre utilization below the optimal 85%.	$EG_1 = \frac{ta - tp}{tp}$ $EG_2 = agtm \cdot nt \cdot nmy$ <i>agtm = average gain per theatre month,</i> <i>nt = number of theatres</i> <i>nmy = number months year</i>	1) Achieved turnover at the end of the year / forecast turnover at the beginning of the year (%) (according to fixed and variable costs of the surgical activity). 2) According to HIMSS, per each 1% of improvement of theatre utilization below the optimal utilisation of 85%, there is an average gain per month of €9,750.	1) If turnover achieved is 100 M€ and the planned turnover was 95M€, the economic gain is 5M€, EG = 5.26%. 2) If theatre utilisation has been improved 10% in a year in 14 theatres, then $EG_2 = 10 \times 14 \text{ theatres} \times €9,750 = €1,365,000$.

Table 8 - Study formulas

Table 5 - Extended information about measured endpoints

