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Enhancing Space Management through Digital Twin: A Case Study of the Lazio Region Headquarters

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Abstract: Digital Twin is becoming an increasingly powerful resource in the field of building production, replacing traditional processes in the Architecture, Engineering, Construction and Operations sector. This study is concerned with the development of a DT, enabled by Building Information Modeling, artificial intelligence, machine learning, and the Internet of Things to implement space management strategies. It proposes an application case for the Lazio Region headquarters, which has partly adopted smart working typology post-COVID-19. The aim is to create an accurate digital replica of the building based on BIM, integrated with real-time data. This will help to improve the use of space, the management of resources, and the quality of services provided to the community. It also improves energy efficiency, reducing consumption by 530.40 MWh per year and reducing greenhouse gas emissions by 641.32 tons of CO_2 per year. The research proposes a holistic framework for the implementation of innovative solutions in the context of public infrastructure space management through the use of digital technology, facilitating the promotion of efficiency and sustainability in decision-making and operational processes through the application of a digital methodology.

Keywords: digital twin; Internet of Things; BIM; artificial intelligence; machine learning; space management

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1. Introduction

In the era of digital innovation, with the increasing need to adapt to the changing dynamics of building production, Digital Twin (DT) is becoming a critically important resource [1]. DT has achieved remarkable attention and is being increasingly adopted in a wide range of sectors, including manufacturing, energy, transport, healthcare, and others [2,3]. By definition, a DT is a digital representation of a physical object, system, or process that is updated in real time with data from the corresponding physical object. This enables detailed monitoring and simulation of the operation and performance of the physical object, which is essential for optimizing the design and operation of complex systems [4]. In the Architecture, Engineering, Construction and Operations (AECO) sector, the adoption of DT is slower than in other sectors [5,6]. This delay can be attributed to several factors peculiar to this sector that have made the implementation of innovation more challenging. Firstly, the complexity and diversity of construction projects means that they are perceived as singularities and, as such, require a tailored approach to the adoption of digital systems. Each project may present unique characteristics, including the type of building and the geography of the location. This makes it challenging to establish general standardization. Furthermore, the construction industry is characterized by considerable fragmentation, with multiple actors involved at different levels of the design, construction, and management process, making the coordination and sharing of data necessary for the effective implementation of shared data environments more complex [7]. Practitioners have been using traditional methods and tools for years and may be reluctant to adopt new technologies and processes, leading to widespread resistance to change in the sector. To overcome these challenges and enable the AECO sector to take full advantage of innovative digital technologies, targeted actions are needed, such as the standardization of data formats and communication protocols, which is essential to ensure that the different systems and software used in the industry can interoperate efficiently [8,9]; the training of personnel, which is crucial to ensure that insiders are able to make the best use of new technologies and fully understand the potential of new intelligent systems; and the development of collaborative business models and processes that encourage data sharing and collaboration between all actors involved in the lifecycle of a construction project.

1.1. Advanced Digital Technologies

In this transition scenario, digital systems play a key role in optimizing the management of the built environment, including via Building Information Modelling (BIM), which offers advanced solutions for the design, construction, and management of buildings and infrastructure [10–13]. BIM has revolutionized the traditional approach to design and construction, enabling better integration and collaboration between the actors involved in the lifecycle of a construction project [14]. Its integration with DT represents the most advanced frontier in the management of the built environment [15]. By creating an accurate digital replica of a building, integrated with real-time data provided by IoT devices, DT offers enormous potential for optimizing space utilization, improving energy efficiency, and ensuring more effective resource management [16]. These devices mainly act as sensors to collect information from the physical environment, or as actuators to control objects (Figure 1).

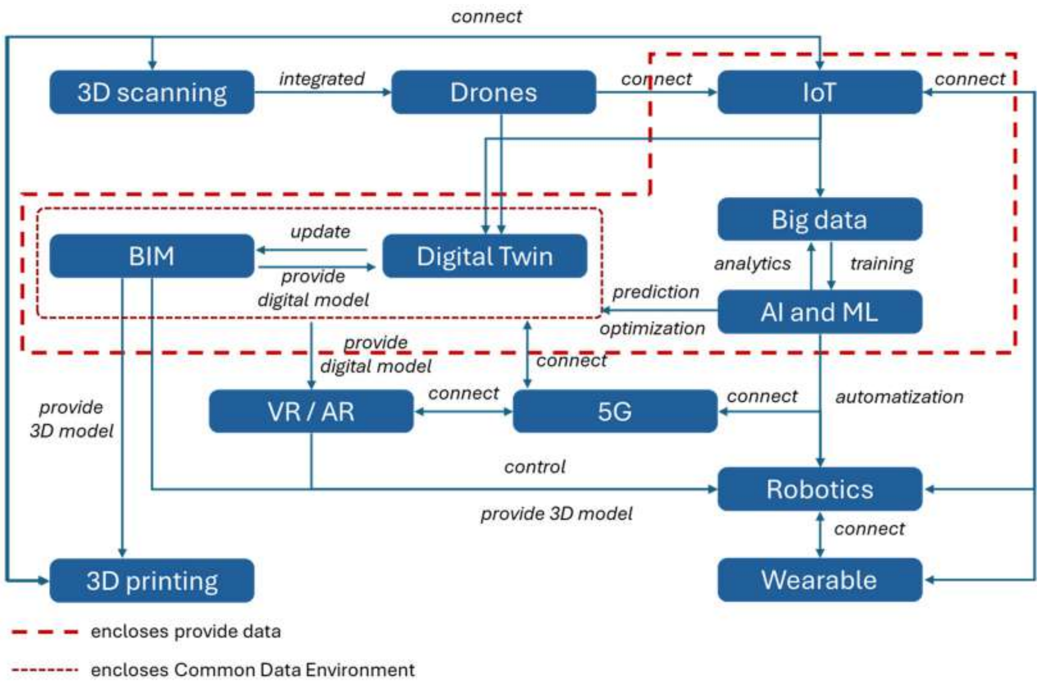


Figure 1. Integration overview of interconnected technologies in smart infrastructure environment.

Cubides et al. examine the potential for improving the energy efficiency of European buildings constructed prior to 2001 through the application of DT technology. They investigate the use of DT in building operations and maintenance, with a particular emphasis on enhancing energy efficiency. A total of 21 case studies were selected for analysis, comprising six DT business solutions. The results revealed five main applications: component monitoring, fault detection, operational optimization, predictive maintenance, and the simulation of alternative scenarios. The findings also highlighted the dependence on BIM and the need for robust data-acquisition systems, which complicate the implementation of DTs in existing buildings. Blut et al. discuss managing building energy systems with a sustainable approach amid climate change. They present a DT toolchain using BIM and extended-reality (VR and AR) technologies. This toolchain creates georeferenced DTs when commissioning TBEs. A scan vs. BIM comparison process identifies discrepancies between the planned and actual construction, allowing automatic updates of the BIM model. Validation methods ensure TBEs are accurate. VR and AR help with commissioning, providing visualization and sensor data. Evaluations show the toolchain is scalable and efficient. Future work aims to integrate more operational data, enhancing DTs' capabilities for managing building energy systems [17].

Among the most commonly employed sensing devices are passive infrared (PIR) sensors, which are electronic devices that detect infrared radiation emitted by objects within their field of view [18]. The advantages of PIR sensors include their low cost, low power consumption, and the ability to interface with various devices while ensuring complete privacy. Wu et al. develop a new approach to improve occupancy detection in buildings. Using passive infrared PIR sensors and smart meters, combined with a convolutional neural network (CNN) model, they analyzed temporal data to increase the accuracy of occupancy detection. A case study in a university office showed that this new model outperformed traditional models, improving accuracy by 26.8%. The model was used to optimize the management of the outdoor air system, improving environmental comfort and saving energy [19]. Futagami examines the effectiveness of image-based sensors for lighting control in relation to passive infrared (PIR) sensors, which monitor changes in infrared radiation caused by occupant movement. A combined approach using both PIR and image-based sensors was evaluated. An experiment in an office showed that the combined sensor reduces overall energy consumption by at least 3.59% compared to the use of single sensors [20]. Additionally, there are humidity sensors that record and track humidity levels in rooms, or even LED lamps that are controlled by ambient light conditions, thereby reducing energy consumption [21–24]. The use of these technologies, which facilitate the development of intelligent environments via their integration with sophisticated digital management systems, enables a lifestyle upgrade in terms of comfort, while concomitantly reducing energy consumption and supporting environmental protection [25].

Based on recent trends, the adoption of these technologies will continue to grow, driving innovation and radically changing the way buildings and infrastructure are designed, built, and operated (Figure 2) [26].

Figure 2. Trends for specific search terms on Google since 2010 (Google Trends).

IoT plays a crucial role in building production, from energy optimization to SM. This technology is helping to develop a range of applications from real-time monitoring to the advanced predictive maintenance of buildings and energy systems, and the intelligent management of electricity grids [27]. Sensors distributed throughout various equipment systems serving a facility can continuously monitor operating conditions and detect anomalies or malfunctions in a timely manner [28]. The collected data are transmitted to a central system that uses artificial intelligence algorithms to analyze patterns and predict potential failures, enabling timely preventive maintenance interventions. In addition, IoT facilitates the improvement of energy distribution through smart grids, enabling a more efficient management of energy supply and demand [29,30]. Connected devices can monitor energy supply and demand in real time and automatically adjust distribution to avoid overloads or blackouts [31,32]. Consumers can be equipped with smart IoT devices, such as thermostats or smart meters, to actively manage their energy consumption based on energy prices or grid conditions. The IoT collects data to analyze building energy consumption and grid performance, allowing the control system to identify patterns and trends to enhance the overall performance of the energy system, contributing significantly to the digital and energy transition towards a more sustainable future and addressing key challenges such as climate change and grid security [33]. The adoption of AI and big data is significantly transforming the global business landscape, leading to significant increases in corporate revenues and 15–20% more employment opportunities compared to competitors that do not adopt these technologies [34,35]. This increase can be attributed to AI's ability to optimize business processes, improve the customer experience, and enable more informed and timely decisions [36]. The implementation of big data allows companies to analyze huge amounts of data in real time, identifying patterns and trends that improve demand forecasting, inventory management, and tailored marketing strategies. Furthermore, AI enables the automation of repetitive tasks and the customization of products and services, increasing operational efficiency and reducing costs [37].

DT platforms can improve and adapt using data collected from installed sensors, enabling the real-time monitoring of environmental conditions and proactive management [38]. First, BIM models of the physical environment are created to develop DT platforms, and then physical data are integrated to create a direct link to the real environment and enable continuous monitoring. In this way, DT platforms become the focal point for the management and control of physical environmental conditions.

This revolutionary paradigm is now more relevant than ever for the progressive and prudent management of physical spaces and the built environment in general in the context of post-pandemic economic recovery and the resulting societal changes from this event; the adoption of innovative solutions such as DT is imperative to address the growing need to upgrade processes in the AECO sector. The pandemic has accelerated the digitization of processes and highlighted the importance of advanced technology solutions to ensure efficiency, sustainability, and resilience. By allowing the accurate digital replication of buildings and infrastructure, DT enables more effective and predictive management, reducing operational costs and improving the quality of services offered. This makes DT a crucial tool to meet the challenges of the post-pandemic recovery era and to promote sustainable and integrated innovation in the AECO sector (Figure 3).

The objective of the research is to develop an advanced digital strategy to optimize the management of corporate spaces, thereby improving operational efficiency, reducing costs, and minimizing environmental impact. The proposed approach employs IoT sensors to assess employee presence or workstation activation and uses innovative machine learning (ML) technologies to automate and refine building management. In this way, building managers can operate with greater awareness and efficiency, thanks to access to timely data and reliable forecasts. This allows them to make more informed decisions on space utilization and resource management. The novelty aspect of this research is the potential for developing a digital system that can autonomously manage an office building, from targeted air conditioning to access at workstations, based on user reservation data and sensor data. The aforementioned data are then processed and managed by an ML-based system, which will be discussed in greater detail in the following sections. Once trained, this system is capable of functioning autonomously.

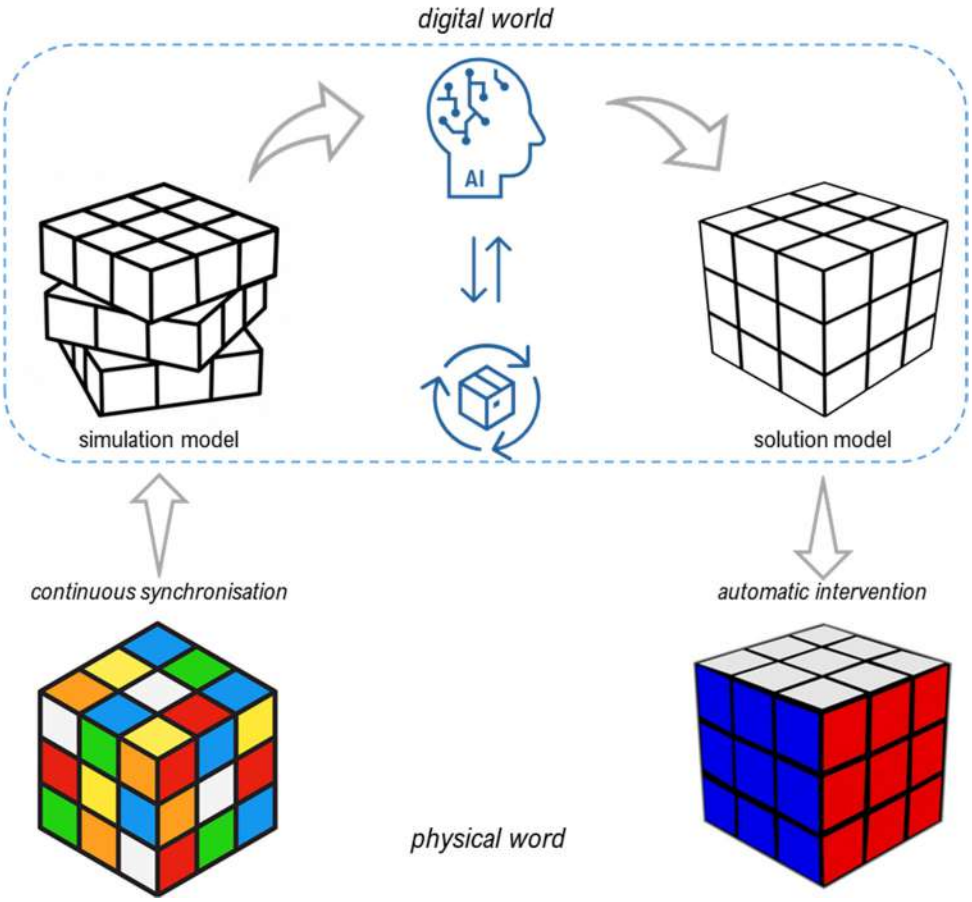


Figure 3. Exploring the DT concept in AI-driven simulation and problem solving.

1.2. Space Management in Smart Working Adoption

The fundamental tenet of the organizational model centered on smart working (SW) is that employees are capable of independently determining the manner, location, and temporal parameters of their work. Conversely, the company must identify processes within its organizational structure that align delegation, control, and evaluation with traditional managerial models. The global pandemic compelled Italy and numerous other nations to implement mandatory SW. At that time, 94% of public administration employees became smart workers. Of these, almost all had never previously experienced this type of work [39]. The sudden imposition of this type of work, as evidenced in countries such as Italy, has highlighted a number of challenges, including a lack of technological resilience and the need to invest in both hardware and software infrastructures, as well as in the global training of employees in each productive sector. The swift implementation of this mode of work has exacerbated the issue of cybersecurity and the lack of prevention of cyber attacks. A study conducted by the International Data Corporation revealed that 31% of the companies surveyed had experienced cyber security incidents caused by the new way of working and that 52% of the same companies lacked a formal policy regulating the use of SW [40].

One of the main benefits for businesses is the possibility of reducing certain costs, such as cleaning services, lighting, and heating. The most important figure is the increase in productivity, understood as the professional efficiency of employees, by around 20% [41]. This increase is attributed to the increased incentive for employees to reduce their time and money spent, which improves work–life balance [42]. In the aftermath of the pandemic, some companies returned to traditional ways of working, while others continued to use smart working, trying to achieve a favorable balance for employees as well. In the case of the Lazio Region, the employees who have their workplace in the building under study were given a 50% SW level, with the possibility to choose when to practice it through a shared cloud platform for business planning, which will be discussed in the next section. This adaptation led to several considerations on the part of the company, especially in terms of Facility Management (FM) [6,43], resulting in the analysis of the work environment to verify the suitability of sharing space among employees. The evolution of work environments from the traditional tailor-made office approach to the innovative smart workplace concept represents a change in the context of office space organization. The tailor-made office concept has historically been characterized by a static division of space, reflecting organizational hierarchies and specific roles within the company [44]. This model was based on the permanent allocation of space according to hierarchical positions and work requirements. The emergence of digital technologies and changes in working patterns have revolutionized this approach, leading to the spread of the intelligent workplace [45]. The latter implies a dynamic and flexible organization in which workspaces are adapted to be multifunctional and accessible according to the contingent needs of users. This model favors flexibility and the optimization of resources, allowing a more efficient distribution of workspaces [46]. The adoption of SW implies the decentralization of work activities, allowing employees to work remotely, reducing the need for daily travel and the intensive use of energy resources in physical workspaces.

Office buildings may become smaller as a higher percentage of employees are able to work remotely. Office space will need to be redesigned to meet the new needs of a hybrid workforce. As employees do more individual work at home, traditional offices will need to provide workspaces for meetings and collaboration. Companies will need to increase connectivity and improve the overall office experience with a medium-to-long-term plan for a new way of managing resources. Many office buildings are virtually empty, others are used only occasionally, and some are occupied on a daily basis but have low occupancy. Workspaces as they are understood today will not disappear completely, but they will certainly change. Business leaders need to invest in technology to make buildings smart and to create smart offices for their employees, while keeping pace with a new and evolving business model. In a context where intellectual work no longer requires going to the office every day of the week and having a desk, spaces can be reconfigured and downsized to take on new functions and purposes. In fact, SM and redesigning the functionality of spaces is one of the most important disciplines for Facility Management today. In the context of smart buildings, there are many opportunities to rethink the use of space thanks to technology, which allows facility managers to easily gather data and information about the needs and habits of the company's population, and to reorganize space according to the increasingly flexible needs of the company and its people. Hybrid working is therefore a way of working that allows employees to be present on company premises or to work remotely (from anywhere with an Internet connection) using a range of devices and methods that allow secure access to company servers.

Furthermore, in light of the EU's targets promoting an increased awareness of environmental sustainability and the necessity to adapt to socio-economic changes, SW appears to be an effective solution for reducing the business expenses and CO_2 emissions associated with traditional ways of working. The Energy Performance of Buildings Directive (EPBD) is an EU initiative with the objective of upgrading the EU building stock and improving its energy efficiency. The main objective of the directive is to prioritize action on the 15% of buildings with the highest energy consumption per member state that currently fall into energy class G, the lowest [41]. By 31 December 2024, non-residential buildings with an effective rated output of more than 290 kW for heating, air conditioning, combined heating and ventilation systems, or combined air conditioning and ventilation systems will be required to be equipped with automation and control systems [45]. Such automation systems must be capable of the continuous monitoring, recording, analysis, and adaptation of the building's energy use. Furthermore, they must be capable of comparing the energy efficiency of buildings, detecting inefficiencies in technical building systems, and promptly notifying the individual responsible for the building's facilities or the technical management of potential avenues for enhancing energy efficiency. These features are reflected in building a DT based on a BIM model, implemented by IoT devices for data collection and an AI system for automation management. This research project aims to explore the potential for reducing expenditure and CO_2 emissions in the workplace through the adoption of SW. In particular, it will examine the benefits of reducing energy consumption for heating in offices and other related practices, presenting a digital SM methodology for the intelligent management of workspaces in buildings.

It is evident that buildings account for a considerable proportion of energy consumption and greenhouse gas emissions within the European Union. Indeed, it has been estimated that 75% of buildings in the EU are still energy inefficient. Natural gas represents the primary energy source for heating buildings, followed by oil and coal [47]. The reduction in energy consumption and the use of renewable energy sources, in particular solar energy, are pivotal to the reduction in greenhouse gas emissions and the alleviation of energy poverty [47]. These measures also assist in reducing reliance on fossil fuels and promoting energy security, while fostering technological development, job creation, and regional development, particularly in isolated, rural, and off-grid areas [48]. It is of the utmost importance to consider the greenhouse gas emissions generated by buildings throughout their life cycle and to integrate emission-reduction measures into national building renovation plans by adopting circular economy strategies.

The field of intelligent energy systems for buildings has been a significant area of research for several years, driven by the need to reduce carbon dioxide emissions and enhance energy efficiency. The International Energy Agency (IEA) has identified building energy efficiency as a critical factor in limiting CO_2 emissions [49,50]. The primary goal is to conserve energy while ensuring a healthy and comfortable environment for occupants. Therefore, it is essential to align the operation of various energy systems within a building with the occupants' usage patterns and to gather precise information on the interaction between occupants and these systems. Indoor occupancy data are becoming increasingly vital for the development of intelligent applications.

2. Materials and Methods

Space management is a multi-stage process that, through data collection and analysis, identifies the optimal layout to meet an organization's needs, taking into account both the needs of the business as a whole and those of individual workers. A variety of space strategies can be employed in hybrid work, with notable benefits for both the business and the employee:

- Strategy 1: Office first. The majority of employees work in the office, with the option of working remotely for a few days a week (e.g., 3–4 days in the office and 1–2 remotely).
- Strategy 2: Virtual first. The majority of employees work remotely, with the option of travelling to the office for specific purposes, such as internal meetings or client-facing activities.
- Strategy 3: Total hybrid. Employees are afforded the autonomy to determine the extent of their work in the office or remotely, according to their individual needs. This approach is the most flexible, yet also the most complex to manage in terms of infrastructure and methodology.

A reduction in the allocated space for workstations would undoubtedly result in significant cost savings. For instance, if 30% of the company population were to engage in smart working two days a week in shifts, a strategy could be implemented to reduce the proportion of space dedicated to workstations by up to 20% [51]. Considering the high cost of utilities, the need to reduce expenditure on electricity and gas, which are becoming increasingly expensive and unsustainable, has become a significant driver for companies to consider alternative approaches to space management, with a focus on virtual-first and full-hybrid systems [52]. It is possible to achieve savings of up to 30% on costs associated with rent, utilities, maintenance, heating, and telephone services. Nevertheless, contemporary SM strategies are not merely concerned with reducing costs; they also seek to enhance the value of space as a means of supporting the achievement of corporate objectives. These objectives include the attraction and retention of talent, the improvement of collaboration, the optimization of resources, and reducing the risk of errors in resource management. Enterprise space management systems in smart buildings must possess certain fundamental characteristics, which can be further subdivided according to the operator: the facility manager and the users. It is important to note that the system should allow occupants to access it from both fixed and mobile devices, ensuring a high flexibility of use; the interface should be intuitive, allowing for easy and untrained workstation booking; and the platform should also provide indoor navigation and people location systems, allowing users to quickly understand how to locate their colleagues and to reach various company areas/buildings with clear and user-friendly guidance.

On the other hand, the facility manager must embody several functions for optimal building management:

- Enable interoperability with room reservation systems, shared calendars, and room edge systems to monitor reservations.
- Enable real-time monitoring of occupancy by tracking occupancy flows. The facility manager can not only plan the reconfiguration of rooms, but also set up customized cleaning and disinfection systems for individual areas.
- Provide real-time monitoring of environmental quality in terms of health and comfort conditions (temperature, humidity, lighting, and IAQ).
- Provide data correlation analysis through business intelligence (BI) systems to define occupancy strategies aimed at correct space allocation and reducing energy and service costs.

In this way, the right combination of user and manager strategies not only optimizes resources and improves results, but also reduces energy costs and environmental impact. In addition to meeting the requisite interoperability criteria, 4.0 systems for SM must provide an intuitive platform for both end users and facility managers. It is therefore recommended that systems capable of providing comprehensive dashboards and data processing be selected. The use of wireless field sensors permits a high degree of flexibility in the relocation, addition, or subtraction of equipment, with minimal impact. The system should permit customization and management by both the software house and the plant team.

The evolution of technology and industry has been a symbiotic process for many years. Indeed, digital innovation has brought about numerous changes to the production process of companies, resulting in enhanced value. The deployment of smart sensors represents a pivotal aspect of Industry 4.0, whereby the technological process is enhanced through the establishment of a networked and autonomous production environment. These devices are networked and analyze data, thereby optimizing production logistics. The real-time monitoring capabilities of these new digital tools enable them to autonomously organize the acquisition and processing of data and information. Smart sensors are next-generation devices that work intelligently, processing information and sending it to the cloud to be shared with machines, data scientists, and active process users authorized by the FM. As smart sensors evolve and machines become more connected, information is constantly collected and analyzed in real time for specific applications. In this way, tailored solutions and configurations can be found to improve efficiency and productivity day after day. The ultimate goal is to optimize resources and time. By constantly monitoring production processes and using the latest technology, logistics can be improved and production made more efficient. In the event of problems or breakdowns, it is important to intervene immediately, as permitted by the real-time management of critical issues, in order to maintain a very high level of efficiency and quality.

The Indoor Environmental Quality (IEQ) of buildings is of paramount importance today, as people spend about 87% of their time in the indoor built environment. This reached almost 100% during the COVID-19 pandemic. The pandemic raised the issue of the spread of the virus through poor indoor ventilation. This inevitably led to the need to improve indoor air quality (IAQ) [42]. The performance of lighting, heating, ventilation, and air-conditioning systems is closely and consistently linked to the performance of indoor air quality. Six factors have been identified that cause variations in energy use in different types of buildings [43], as follows:

- Climate;
- Building envelope;
- M&E systems;
- Interior design criteria and operation;
- Maintenance of building energy use;
- Occupant behavior.

Information on the occupancy of indoor spaces, such as residential, office, or school buildings, plays an increasingly important role in the development of smart applications and services. This type of information can be obtained thanks to IoT devices such as the sensors described above. Through these sensors, it is possible to have a collection of data that is useful for determining what is happening in the environment, as they are able to capture data such as temperature, air quality, and vibrations generated; thus, it is possible to determine what is happening by triggering a consequent action through actuators. With this amount of data collected, it is possible to implement useful strategies for resource optimization, building management, and user comfort. Significant energy savings can be achieved through the advanced management of HVAC (heating, ventilation, and air conditioning) systems by adjusting them according to the number of people in each room, detected by sensors that communicate directly with the air-conditioning system to close/reduce airflow, with the electrical system turning off excess lighting and the thermostat setting the temperature. Variations in building energy use due to occupants can be divided into two main categories:

1. Variations due to the active interaction of occupants with building systems. The active interaction of occupants with building energy systems is a complex mechanism, where numerous parameters, including the number of occupants, occupant behavior, type of space, type of work, day, and time, exert a significant influence. The aforementioned parameters can be classified into three distinct groups: temporal, spatial, and occupancy. Temporal parameters indicate the time scale, while spatial parameters indicate spatial information. Occupancy parameters, on the other hand, indicate occupant behavior. It can be reasonably argued that psychological and sociological aspects exert a considerable influence on occupant behavior. Given the inherent unpredictability of occupants' behavior, it remains challenging to identify any specific circumstances that may influence the consumption of energy. This uncertainty has a significant impact on the indoor environment, which in turn contributes to the observed variations in energy consumption. Other factors that influence occupants' behavior include temperature, humidity, illuminance factor, and several others, which collectively affect the building's energy consumption. The most common forms of occupant behavior are adjusting the thermostat, dimming the lighting, switching off lights, and using electronic devices.
2. Variations due to the passive interaction of occupants with building systems. Passive interaction depends on the presence of occupants, reported as hours of occupancy in the building, and the absence of occupants, reported as hours of unoccupied building operation. It is possible that there is inefficient operation of the electrical and mechanical systems, which would result in high energy wastage during the unoccupied/occupied hours; this issue was further investigated to estimate the amount of energy wasted during unoccupied hours, with between 26% and 65% of energy being used during unoccupied/occupied hours, compared to working hours between 7.30 a.m. and 5 p.m. Of the total consumption, between 19% and 28% (mainly electricity and HVAC) is used during the weekend when the building is unoccupied [44].

2.1. Methodology

In this context, an advanced digital strategy is developed to optimize the management of corporate spaces, improve operational efficiency, and reduce costs and environmental impact. The proposed approach uses IoT sensors to assess employee presence or workstation activation, and innovative ML technologies to automate and refine building management [53]. The building manager can operate with greater awareness and effectiveness, thanks to access to timely data and reliable forecasts. This allows more informed decisions to be made about space use and resource management [54]. The developed methodology consists of 4 main phases (Figure 4):

1. Space analysis via the BIM model: Through the use of IoT sensors, which can be easily installed and configured, it is possible to start the occupancy assessment process.
    - Use analysis: Evaluation of office space use to identify inefficiencies or cases of overutilization.
    - Occupancy measurement: Determine the occupancy percentage for each floor, with a detailed map of space use.
2. Space analysis and management (statistics): Using data obtained from a dedicated booking application, through the utilization of BIM-integrated software, facilitates the examination of the actual use of workspaces, with the objective of optimizing their management. The specific objectives are as follows:
    - Presence forecasting: Estimating building occupancy over the next 30 days based on historical booking data, allowing better maintenance services and the anticipation of space and resource requirements.
    - Savings analysis: Quantification of potential maintenance cost savings through appropriate operational downsizing. By analyzing space utilization, it is possible to identify areas that can be consolidated or downsized, thus reducing operating costs.
    - Duration of bookings: Calculation of the average duration of room bookings to optimize space availability. Knowing the typical duration of bookings allows you to better plan the use of meeting rooms, avoiding overlaps and improving efficiency in resource allocation.
    - Temporal assessment of room use: Examination of meeting room usage by time of day and day of the week and the identification of high- and low-occupancy periods. This provides a better understanding of space utilization patterns, allowing for more flexible and adaptive management.
3. Insight and automated alerts: Provide automatic alerts to the building manager [55] to improve space management [56]. These alerts signal when there is a high probability that a particular floor or the entire building will reach 100% occupancy on a particular day or period, allowing for more efficient planning of the necessary resources.
4. Machine learning: This stage uses ML to make reliable predictions and generate insights [57], going beyond the traditional programming approach [58]. The system learns from the relationships between data and outcomes, identifying patterns and connections that may not be obvious to human intelligence [59]. This ‘knowledge discovery’ process not only provides useful results, but can also reveal new, previously unknown/ignored/unexpected information.

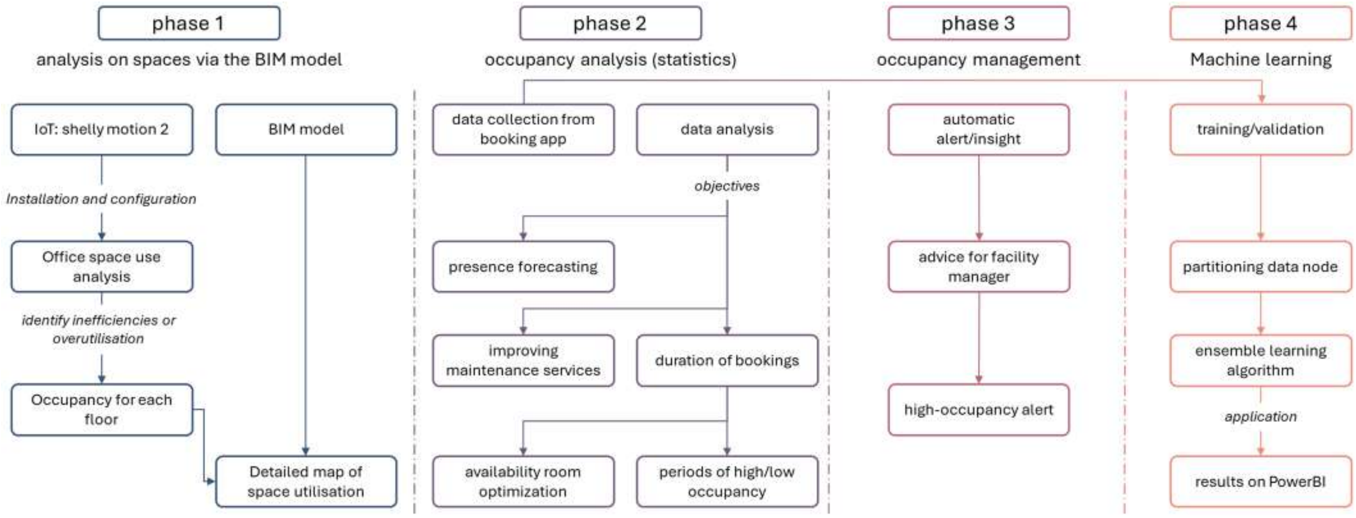


Figure 4. Proposed methodology workflow: outline of phases.

2.1.1. Analysis of Spaces via the BIM Model—Phase 1

The first step in creating a DT was to create a complete BIM model, integrating both architectural and mechanical aspects of the building. The modelling of a multi-tenant building was based on available technical documentation, such as floor plans and the as-built documentation of the installations. The BIM model was enriched with details of the fit-out and coding of the interior spaces, in addition to the simple transposition of the floor plans, information that proved crucial for the spatial analyses in the subsequent phases. Using software such as Autodesk's Revit 2024, a leader in the BIM sector, it is possible to implement a high level of detail and accuracy, integrating structural and non-structural aspects such as the arrangement of furniture and the technical specification of spaces, thus facilitating the entire building management and analysis process [60].

The information in the BIM model is divided into environmental components, such as walls, floors, and roofs, and model components, such as stairs, windows, doors, and furniture. These are described in detail, including dimensions, location, orientation and fabrication, as well as assembly and installation specifications, to a level of detail (LOD) of 400 [61].

The adoption of a detailed LOD in the BIM model has made it possible to accurately classify several categories of data that are critical [62] to SM practices, such as the management of workplace and meeting room reservations. This information is crucial for optimizing the management of available space, improving resource efficiency, and identifying areas of overutilization or underutilization. This level of detail allows for more targeted and effective interventions, ensuring that space and people management responds dynamically to the real needs of the organization [63].

In this phase, the role of IoT sensors becomes evident, as they are capable of detecting motion and occupancy. This functionality enables the programming of devices to facilitate the operation of lighting, the control of HVAC systems, and the activation of pre-programmed energy-saving modes when no one is present in the space. The sensors employed in this project are from Shelly Motion 2, a line of innovative microprocessor-controlled devices that permit the remote control of electrical circuits via a smartphone, personal computer, tablet, or home automation device. This type of sensor is capable of detecting motion, temperature, and brightness. The devices are capable of operating autonomously within a local Wi-Fi network. The sensors can be accessed, controlled, and monitored remotely from any location where the user has Internet connectivity, provided that the devices are connected. The response time of Shelly Motion 2 is 200 m/s, which is equivalent to the blink of an eye. This speed of communication allows the device to alert anyone of any incident in a timely manner. The devices are installed in the vicinity of the workstation with the objective of detecting the presence or absence of the worker by interpolating data on presence and temperature/humidity. Following the collection of data over a specified period, which is dependent on the number of workstations and employees, as well as the shift cycle, an initial space management analysis can be conducted. This assesses the number of workstations that can be utilized in practice, as opposed to those that remain unused.

The data obtained from the sensors are validated through a double comparison with the web app system and the badge recognition system at the building entrance for security purposes. The comparison process is conducted as follows: data from the sensors, which monitor presence parameters, are periodically collected and stored in CSV format. Concurrently, the access data recorded by the badge recognition system and the web app are exported in CSV format. Three sets of data are imported into an AI analysis system based on an ML algorithm, namely random forest. This system is programmed to identify patterns and anomalies in the data.

The ML algorithm is employed for the comparison of the sensor data with the access logs of the badge system. To illustrate, if a sensor identifies the presence of an individual in a specific zone of the building, the AI assesses whether the corresponding access badge was used to gain entry to that zone concurrently. Subsequently, the AI performs an analysis of the discrepancies between the two datasets, identifying any notable differences, such as a presence detected by the sensors without a corresponding badge use, which are then subjected to further investigation. A comprehensive report of discrepancies and matches is generated and disseminated to security managers. In the event of discrepancies, corrective action can be taken, such as manual verification or the updating of access protocols. This integrated approach of data collection, integration, and comparison through an AI system ensures a high level of security and accuracy in the validation of presence and access in buildings.

2.1.2. Optimizing Space Management through Data Analysis (Statistics)—Phase 2

The data analytics platform was selected for its versatility and potential, particularly in terms of the accessibility of the no-code/low-code approach, which facilitates rapid and efficient processing. The pre-programmed nodes [64] guarantee direct integration with business intelligence tools such as Microsoft PowerBI 2.132 [65], simplifying data analysis and minimizing the difficulties associated with learning programming languages such as Python [66]. The Microsoft PowerBI Service, in its PRO and PLUS paid versions, provides users with the option of accessing dashboards from both laptops and mobile devices, thereby enhancing the data visualization experience. Furthermore, the platform enables users to tailor their profiles and configure automated email alerts, which represents an initial step towards the exploration of prescriptive analytics. The use of Microsoft PowerBI to create structured dashboards in conjunction with BLogic srl's VCad 1.4.3 application, which integrates BIM modelling, significantly enhances the transparency and comprehension of information. The automatic alerting capabilities, implemented via Microsoft's WebAPP PowerBI Service, send notifications based on specific key performance indicators (KPIs) and introduce the use of prescriptive analytics on an experimental basis (Figure 5).

In a modern working environment that adopts hot desking systems [67], each employee is required to book his or her own workspace through a web app [68], based on various criteria such as the location and the specific area of the building in which he or she will be working [69], provided that he or she has the permissions to work in more than one location. This reservation system makes space management flexible and dynamic [70], adapting to the day-to-day needs of the organization and its staff [71].

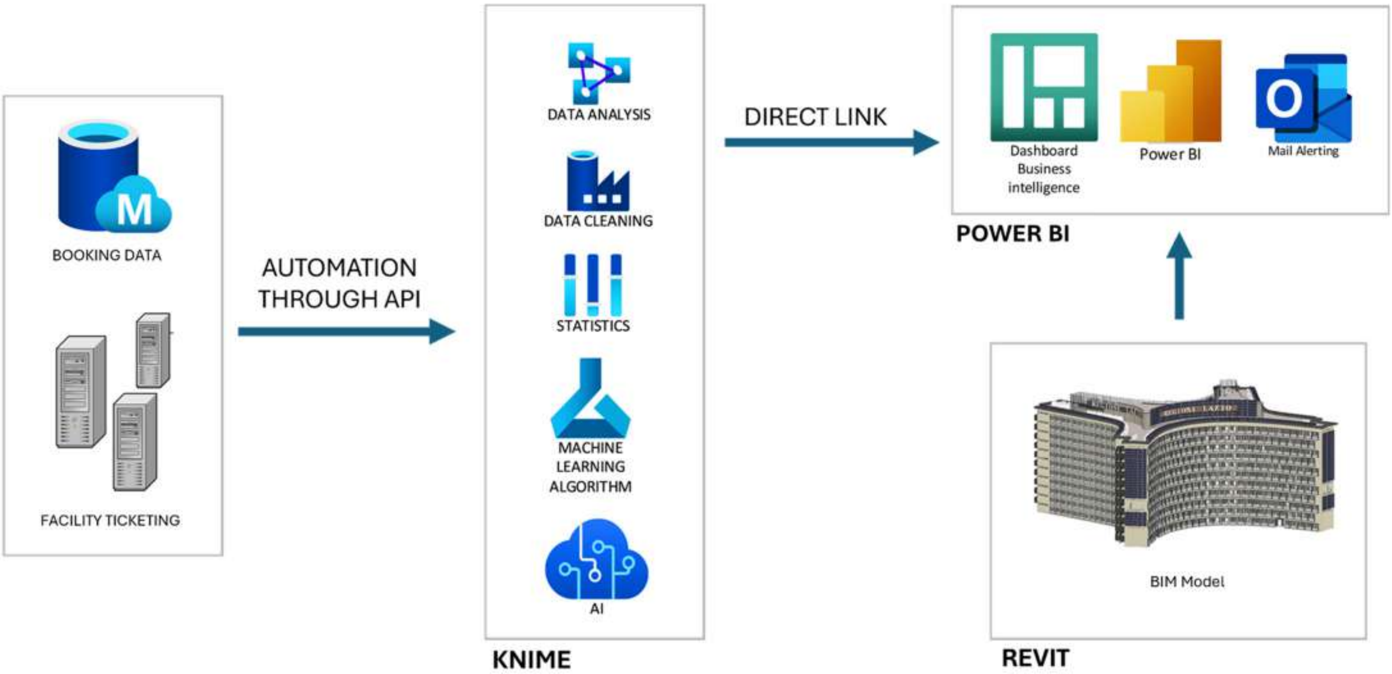


Figure 5. Proposed data analytics workflow for space management optimization.

On the other hand, employees who have a fixed, permanently assigned workstation enjoy simplified management of their workspace. They do not need to use the web app for daily bookings and can benefit from a constant and predictable working environment (Figure 6). However, even in this scenario, it is crucial that the space management system monitors fixed assignments to ensure efficient maintenance and the optimized use of available resources [72]. This integrated approach ensures that both flexibility and stability requirements are effectively managed within the same working environment. The process of downloading data from the booking web app is initiated by exporting the information to files in the .csv format (Figure 7). This method allows the data to be stored in a structured manner, which facilitates subsequent analysis and processing. The .csv file is compatible with a wide range of data analysis tools and management software, allowing users to easily access the collected information and manipulate it according to the specific needs of their work or desired analysis (Figure 8).

The data collected via the web app were meticulously cleaned and processed using the Konstanz Information Miner (KNIME) platform, thus enabling in-depth analysis in order to detect any repeatable and predictable behavioral patterns. To enhance the analytical process, the KNIME workflow was augmented with supplementary datasets, thereby facilitating a more comprehensive and detailed understanding:

- A dataset of Italian holidays up to the year 2100 (Figure 9);
- Maximum capacity of each floor of the building;
- Detailed links between location codes, floors, and tenants.

This integration introduced additional analytical variables into the model, such as seasons and holidays, both one-day and two-day, greatly increasing the system's analysis and forecasting capabilities.

The use of advanced predictive analysis techniques made it possible not only to interpret the general data, but also to analyze the outputs in detail for each plan and each tenant [73]. To optimize data visualization and enrich the user experience, data processed through KNIME were transferred and visualized in dashboards on Microsoft PowerBI [74,75]. These dashboards were further enriched through the use of BLogic's VCad, an application that allows the advanced integration and manipulation of visualized data.

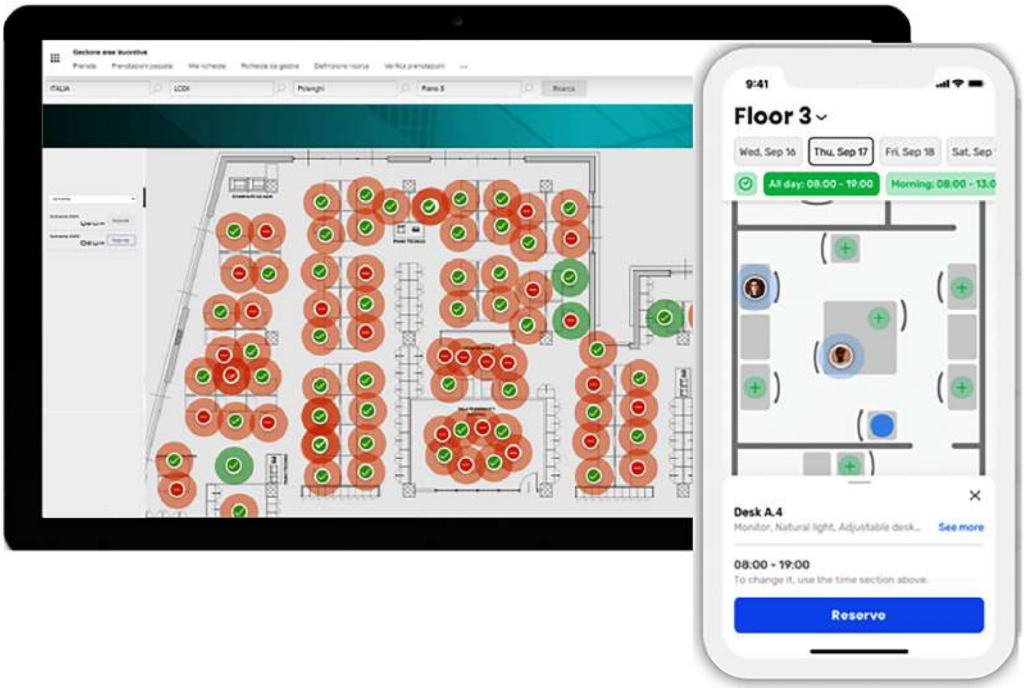


Figure 6. Space management web/smart device app for booking stations.

Table «default» Rows: 29,039 Spec - Columns: 8 Properties Flow Variables

Row ID	Event name	Start date	End date	Cod. post.	Resource category	Resource position	Floor	Postation
Row0	Prenotazione Desk	2022-05-05 09:00 CEST	2022-05-05 20:00 CEST	PSM1	DESK	Roma	P5	M1
Row1	Prenotazione Desk	2022-05-13 12:00 CEST	2022-05-13 20:00 CEST	PSM1	DESK	Roma	P5	M1
Row2	Prenotazione Desk	2020-10-01 08:00 CEST	2020-10-01 21:00 CEST	PSM2	DESK	Roma	P5	M2
Row3	Prenotazione Desk	2021-02-09 08:52 CET	2021-02-09 21:00 CET	PSM2	DESK	Roma	P5	M2
Row4	Prenotazione Desk	2021-02-10 09:14 CET	2021-02-10 19:30 CET	PSM2	DESK	Roma	P5	M2
Row5	Prenotazione Desk	2021-02-11 07:00 CET	2021-02-11 21:00 CET	PSM2	DESK	Roma	P5	M2
Row6	Prenotazione Desk	2021-03-03 09:03 CET	2021-03-03 21:00 CET	PSM2	DESK	Roma	P5	M2
Row7	Prenotazione Desk	2021-04-28 09:36 CEST	2021-04-28 21:00 CEST	PSM2	DESK	Roma	P5	M2
Row8	Prenotazione Desk	2021-06-10 13:30 CEST	2021-06-10 18:00 CEST	PSM3	DESK	Roma	P5	M3
Row9	Prenotazione Desk	2021-06-15 07:45 CEST	2021-06-15 20:00 CEST	PSM3	DESK	Roma	P5	M3
Row10	Prenotazione Desk	2021-06-16 07:00 CEST	2021-06-16 18:00 CEST	PSM3	DESK	Roma	P5	M3
Row11	Prenotazione Desk	2021-06-17 07:00 CEST	2021-06-17 19:00 CEST	PSM3	DESK	Roma	P5	M3
Row12	Prenotazione Desk	2021-06-22 07:00 CEST	2021-06-22 21:00 CEST	PSM3	DESK	Roma	P5	M3
Row13	Prenotazione Desk	2021-06-23 09:25 CEST	2021-06-23 18:30 CEST	PSM3	DESK	Roma	P5	M3
Row14	Prenotazione Desk	2021-06-25 07:00 CEST	2021-06-25 21:00 CEST	PSM3	DESK	Roma	P5	M3
Row15	Prenotazione Desk	2021-06-30 09:15 CEST	2021-06-30 11:15 CEST	PSM3	DESK	Roma	P5	M3
Row16	Prenotazione Desk	2021-06-30 17:57 CEST	2021-06-30 21:00 CEST	PSM3	DESK	Roma	P5	M3
Row17	Prenotazione Desk	2021-07-14 14:00 CEST	2021-07-14 18:30 CEST	PSM3	DESK	Roma	P5	M3
Row18	Prenotazione Desk	2021-07-26 09:15 CEST	2021-07-26 18:15 CEST	PSM3	DESK	Roma	P5	M3
Row19	Prenotazione Desk	2021-09-09 09:15 CEST	2021-09-09 15:45 CEST	PSM3	DESK	Roma	P5	M3

Figure 7. Extraction of data from web app.

This integration and synergy between advanced analysis and visualization tools transforms complex datasets into clear and effective visual insights. This has significantly improved not only the understanding of spaces and their usage dynamics, but also the ability to make more informed strategic decisions. Through these technologies, it is possible to quickly identify areas of overutilization or underutilization, optimize the distribution of resources and anticipate future needs, making a decisive contribution to the efficient management of corporate space.

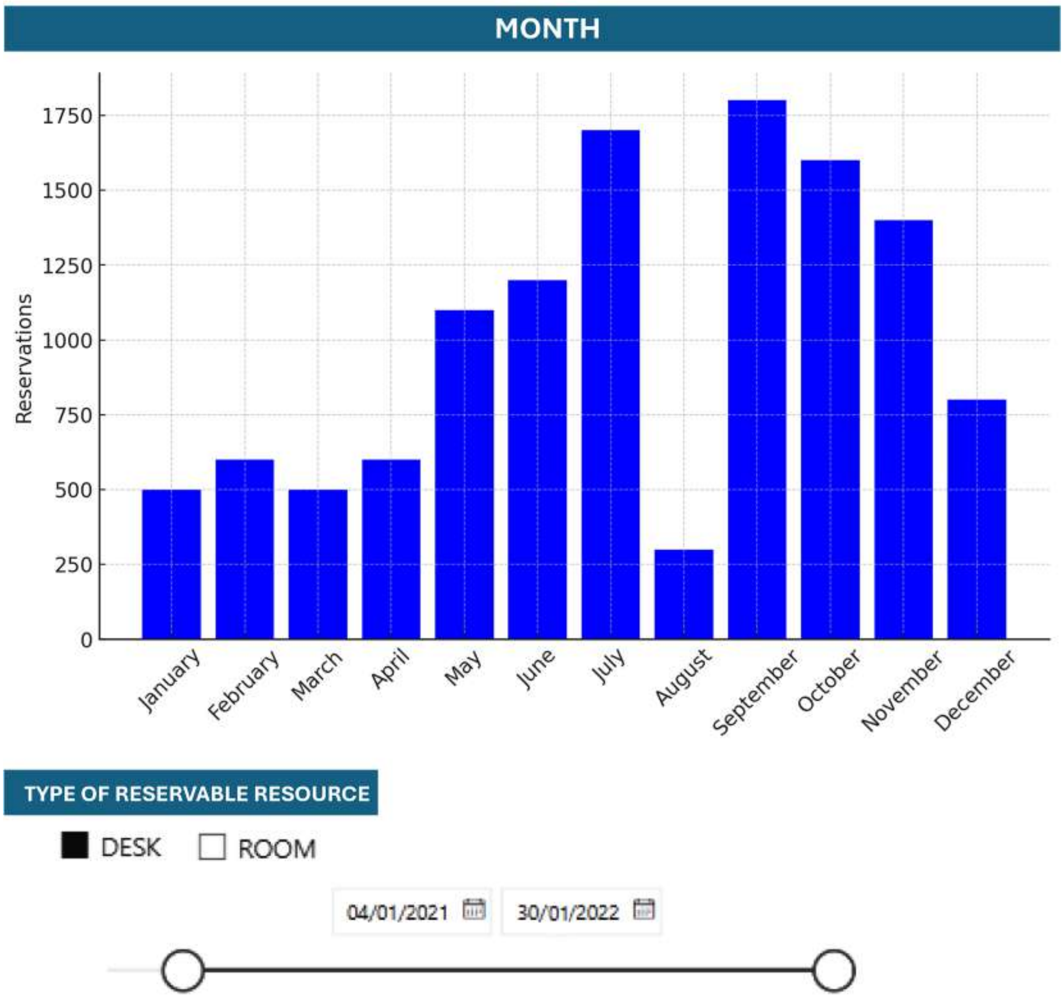


Figure 8. Month view of booking trends.

Row ID	Anno	Pasqua	lunedì a...	CAPOD...	EPIFANIA	LIBERA...	PRIMO ...	REPUB...	SS PIET...	FERRA...	OGNIS...	IMMAC...	NATALE	SSTEFA...	FESTIVO
Row0	2021	2021-04-04	2021-04-05	2021-01-01	2021-01-06	2021-04-25	2021-05-01	2021-06-02	2021-06-29	2021-08-15	2021-11-01	2021-12-08	2021-12-25	2021-12-26	TRUE
Row1	2022	2022-04-17	2022-04-18	2022-01-01	2022-01-06	2022-04-25	2022-05-01	2022-06-02	2022-06-29	2022-08-15	2022-11-01	2022-12-08	2022-12-25	2022-12-26	TRUE
Row2	2023	2022-04-09	2022-04-10	2023-01-01	2023-01-06	2023-04-25	2023-05-01	2023-06-02	2023-06-29	2023-08-15	2023-11-01	2023-12-08	2023-12-25	2023-12-26	TRUE
Row3	2024	2022-03-31	2022-04-01	2024-01-01	2024-01-06	2024-04-25	2024-05-01	2024-06-02	2024-06-29	2024-08-15	2024-11-01	2024-12-08	2024-12-25	2024-12-26	TRUE
Row4	2025	2022-04-20	2022-04-21	2025-01-01	2025-01-06	2025-04-25	2025-05-01	2025-06-02	2025-06-29	2025-08-15	2025-11-01	2025-12-08	2025-12-25	2025-12-26	TRUE
Row5	2026	2022-04-05	2022-04-06	2026-01-01	2026-01-06	2026-04-25	2026-05-01	2026-06-02	2026-06-29	2026-08-15	2026-11-01	2026-12-08	2026-12-25	2026-12-26	TRUE
Row6	2027	2022-03-28	2022-03-29	2027-01-01	2027-01-06	2027-04-25	2027-05-01	2027-06-02	2027-06-29	2027-08-15	2027-11-01	2027-12-08	2027-12-25	2027-12-26	TRUE
Row7	2028	2022-04-16	2022-04-17	2028-01-01	2028-01-06	2028-04-25	2028-05-01	2028-06-02	2028-06-29	2028-08-15	2028-11-01	2028-12-08	2028-12-25	2028-12-26	TRUE
Row8	2029	2022-04-01	2022-04-02	2029-01-01	2029-01-06	2029-04-25	2029-05-01	2029-06-02	2029-06-29	2029-08-15	2029-11-01	2029-12-08	2029-12-25	2029-12-26	TRUE
Row9	2030	2022-04-21	2022-04-22	2030-01-01	2030-01-06	2030-04-25	2030-05-01	2030-06-02	2030-06-29	2030-08-15	2030-11-01	2030-12-08	2030-12-25	2030-12-26	TRUE
Row10	2031	2022-04-13	2022-04-14	2031-01-01	2031-01-06	2031-04-25	2031-05-01	2031-06-02	2031-06-29	2031-08-15	2031-11-01	2031-12-08	2031-12-25	2031-12-26	TRUE
Row11	2032	2022-03-28	2022-03-29	2032-01-01	2032-01-06	2032-04-25	2032-05-01	2032-06-02	2032-06-29	2032-08-15	2032-11-01	2032-12-08	2032-12-25	2032-12-26	TRUE
Row12	2033	2022-04-17	2022-04-18	2033-01-01	2033-01-06	2033-04-25	2033-05-01	2033-06-02	2033-06-29	2033-08-15	2033-11-01	2033-12-08	2033-12-25	2033-12-26	TRUE
Row13	2034	2022-04-09	2022-04-10	2034-01-01	2034-01-06	2034-04-25	2034-05-01	2034-06-02	2034-06-29	2034-08-15	2034-11-01	2034-12-08	2034-12-25	2034-12-26	TRUE
Row14	2035	2022-03-25	2022-03-26	2035-01-01	2035-01-06	2035-04-25	2035-05-01	2035-06-02	2035-06-29	2035-08-15	2035-11-01	2035-12-08	2035-12-25	2035-12-26	TRUE
Row15	2036	2022-04-13	2022-04-14	2036-01-01	2036-01-06	2036-04-25	2036-05-01	2036-06-02	2036-06-29	2036-08-15	2036-11-01	2036-12-08	2036-12-25	2036-12-26	TRUE
Row16	2037	2022-04-05	2022-04-06	2037-01-01	2037-01-06	2037-04-25	2037-05-01	2037-06-02	2037-06-29	2037-08-15	2037-11-01	2037-12-08	2037-12-25	2037-12-26	TRUE
Row17	2038	2022-04-25	2022-04-26	2038-01-01	2038-01-06	2038-04-25	2038-05-01	2038-06-02	2038-06-29	2038-08-15	2038-11-01	2038-12-08	2038-12-25	2038-12-26	TRUE
Row18	2039	2022-04-10	2022-04-11	2039-01-01	2039-01-06	2039-04-25	2039-05-01	2039-06-02	2039-06-29	2039-08-15	2039-11-01	2039-12-08	2039-12-25	2039-12-26	TRUE
Row19	2040	2022-04-01	2022-04-02	2040-01-01	2040-01-06	2040-04-25	2040-05-01	2040-06-02	2040-06-29	2040-08-15	2040-11-01	2040-12-08	2040-12-25	2040-12-26	TRUE
Row20	2041	2022-04-21	2022-04-22	2041-01-01	2041-01-06	2041-04-25	2041-05-01	2041-06-02	2041-06-29	2041-08-15	2041-11-01	2041-12-08	2041-12-25	2041-12-26	TRUE
Row21	2042	2022-04-06	2022-04-07	2042-01-01	2042-01-06	2042-04-25	2042-05-01	2042-06-02	2042-06-29	2042-08-15	2042-11-01	2042-12-08	2042-12-25	2042-12-26	TRUE
Row22	2043	2022-03-29	2022-03-30	2043-01-01	2043-01-06	2043-04-25	2043-05-01	2043-06-02	2043-06-29	2043-08-15	2043-11-01	2043-12-08	2043-12-25	2043-12-26	TRUE
Row23	2044	2022-04-17	2022-04-18	2044-01-01	2044-01-06	2044-04-25	2044-05-01	2044-06-02	2044-06-29	2044-08-15	2044-11-01	2044-12-08	2044-12-25	2044-12-26	TRUE
Row24	2045	2022-04-09	2022-04-10	2045-01-01	2045-01-06	2045-04-25	2045-05-01	2045-06-02	2045-06-29	2045-08-15	2045-11-01	2045-12-08	2045-12-25	2045-12-26	TRUE
Row25	2046	2022-03-25	2022-03-26	2046-01-01	2046-01-06	2046-04-25	2046-05-01	2046-06-02	2046-06-29	2046-08-15	2046-11-01	2046-12-08	2046-12-25	2046-12-26	TRUE
Row26	2047	2022-04-14	2022-04-15	2047-01-01	2047-01-06	2047-04-25	2047-05-01	2047-06-02	2047-06-29	2047-08-15	2047-11-01	2047-12-08	2047-12-25	2047-12-26	TRUE
Row27	2048	2022-04-05	2022-04-06	2048-01-01	2048-01-06	2048-04-25	2048-05-01	2048-06-02	2048-06-29	2048-08-15	2048-11-01	2048-12-08	2048-12-25	2048-12-26	TRUE
Row28	2049	2022-04-18	2022-04-19	2049-01-01	2049-01-06	2049-04-25	2049-05-01	2049-06-02	2049-06-29	2049-08-15	2049-11-01	2049-12-08	2049-12-25	2049-12-26	TRUE

Figure 9. Schedule of national holidays.

2.1.3. Insight and Automatic Alarms—Phase 3

One of the main objectives of the work that follows is to attempt to maximize the building manager's operations by attempting to provide specific insights and automatic alerts that can assist them. For example, an alert that warns of a high probability that the occupancy rate for a given day/period will be close to 100% (of the whole building or a specific floor) can allow the building manager to have an optimized number of staff available at any given time. To make the prediction reliable, ML techniques have been used [76]. ML is a variant of the traditional approach to computer programming. Traditional programming involves four basic elements: the source data; the program, i.e., the code to be executed [77]; a computer that executes the code using the source data as input; and the results, i.e., new output data (Figure 10).

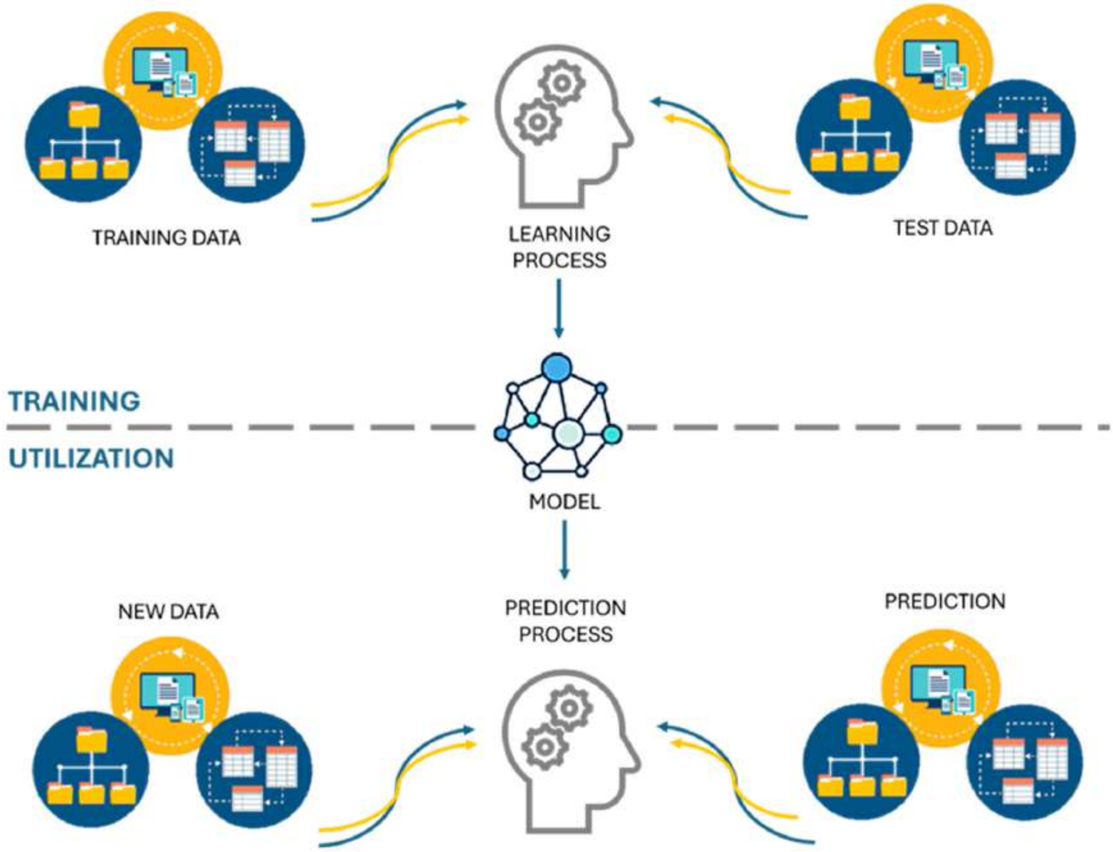


Figure 10. Training and utilization workflow of machine learning process.

The traditional method of programming requires the presence of a programmer who is able to encode, i.e., formally describe, the steps required to get from the source data to the result. This requirement is replaced by the ML approach [78], where the machine is asked to "understand" how data and results are related.

It is conceivable that the machine will be able to evaluate much more data together than a human can, and therefore identify extremely complex relationships between data and results. Sometimes these patterns are unusual, unexpected, or simply unrecognizable to human intelligence. Consequently, in some cases, humans can learn something explicit from the data using ML [79], which gives us the advantage of being able to "create knowledge". The goal of an ML approach applied to space management is to forecast the occupancy rate on a given floor (and subsequently, the entire building) for a period of up to 30 days, based on the historical booking data. The initial dataset, which was subsequently subjected to cleansing, comprised booking start and end dates and the booked location code.

Through the application of specific algorithms and nodes (Figure 11), the following variables were identified and added:

- Season (winter, spring, summer, autumn);
- Reference month;

- Bank holidays, weekdays, 1-day bank holidays, and 2-day bank holidays;
- Days of the week.

Table "default" - Rows: 2941 Spec - Columns: 11 Properties Flow Variables

Row ID	S PIANO	I Capienza	S NR TENANT	I Start_Month (number)	S Start_Day of week	S	I Resource category	Start date
Row2585_Row1	P6	61	TENANT 5	3	mercoledì	...	1	2022-03-23
Row2586_Row1	P6	61	TENANT 5	3	venerdì	...	3	2022-03-25
Row2587_Row1	P6	61	TENANT 5	3	martedì	...	6	2022-03-29
Row2588_Row1	P6	61	TENANT 5	3	mercoledì	...	13	2022-03-30
Row2589_Row1	P6	61	TENANT 5	3	giovedì	...	7	2022-03-31
Row2590_Row1	P6	61	TENANT 5	4	venerdì	...	7	2022-04-01
Row2591_Row1	P6	61	TENANT 5	4	sabato	...	1	2022-04-02
Row2592_Row1	P6	61	TENANT 5	4	domenica	...	1	2022-04-03
Row2593_Row1	P6	61	TENANT 5	4	lunedì	...	5	2022-04-04
Row2594_Row1	P6	61	TENANT 5	4	martedì	...	6	2022-04-05
Row2595_Row1	P6	61	TENANT 5	4	mercoledì	...	12	2022-04-06
Row2596_Row1	P6	61	TENANT 5	4	giovedì	...	2	2022-04-07
Row2597_Row1	P6	61	TENANT 5	4	venerdì	...	6	2022-04-08
Row2598_Row1	P6	61	TENANT 5	4	lunedì	...	2	2022-04-11
Row2599_Row1	P6	61	TENANT 5	4	martedì	...	8	2022-04-12
Row2600_Row1	P6	61	TENANT 5	4	mercoledì	...	5	2022-04-13
Row2601_Row1	P6	61	TENANT 5	4	giovedì	...	6	2022-04-14
Row2602_Row1	P6	61	TENANT 5	4	venerdì	...	1	2022-04-15
Row2603_Row1	P6	61	TENANT 5	4	martedì	...	4	2022-04-19
Row2604_Row1	P6	61	TENANT 5	4	mercoledì	...	4	2022-04-20
Row2605_Row1	P6	61	TENANT 5	4	giovedì	...	5	2022-04-21
Row2606_Row1	P6	61	TENANT 5	4	venerdì	...	5	2022-04-22
Row2607_Row1	P6	61	TENANT 5	4	martedì	...	4	2022-04-26
Row2608_Row1	P6	61	TENANT 5	4	mercoledì	...	10	2022-04-27
Row2609_Row1	P6	61	TENANT 5	4	giovedì	...	2	2022-04-28

Figure 11. Data after the data cleaning and transformation phase.

2.1.4. Machine Learning for Enhanced Predictive Insights—Phase 4

Subsequently, the data from each plan were organized and divided into two distinct groups: a training set and a validation set. This was achieved through the use of the partitioning node, allowing the algorithm to be trained with the initial dataset and subsequently tested with the second dataset within the partition diagram before the learning phase [80].

The partitioning node was configured to perform stratified sampling, as indicated by the nominal variable "Holidays_Festivities". Stratified sampling entails the random division of rows in a dataset, thereby ensuring that the distribution of the nominal variable remains similar in both partitions. This method was selected in order to ensure an even distribution of weekdays, holidays, and bridges between the two datasets. Furthermore, a random seed was established to guarantee the consistency of the results [81]. This enables the choices of the partitioning node to be fixed and the same output to be obtained against the same input, regardless of the machine on which the workflow is executed. Regarding the choice of learning algorithm, the use of a tree ensemble learning algorithm was opted for, which is particularly suitable for the estimation of numerical variables, such as the occupancy of a floor [82]. This technical choice enables the use of multiple decision trees, thereby facilitating the generation of more accurate and robust predictions.

Ensemble learning is a ML algorithm in which multiple learners are trained and combined to solve the same problem [83]. When multiple learners are used, the ability of the ensemble to generalize can be much stronger than that of a single learner (the "wisdom of the masses" principle applies). In this specific case, ensemble learning was applied to decision trees. The tree ensemble uses a set of regression trees (like random forest variants). Typically, each tree is constructed with a different set of rows (records) and/or columns (attributes) used alternately. The output model describes a set of regression tree models and is applied in the corresponding predictor node using a simple average of the individual predictions [84]. In a regression tree, the (numerical) predicted value for a leaf node is the average target value of the records within the leaf [85]. Thus, predictions are better (compared to the training data) if the variance of the target values within a leaf is minimal.

As defined in the KNIME application, values are obtained from divisions that minimize the sum of squared errors in the respective children.

Once the algorithm had completed the training phase on the partitioned data, it was applied to the new input dataset consisting of the new date range in order to obtain a prediction of the possible occupancy of each location, broken down by floor and tenant. This resulted in a new range of 30 days from the date of execution of the workflow (Figure 12). The output was then visualized on PowerBI in order to facilitate its usability and exploration by period and by individual tenant (Figure 13).

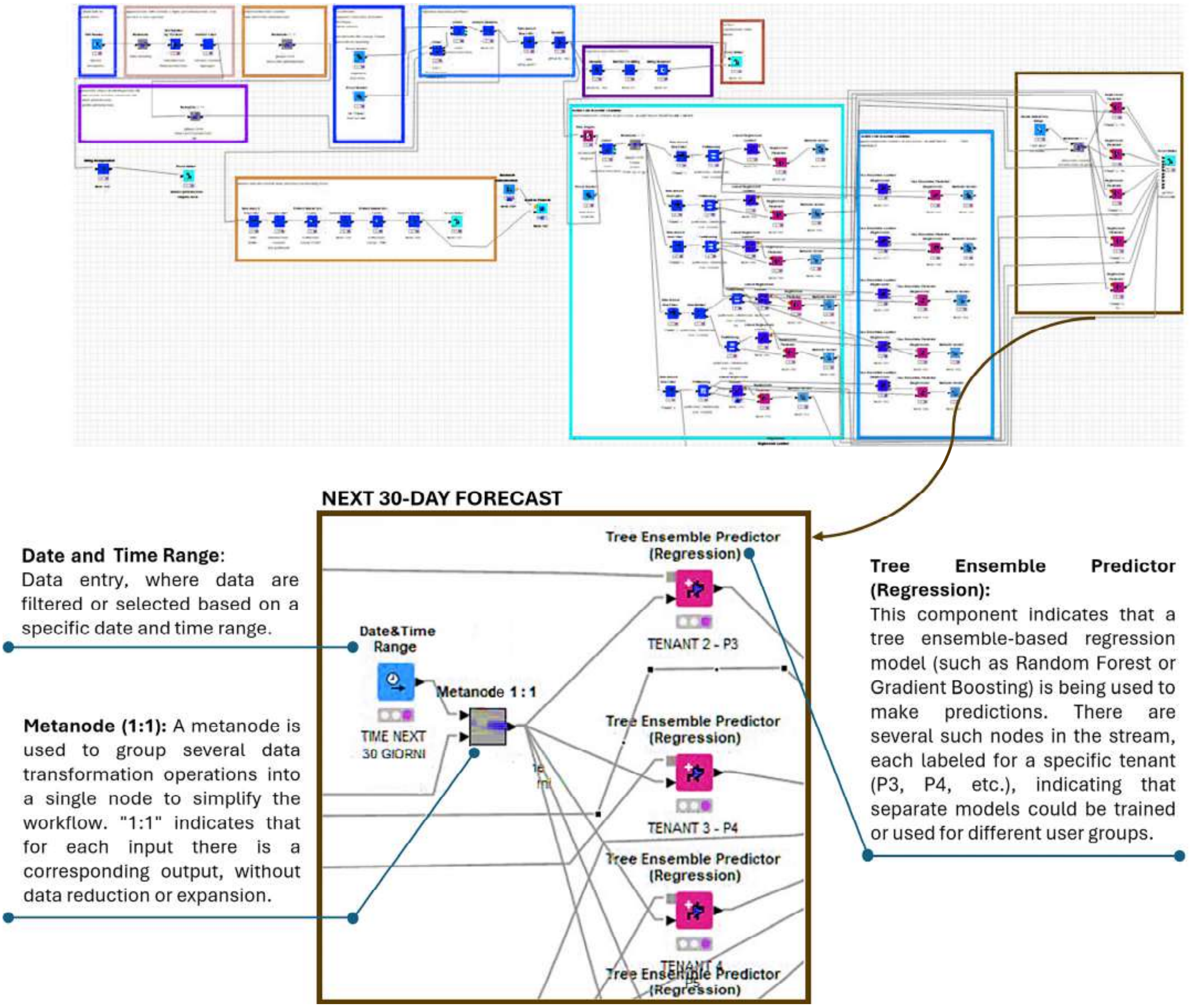


Figure 12. The application of the trained model on new data, from the theoretical to the practical, using KNIME.

Figure 13. Space management output dashboard—user interface.

3. Results and Discussion

3.1. Case Study: Lazio Region Headquarters

The Lazio Region headquarters is an architectural complex situated in Rome at 7 Via Rosa Raimondi Garibaldi, serving as the headquarters of the Lazio Regional Council. The building is a sky–ground construction with ground-level offices, comprising twelve floors and two basement levels (Figure 14). Each floor is designed to accommodate 120 employees, with 60 offices. The ground floor, however, has 50 employees, resulting in a total of 1370 workstations.

The occupational analysis conducted with the Shelly sensors described above revealed a maximum total presence of 991 employees on the same day over a three-month period. This figure still reflects the post-pandemic situation, with the spread of smart working and a reduced physical presence of workers in the office. The sensor report was analyzed and integrated with the BIM model (Figure 15), and in addition to the total presence, the relative distribution of occupants on each floor was also assessed (Table 1). The aforementioned data were then subjected to analysis and processing by the aforementioned ML system, which was employed to simulate potential future occupancies.

Figure 14. Top view of Lazio Region headquarters.

Figure 15. Three-dimensional view of BIM model (Revit 2024).

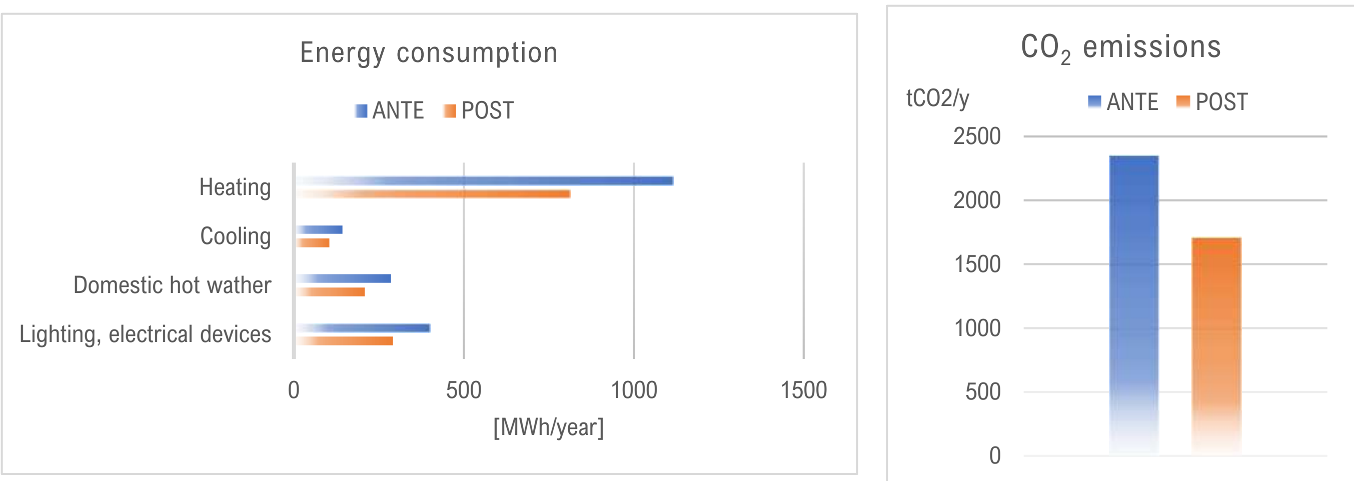
A remodeling of the building space is possible for a full employee rotation cycle, given that the maximum measured capacity for each floor has been taken into account. In fact, to accommodate 991 employees, eight floors would be sufficient, without considering the ground floor. Consequently, the potential exists for three entire floors of the facility to be rendered totally unused, leading to considerable energy and CO_2 emission savings (Table 2, Figure 16). The three floors currently deemed surplus to requirements are currently under observation by the Lazio Region, which is in the process of determining the most appropriate use strategy to ensure that the value of the property is not eroded and that the architectural integrity of the building is not compromised. The most cost-effective solution is to rent the three floors to third parties. The architectural configuration of the edifice, and particularly the principal entrance, would permit the coexistence of two distinct entities within the same edifice. It is evident that a strategic building such as this could never be leased to another company or be occupied by a third party. The option was only considered for the sake of completeness of the research.

Table 1. Detection of workstations deployed.

Floor	Available Stations	Maximum Detected	Unused Stations
0	50	36	14
1	120	104	16
2	120	105	15
3	120	97	23
4	120	102	18
5	120	88	32
6	120	91	29
7	120	106	14
8	120	78	42
9	120	58	62
10	120	66	54
11	120	60	60
Total	1370	991	379

Table 2. Comparison between current status (ANTE) and after application of the SM strategy (POST).

	ANTE, 28.600 m^2				POST, 20.800 m^2			
	kWh/Year	MWh/Year	Costs [EUR/Year]	t CO_2/Year	kWh/Year	MWh/Year	Costs [EUR/Year]	t CO_2/Year
Lighting, electrical devices	400,400.00	400.40	100,100.00	774.77	291,200.00	291.20	72,800.00	563.47
Domestic hot water	286,000,00	286.00	100,100.00	27.17	208,000.00	208.00	72,800.00	19.76
Cooling	143,000,00	143.00	35,750.00	774.77	104,000.00	104.00	26,000.00	563.47
Heating	1,115,400.00	1115.40	278,850.00	774.77	811,200.00	811.20	202,800.00	563.47
Total	1,944,800.00	1944.80	514,800.00	2351.49	1,414,400.00	1414.40	374,400.00	1710.18



(**a**) (**b**)

Figure 16. Comparison between ANTE and POST scenarios: (**a**) energy consumption; (**b**) CO_2 emissions.

Subsequently, the data from the attendance surveys of the employee shift period are entered as input into the ML system described above, which is able to simulate occupancy in subsequent periods.

The implementation of this SM strategy has resulted in a reduction in energy consumption of 530.40 MWh per year, thereby avoiding the emission of 641.32 tons of CO_2.

The electrical and air-conditioning systems, which are the most energy-intensive devices, can be automated with the aid of IoT devices and AI access control systems. In fact, the application that manages bookings informs the general control system of which locations have been booked, and the air-conditioning system is then switched on and calibrated to those portions of the building. It is evident that this automation is only applicable in instances where the number of employees is relatively low.

The energy consumption of the building was calculated using a combined approach that integrated data collected by energy sensors with data from utility bills provided by the client.

Energy sensors, strategically positioned at various points within the building, monitored electricity consumption, heating, cooling, and domestic hot-water production in real time. These IoT devices provided data, enabling the recording of energy consumption on an hourly, daily, and weekly basis. This resulted in the creation of a detailed map of the building's energy needs under different operating conditions. Following collection, these data were processed to identify consumption peaks and areas of inefficiency.

CO_2 emissions were calculated using a conversion factor provided by the IEA [84]. This factor, based on standardized data, makes it possible to convert the recorded energy consumption into the amount of carbon dioxide emitted. Using this factor, it was possible to estimate the environmental impact of the building's energy activities and to evaluate the potential emission reductions resulting from the implementation of energy efficiency strategies.

In a broader context, saving energy and reducing CO_2 emissions are of fundamental strategic value in achieving global sustainability goals and promoting more equitable and resilient economic development. Initiatives at the individual building or company level are part of a global network of efforts to transform the way we produce and consume energy while minimizing our impact on the planet. This integrated approach is essential to address the challenges of population growth, urbanization, and climate change, while ensuring that economic development is sustainable and inclusive.

The technologies and strategies developed and implemented to save energy and reduce emissions in a specific area, such as the one proposed, can be adapted and applied on a wide scale, thus contributing to a faster and more efficient energy transition. The implementation of these practices presents novel market opportunities pertaining to the utilization of cutting-edge digital systems for environmental energy-control technologies and their advancement, with the potential for the emergence of new professional roles.

3.2. Digital Transformation in Modern Work Environments

A modern working environment could never foster employee engagement without a strong technological contribution to underpin the new working paradigms. Sensors, devices, and analytics platforms make the most advanced offices almost 'sentient', ready to adapt to the needs of those who occupy them. The only management approach capable of creating engagement is one based on the exploitation of data: these, collected and processed by IoT platforms, devices, and systems available to the workforce, can guide the SM processes of the building, increasing knowledge of the use of resources and the interactions between space and people. Today, technology is not limited to monitoring services, and, far from being secondary, it can intervene proactively to ensure continuity; however, it can go much further, measuring subjective well-being and the quality of relationships to understand whether the ecosystem is growing or not, whether virtuous relationships are developing, and whether the system of relationships is positive, generating value.

The digital competencies of a company, that is to say, its managers' capacity to use a variety of technologies for the integration of data and processes, are indispensable to the development of novel business strategies. The emergence of the COVID-19 pandemic has profoundly impacted the corporate landscape, driving an acceleration in the adoption of digital solutions to overcome interpersonal restrictions and ensure business continuity. During the crisis, companies encountered several challenges, including liquidity issues, risks to business continuity, and significant job losses. In this context, digital technologies have played a pivotal role, enabling companies to adapt swiftly and maintain their operations. This transformation has had a profound impact on lifestyles and working patterns, marking a significant turning point for several sectors [86,87].

The adoption of advanced digital systems during the pandemic has stimulated considerable research, which has highlighted the importance of adopting and integrating new technologies to overcome the crisis. These studies align with Dynamic Capability Theory, highlighting the ability of organizations to detect, seize, and reconfigure resources in times of turbulence, as described by Teece et al. [88]. In support of this, McKinsey & Company and the OECD (2020) have observed that strategies such as teleworking and the expansion of digital sales channels have become common responses to the crisis, resulting in increased investment in ICT, indicating that technology skills will be essential to the resilience and future success of businesses [89,90].

This research examined the potential of digital transition and strategic change to enhance operational efficiency while simultaneously opening up new avenues for value creation [91]. It is evident that, in addition to supporting companies during the crisis, this transformative process has also paved the way for future innovations in business models. By embracing digital transformation, companies aim to use technological innovation to enhance their efficiency, effectiveness, and competitiveness in the market. In this context, the term "digital transformation" assumes a more strategic connotation, as digitization facilitates the improvement of business processes and operations, thereby increasing efficiency and innovation [92]. Nevertheless, despite the advantages, it is crucial to acknowledge that small- and medium-sized enterprises frequently encounter significant obstacles, such as a lack of financial resources and technological expertise, which can impede their progress towards digital transformation [93–96].

The main challenges in developing the methodology were found in the implementation of the different technologies used, i.e., the integration of BIM with IoT, AI, and DT systems. The successful integration of these technologies requires data exchange with open formats and consistent information to ensure an accurate and efficient flow of information between systems. Industry Foundation Classes (IFC) is an open, international standard for BIM data exchange, providing a common data format that facilitates the integration of various systems and technologies [97]. By defining a standardized schema for building information, IFC ensures that data can be accurately shared and interpreted across different platforms, enhancing interoperability among BIM, IoT, AI, and DT systems. However, despite its benefits, the implementation of IFC can be complex, as it requires the alignment of data models and protocols across diverse systems. The effective utilization of IFC is crucial for achieving seamless data integration and enabling a holistic approach to building management and operations, ultimately improving efficiency and performance in the AECO sector.

In some buildings, an additional challenge is the wait time for elevators, which can significantly impact occupant satisfaction and building efficiency. The integration of advanced technologies can help optimize elevator operations by analyzing usage patterns and dynamically adjusting schedules to reduce wait times. This further highlights the importance of effective data integration and management to address various operational issues within smart buildings.

4. Conclusions

The use of DT in building production management, particularly its integration with advanced technologies such as BIM, ML, and IoT, is revolutionizing the AECO sector, enabling more efficient and optimized building lifecycle management. The focus of the research on the development of a DT for SM strategies, with an application case from the Lazio Region, has provided promising results. The implementation of an accurate digital replication of the building based on BIM and the integration of real-time data has proven to optimize space utilization and improve resource management [92]. The implications of this study are not limited to the management of public spaces and infrastructures, but extend to the promotion of efficiency and sustainability in decision-making and operational processes through the adoption of digital methodologies. In particular, the study highlighted the potential to improve energy efficiency and reduce greenhouse gas emissions, thereby helping to mitigate the effects of climate change. Specifically, the application of the SM methodology at the headquarters of the Lazio Region demonstrated an energy saving of 530.40 MWh and a reduction in emissions of 641.32 tons. This provides a holistic view of the potential of digital transformation in the context of public infrastructure space management. Its implications are relevant not only for the Lazio Region, but also for other areas seeking innovative solutions to address challenges related to efficiency, sustainability, and the quality of services offered to the community.

The management of a DT presents a number of significant challenges in relation to data security and privacy. The collection and integration of large amounts of data in real time can result in the exposure of information to risks of unauthorized access. It is of the utmost importance to implement robust security measures in order to protect this sensitive information. Moreover, the introduction of new technologies may encounter resistance from personnel, who may be hesitant to alter established operational procedures. This necessitates the implementation of effective change management strategies and the establishment of suitable training programs to guarantee a seamless transition. The initial deployment of a DT entails considerable financial outlay, particularly in the context of purchasing the requisite hardware and software, as well as the costs associated with staff training. This represents a significant financial barrier for many organizations. Furthermore, integrating a DT with existing management systems can be a complex undertaking, necessitating careful planning and coordination to avoid incompatibilities and ensure that all systems function harmoniously, thereby optimizing the benefits of DT technology.

Despite this, industry research indicates that approximately 70% of digital transformation programs fail to achieve their intended outcomes, primarily due to internal resistance and a lack of management support [98]. The ability to define, execute, and modify digital strategies in a timely and flexible manner is of paramount importance for the economic performance of companies. Considering these challenges, there is a clear need to develop a robust methodology that supports the implementation of organizational, technological, and innovative systems, while simultaneously promoting motivation and flexibility. This holistic approach is of significant importance for enhancing the well-being and productivity of employees in the workplace [99–101]. In times of crisis, it is of the utmost importance that companies are able to access cost-effective technological incentives and macroeconomic supports that facilitate business continuity and the preservation of stakeholder relations [102].

The proposed methodology for the development and/or management of a smart city appears to be a logical extension of the research. This approach could be extended beyond the management of public spaces and infrastructure to address broader challenges related to the creation of smart urban communities. In particular, the methodology could be applied to the management of reservations of activities open to the public, with the objective of optimizing the use of spaces and improving the experience of citizens. Furthermore, the methodology could be adapted to address urban traffic issues, with the implementation of real-time data-driven systems designed to improve transport efficiency and reduce road congestion. Similarly, the implementation of DT could be extended to the management of port and airport areas, enabling more effective planning of operations and enhanced safety. The implementation of advanced DT applications could significantly contribute to the creation of smarter, more efficient, and sustainable cities, thereby improving the quality of life of citizens and addressing the urban challenges of the future.

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