Detailed Description of the Research Program

**Simulation-Powered Building Operations Management in Smart Hospitals**

**1. Scientific Background**

As healthcare facilities become ever-more complex, expensive, and mission-critical, it is imperative their functioning be made more efficient and adaptive to rapidly changing spatial, operational, and staffing needs [1]–[3]. In this way, they can deliver better care to patients while ensuring staff satisfaction and saving capital and operational costs. The need for such adaptive systems has been brought to sharp focus during the coronavirus pandemic as hospitals scramble to meet growing hospitalization needs due to staff, space, and equipment shortages. Yet, these problems are not new, nor are they limited to healthcare facilities.

The design and operation of all buildings are characterized by the interweaving of three dominant factors: *spaces* that are designed to host *people* who are engaged in a variety of *operations* depending on the organization that occupies the building. When operational challenges arise, the environment must be able to dynamically adapt and accommodate the newly emerging needs. Since the *space* is often the least adaptive of the three components, *occupancy* and *operational* protocols must dynamically adapt while accounting for the existing fabric of the built environment, ongoing operations, and the abilities/limitations of the people involved.

Built environments, however, have been traditionally considered as passive receptacles in which occupants’ activities take place. As such, they are to a large degree unaware of the people who inhabit them, and the operations they are involved in. People also have limited awareness of building operations as well as the impact that their activities may produce on the overall operational performance of a building. Such limited reciprocal awareness between spaces, people, and operations hampers hospitals’ ability to wisely allocate resources (i.e., people, spaces, and equipment) in response to – and anticipation of – future needs.

The progressive introduction of Information Technology (IT) into built environments is expected to provide buildings and people with increased awareness about building operations, potentially bringing about a massive shift in the way buildings are conceived and dynamically managed. ***This research explores the role of simulation in enabling dynamic and intelligent spatial, occupancy, and operational adaptability in complex IT-enhanced buildings, like healthcare facilities.***

**1.1 IT-Enhanced Buildings**

Buildings, unlike most other designed artifacts, are not merely physical objects: they are environments that host a variety of activities. This connection between spaces and people has been broadly described under the notion of Place [4]–[7]. Canter [5] defined Place as the confluence of a *space*, a set of *activities* carried out in that setting, and the *people* who perform them. Scholars in a variety of disciplines (including anthropology, environmental psychology, and architectural design) have investigated how places actively affect and regulate people’s interactions among themselves and with the built environment [8]–[13]. These approaches, however, considered spaces as ‘passive’ containers where behaviors take place.

Recent developments in ubiquitous computing and IT systems fostered the introduction of sensing technologies into the very fabric of built environments [14], [15] potentially transforming spaces from *passive containers* into *active* *actors* in the life of a place. Real-Time Location Systems (RTLS) use Radio Frequency Identification (RFID) technologies to track the position of people and assets over time, under day-to-day or emergency conditions [16]–[18]. Other sensors (e.g. temperature, humidity, illuminance, CO2, occupancy, noise, and plug meters) have been coupled with Building Management Systems (BMS) for demand-based control strategies of mechanical and electrical services to improve occupant comfort and energy efficiency [19], [20][21]. Wearable devices have been deployed to monitor people’s physiological conditions and provide feedback to care providers [22] or inform environmental adaptations to improve people’s well-being [23]. Ambient sensing technologies (e.g., cameras, depth, thermal, radio, and acoustic sensors) have been used in healthcare facilities for patients’ movement management, elderlies’ fall detection, gait analysis, and mental wellbeing symptoms screening [24].

These methods, however, provide local awareness of people' presence and activities to inform *reactive* responses to a detected phenomenon. To provide *proactive* recommendations towards optimal resource allocation in anticipation of emerging needs, an intelligent system should be capable of predicting and evaluating the implications of alternative building management on the behavior of building occupants.

**1.2 Human Behavior Prediction and Analytics**

Simulation methods have been developed to predict and analyze the mutual interactions between buildings and their occupants [25]–[29] [30]. Simulation is considered the most appropriate prediction method for testing and analyzing the behavior of a system when many variables interact in complex ways (and when no mathematical solution is available) [31]. Here, I categorize existing simulation methods based on their underlying modeling approaches.

***Space-Centric*** methods provide aggregated and static representation of space utilization in the form of space usage profiles, which predict occupants’ presence [32], [33] or actions [34] that have an impact on energy consumption. However, they do not consider the different occupants’ roles and their dynamic movement and activities.

***Activity-Centric*** methods use probabilistic and queuing models to simulate the dynamic flow of resources (i.e. people and equipment) within a network where *nodes* represent spaces (e.g. rooms), and *edges* represent the connections between spaces with an associated traversal time [35], [36] [37]. People and spaces, however, are often modeled as homogeneous entities, abstracting away key differences between occupant roles and space functions, which can vary at different times of the day depending on evolving operational needs. Besides, they mostly ignore the impact produced by unplanned activities (e.g., an emergency Code Blue), which may require the dynamic reallocation of resources (e.g., spaces, people, and equipment) to address emergent needs.

***People-Centric*** methodsmodel the behavior of autonomous agents that interact among themselves and with the surrounding spatial context. Agent-based models (ABM) represent the movement of homogeneous *crowds* [38], [39], as well as the context-specific behavior of individual agents in response to social and environmental conditions [40]–[42] [41]. However, ABM shows limitations in modeling complex behaviors in goal-oriented settings such as healthcare facilities since vast amounts of knowledge must be stored in each agent before collaborative behaviors cognizant of cultural norms as well as spatial and social circumstances can emerge.

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| **Figure 1**: The Narrative-based model enables to predict and analyze *Spaces*, *People*, and *Activities interactions* [43] |

***Narrative-Centric*** modeling is a recent approach developed by the PI that uniquely combines *space*- *activity*- and *people*-centric approaches into a coherent model centered on the concept of *Narratives*: self-contained computational entities that direct the individual or collaborative behavior of multiple agents in complex environments [43]. Narratives encapsulate a set of procedures for directing the behavior of *people*, performing *activities*, in specific *spaces*. For example, a narrative representing a ‘patient examination’ in a hospital ward consists of three people (doctor, nurse, patient) who meet in the patient’s room (the space) to perform the collaborative activity of examining the patient. Unlike ABM, where decision-making abilities are stored within the agents themselves, in the Narrative-based model the decision-making authority is stored in the *Narrative* entity, which in turn directs the collaborative behavior of a group of actors to perform an activity in a given space. As such, the Narrative script affords top-down agents’ coordination while also handling bottom-up exceptions and contingencies (for example, when one of the resources needed to complete the task is unavailable). Narratives are modular, so they can be reused across scenarios. They are also hierarchical to describe behaviors at increasing levels of detail. A Narrative Modeling Language has been developed by the PI to efficiently model new narratives by reusing components of existing ones [44]. A *Narrative* *Manager* determines which narrative to execute at any given time frame based on a dynamic priority factor calculated for each narrative. It uses a centralized scheduling strategy to dynamically allocate resources (e.g., actors, spaces, and equipment) to the most urgent narrative at any given time frame, thereby resolving conflicts among narratives competing for the same resources.

The capabilities of narrative-based modeling have been demonstrated to predict and analyze the impact of alternative hospital design strategies on operational efficiency before a building’s construction and occupancy [45], [46].

The model, however, is not currently suitable to represent dynamic hospital operations for the following reasons: (a) it is informed by data collected in the facility’s design stage, where little information is available on future building operations; (b) it is applied to test the impact of a single variable (the space layout) on the overall building performance; and (c) it cannot systematically test different scenarios to provide recommendations on how to improve building operations. These features are critical to simulate the future implications of holistic resource allocation strategies and enable spatial, occupancy, and operational adaptability of hospital operations.

**1.3 Total-Environmental Adaptability of Building Operations**

Adaptability is a critical component of a built environment to dynamically cater to the changing needs of an organization and its individuals. I distinguish between three levels of buildings’ ‘adaptability’, defined as the degree of awareness and responsiveness of a building to the presence and activities of its occupants [47].

***Feedback-regulated***adaptability is the simplest way for an environment to sense and respond to human presence and activities. It is based directly on the feedback loop, where an action occurs in response to an external stimulus. This type of automation is commonly implemented in BMS for the electrical, mechanical, and climatic control of buildings. For example, thermostats direct HVAC operations depending on the perceived temperature in a room, which is impacted by the number of inhabitants [48].

***Model-based*** adaptability requires adding a *functional model* to a building management system to regulate the environment in expectation of events, rather than in response to them. In a functional model, occupants’ behavior patterns are programmed in advance or learned from collected data so that a building system can pre-position itself to support recurring events. For example, elevator cars in high-rise buildings can be automatically stationed on specific floors to meet peak demand [49]. Predictive models have also been applied for real-time energy management in buildings [50], [51].

***Total-environmental*** adaptability is reached when the building not only responds to its inhabitants’ behavior but will proactively engage and even manage them. To achieve this ultimate level of adaptability, a building management system must consider: (a) *Space* information such as the configuration of the building, the function of each room (e.g., a hospital patient room, a nurse station, etc.), the equipment contained in each space, and the prevailing usage of the space, which depends on the people inside the space and their current activities. (b) *People* information such as the organizational role of each occupant (e.g., doctor, nurse, patient, visitor, etc.), abilities, and dynamic status (e.g., waiting times of patients, or working hours of staff members); and (c) *Activities* information including each inhabitant’s current, past, and future/planned activity, as well as customary procedures to deal with unplanned activities (e.g., ‘Code Blue’ in a hospital). An active building management system that has access to all this information could potentially form an ‘image’ or ‘snapshot’ of the current state of the building and its inhabitants, predict and analyze alternative operational workflows, and provide dynamic recommendations to the building inhabitants on which strategy leads to the best outcome from a holistic perspective, which (a) accounts for both spatial, occupancy, and operational criteria and (b) considers the often-competing needs of different stakeholders (e.g., in the case of a hospital: doctors, patients, visitors, and hospital managers).

**2. Research Objectives and Expected Significance**

***The overarching goal of this proposal is to explore how simulation-powered computational methods can transform IT-enhanced buildings from passive containers into ‘smart’ environments that provide intelligent and proactive recommendations for enhanced building operations.*** This research leverages recent developments in IT systems that augment buildings’ capabilities to sense data about usage patterns and inform building operations. The proposed approach, however, aims at being independent of specific IT systems and sensor technologies embedded in the built environment. Instead, it focuses on developing fundamental modeling and simulation principles for generating context-aware operational insights in IT-enhanced environments. The research objectives include:

*(1)* Creating a***Multi-Modal Knowledge Base of Human Behavior Patterns*** based on data collected using a combination of ethnographic and IT-driven approaches, which traditionally have been considered independently. The combination of these methods is expected to generate a new understanding of the dynamic unfolding of building operations in built environments (WP1).

*(2)* Defining a***Narrative-based Model of Building Operations***that leverages the knowledge base developed in WP1 to support the joint and interdependent modeling of spaces, people, and activities. This approach builds upon and significantly extends concepts of Narrative-based modeling to generate context-aware recommendations for intelligent spatial, occupancy, and operational adaptations (WP2).

*(3)* Developing a***Simulation-Powered Recommendation Engine for Total-Environmental Adaptability***that leverages the computational model developed in WP2 to explore and analyze the implications of alternative resource allocation strategies and identify the one that best balances multiple evaluation criteria defined with hospital stakeholders (WP3).

*(4)* Experimentally***verifying, validating, and evaluating*** *the proposed approach* in collaboration with hospital stakeholders. The aim is to explore the potential benefits of simulation-powered building operations management over more traditional methods that substantially rely on human intuition. (WP4).

Graphical user interface

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**Figure 2.** Proposed Framework for simulation-powered building operations management in Smart Hospitals to proactively inform spatial, occupancy, and operational adaptations in response to – or anticipation of – emerging needs.

**3. Working Hypotheses**

***The main research hypothesis is that computational simulation can enable the efficient allocation of resources in IT-enhanced environments to enable spatial, occupancy, and operational adaptability in response to – and anticipation of – the dynamic needs of building occupants****.* To tackle this main hypothesis, four secondary hypotheses are generated, each of which underlies a different work package: (WP1) a combination of multi-modal data collection strategies can inform the generation of a knowledge base that formalizes the unfolding of human behavior patterns; (WP2) the narrative-based model could be extended to represent salient features of building operations and enable predictive analytics of alternative management strategies; (WP3) a simulation-powered recommendation engine can explore the implications of alternative resource allocation strategies over time from a spatial, occupancy and operational; and (WP4) the proposed framework can extend traditional decision-support methods that heavily rely on human intuition.

**4. Research Approach and Work Packages**

**Case Study:** The proposed research will be developed in collaboration with the Rambam Healthcare Campus in Israel, the largest tertiary medical center (1,000 beds) in Northern Israel. Hospitals have been chosen as test-case for the following reasons: (a) they are designed and operated by a formalized and agreed-upon set of procedures defined by the healthcare organization, making the development of predictive models more tractable than less process-driven settings (e.g. museums and public spaces); (b) established performance criteria can be identified and measured to evaluate building operations, which are impacted by spatial, occupancy, and operational conditions [52], [53]; (c) failures to manage building operations can lead to inefficient patient throughput, prolonged length of stay, communication breakdowns between departments, misplaced equipment, space under/over utilization, staff fatigue, patient dissatisfaction, staff distractions, all of which severely affect patient care [54]–[56]; (d) the rate of progress of medical procedures and technologies and the growing demand for specialized care far outpaces that of the buildings themselves, making hospitals in need of continuous adaptation; and (e) hospital efficiency is a multifaceted issue that must consider the often-conflicting needs of different stakeholders, such as patients, staff members, and managers.

A specific case study has been selected to execute the proposed research tasks using the following criteria: (a) medium-size ward with multiple types of users and activity flows, (b) constrained availability of space and staff resources that may cause operational bottlenecks, (c) access to data collected through IT systems, (d) adaptive spaces that can serve multiple functions.

The chosen case study is the Rambam Institute for Pain Medicine – the largest pain unit in the North of Israel and the only interdisciplinary one (see collaboration letter). It employs 45 staff including physicians, nurses, physical therapists, psychologists, complementary and alternative medicine practitioners, and administrative staff. The unit includes 15 treatment rooms on two floors in addition to a patient reception and waiting area. Some rooms are used for multiple purposes, including invasive procedures, intravenous infusions, admittance, acupuncture, group psychological therapy, and observation of patients prior to - and following - invasive procedures.

**WP1: Multi-Modal Knowledge Base of Human Behavior Patterns**

Existing approaches for collecting data about human behavior patterns either provide a detailed account of a specific human activity using IT systems (as discussed in Section 1.1) or focus on a broader understanding of human behavior using ethnographic studies such as Post-Occupancy Evaluations [57], [57], [58]. To provide a detailed yet holistic understanding of human behavior patterns, I propose to integrate multi-modal data using a combination of ethnographic methods (including experts’ interviews and field observations) and continuous data logs from hospital IT systems. I hypothesize that both approaches can inform one another: overview information collected using ethnographic methods can inform the interpretation of fine-grained data collected through IT systems. In turn, continuous data streams collected through IT systems can enrich ethnographic accounts through data sets of actual utilization patterns. The main research challenge thus concerns the creation of a novel framework to integrate different types of data collected at different time intervals and generate knowledge amenable for computational modeling of human behavior patterns. I detail below each one of these data collection methods:

*(a) Experts’ interviews*. Physicians, nurses, therapists, and psychologists (between 3 to 5 people per user type) will be interviewed for 1 hour each to extrapolate a general overview of the activities performed in the ward. An initial interview (30 mins) will be conducted before the field observation study (detailed below) to provide a general account of the hospital operations, including the different functions of each space, the roles of main actors, and an overall description of patients’ flow. A second interview (30 mins) will be conducted after the field observations to verify, interpret, and generalize the context-dependent data collected and extrapolate the description of human behavior patterns. The institute director and deputy director will also be interviewed to define key performance indicators (KPI) of spatial, social, and operational performance of the ward that will be used as target metrics for the proposed simulation system.

*(b) Field Observations*. Between 3-5 trained observers acting as ‘recognized outsiders’ (Zeisel, 1984)will record the location of people and the activities they perform through unobtrusive, direct observations for a period of 4-6 days through a typical hospital shift (approximately 7:00 am – 3:00 pm). Data will be collected using two methods: (1) Shadowing:the observers will follow a selected staff member through the shift to gather information about performed tasks, duration, and potential operational bottlenecks that arise due to the lack of space or staff availability; and (2) Behavior Mapping: Between 3-5 observers will be stationary in selected areas of the ward to record people’s presence and activities at discrete intervals of 15 mins. Both methods are complementary: the first provides specific people-centered information that is continuous over time, while the second provides space-centered information at discrete time steps. When combined, they can produce a detailed account of space utilization patterns. Prior studies demonstrated the benefits of behavior mapping to analyze spatiotemporal behavior patterns [59][60]

*(c) IT systems.* The following data will be obtained from the hospital administrative data servers:  
(1) Patient scheduled visits including visit type (first medical evaluation, follow up medical visit, nursing procedure, medical procedure, psychological treatment, physical treatment, etc.), and (2) Patient arrival and queue management data from the QFlow system including date and hour of arrival, destination room, time of clinical visit start and end, and calculated delays and waiting times per room. Additional sources of data collection will be considered, including (3) occupancy sensors to analyze waiting patterns in the front desk and waiting area, and (4) RFID tracking for selected staff members including nurses and physicians.

The data collection methods comply with ethics and privacy regulations defined by the Rambam Healthcare Campus, Technion Research Authority, and the Institutional Review Board (IRB). The data will be anonymized to prevent the identification of patients and staff members, encrypted, and stored in a secured cloud platform accessible by authorized personnel.

The different types of data collected will be compared and integrated to identify spatiotemporal behavior patterns that consist of a structured sequence of activities performed in one or more spaces by a single or group of participants. Specifically, *interviews* will provide an overview of activity flows, *field observations* will situate the activities in a spatiotemporal context to identify potential dependencies between different activities occurring in the same space, and *IT systems* data will inform the actual durations of treatments and patients’ stay in the institute as well as daily/weekly/annual data-driven insights on operational performance.

Prof. Efrat Eizenberg, as an expert in environmental psychology, will assist the processes of data collection and analysis using interviews and field observations. Prof. Avigdor Gal, as an expert in data science, will assist the process of data collection and analysis using IT systems (see collaboration letters). Prior work of the PI involved the creation of a preliminary knowledge base of human behavior patterns based on experts’ interviews and field observations (Figure 3). The expected contribution of this WP include: (a) a new framework for encoding knowledge about human behavior patterns that support the modeling and simulation of holistic building operations, and (b) a scientific paper in a peer-reviewed journal (Q1 ranked) in the field of Social Sciences and Environmental Psychology, such as *Environment and Behavior* or *Building and Environment*.

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| **Figure 3.** Preliminary experiment to create a human behavior knowledge base from interviews and field observations |

**WP2: Narrative-based Modeling of Building Operations**

Data collected in WP1 will inform the development of a computational model that supports a holistic representation of hospital operations from a spatial, social, and operational perspective. The main research challenge will involve the exploration and modeling of spatial, occupancy, and operational adaptabilities in anticipation of emergent needs. In fact, the model should be capable of proactively anticipating and resolving the inefficient utilization of hospital resources (i.e., spaces, people, and equipment). To overcome this challenge, I proposed to extend the previously developed narrative-based modeling framework. Different from traditional Agent-based models (ABM) that focus on the independent behaviors of individual agents/occupants, the proposed approach aims at representing the interdependent interactions of multiple occupants as they use a variety of hospital resources over time (as discussed in Section 1.2). The proposed model includes the following components:

***(a) Space entities*** represent the environment where behaviors take place. They comprise of (a) *static* information about physical (walls, floors, doors, furniture, equipment, etc.) and non-physical components (rooms, corridors, and open areas), and (b) *dynamic* information that describes how spaces are dynamically used by virtual occupants (e.g., who are the users located in the space, which activities they are performing, etc.). This approach augments traditional Computer-Aided Design (CAD) or Building Information Modeling (BIM) space models with (a) semantic information that determines a prevailing space utilization pattern at a given time, which is determined by who the occupants are, what they do, when, and with whom [61], and (b) spatial affordances [62]–[64] that indicate which activities are supported by the space at any given time. A ‘clinic room’ semantics, for instance, indicates that the space is used for clinical activities, such as treating a patient, and cannot support other activities, such as a patient’s visit from family members. Spatial affordances and semantics will enable the simulation of dynamic space adaptations that respond to dynamic operational needs.

**(b)** ***People entities*** represent the building occupants. They are modeled as computational agents comprised of (a) *static* information about an organizational role (e.g., patient, nurse, doctor, visitor) and individual abilities (e.g., treating patients, performing medical procedures) and (b) *dynamic* information about their current location, activity currently performing, perceived spaces and people, proximity with equipment or other staff members, time spent with patients, walked distances during their shift, number of interactions with other staff members, etc. Agents’ behavior will be mostly driven by operational workflows (encoded in WP1). Nevertheless, agents’ models will be enriched with insights from established psychological, sociological, and economic theories related to building-human interactions [65] such as privacy, territoriality, and sense of control, which have been proven relevant in healthcare settings [66]. Much like spaces, the proposed system considers people as critical resources that need to be dynamically allocated to achieve operational goals.

**(c)** ***Activity entities*** represent the interactions between people and the built environment. This research is concerned with abstracted activity descriptions, their spatial location, the identities of the participating actors, and their duration. In this way, the number of activities modeled can be limited and focused on their spatial/social implications in real-world situations. Activity models will be modular and hierarchical to describe individual or collaborative behaviors at an increasing level of complexity using a minimal set of generic and reusable activity building blocks that describe people’s movement and interactions [44]. Activity information will include their expected duration, involved participants and equipment, and spatial location.

**(d)** ***Narrative entities*** represent goal-oriented and context-dependent behavior patterns [43]. They associate *people* with specific *activities* to be performed in a specific *space* at a given time. Narratives can be *scheduled*, such as the patient examination round, where doctors systematically visit each patient in the ward, and *unscheduled* such as a Code Blue, where patients in a life-threatening situation must be resuscitated. Each narrative will contain information about workflow protocols, collected during WP1. For example, the ‘patient treatment’ narrative will store information about the activities required to treat a patient, the staff members who can perform the procedure, the equipment required, and the type of spaces where the patient can be treated.

**(d)** ***Narrative Management System.*** It is the brains of the proposed model: it is responsible for coordinating the unfolding of multiple narratives, detecting potential conflicts between narratives, and exploring the implications of alternative conflict resolution strategies through simulation. A Conflict Detection mechanism compares the possible unfolding of multiple narratives to detect operational bottlenecks that may arise within a set time horizon. For example, if two different patients require access to a holding area but there is a single bed available, a ‘space’ conflict is flagged. Instead, if two beds are available but there is a single nurse in charge who can transport only one patient, a ‘people’ conflict is flagged. A Conflict Resolution mechanism identifies possible alternative solutions to resolve the conflict. Solutions may span from directing a patient to a different treatment area, reallocating staff members to different activities, delaying treatment procedures, or temporally placing patients in waiting areas. The secondary and tertiary effects of each conflict resolution strategy need to be simulated and evaluated before the solution can be recommended (as detailed in WP3).

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| **Figure 4.** Preliminary working model of a narrative management system that operates on a graph-based space representation and predicts potential resource allocation conflicts |

Prior work of the PI applied narrative-based modeling for long-term environmental adaptability through design changes [46][45]. In this work, I focus on extending the narrative-based model to enable short-term operational adaptability in a spatial context. Figure 4 outlines a preliminary system architecture that extends the narrative-based model to explore strategies for conflict detection. Expected outcomes of this WPinclude (a) a computational model for simulating holistic building operations, (b) an open-source release of the software package, and (c) a scientific paper in a peer-reviewed journal (Q1 ranked) in the field of Computer-Aided Design and Computer Science, such as *Automation in Construction* or *Architectural Science Review.*

**WP3: Simulation-Powered Recommendation Engine for Total-Environmental Adaptability.**

The proposed recommendation engine leverages the computational model developed in WP2 to simulate the implications of alternative building operation strategies and proactively recommend the one that prevents operational inefficiencies and generates the most favorable outcomes over time. Existing approaches only consider limited implications of building management systems mostly for energy savings (as discussed in Section 1.3) or for staff allocation to work shifts [67]. Instead, this approach aims at exploring, filtering, evaluating, and selecting holistic strategies that may involve adaptations in occupancy, space utilization, operational workflows, or combinations of the above. I consider this to be a demonstration of the power of *total-environmental adaptability* since it does not consider only a single performance criterion, but rather many criteria, including the side- and after-effects of enacting one or multiple actions. The main research challenge in this WP will thus involve the exploration and categorization of possible adaptation strategies to identify the most appropriate one that considers the needs of different stakeholders.

To address this challenge, the proposed engine will simulate the implications of alternative resource allocation strategies (as discussed in WP2) and generate a data log that comprises spatiotemporal information about the people, the activity each person is involved in, and the space in which they are located. This data log will be represented in numerical form or as spatiotemporal data-maps [68] illustrating the relationship between different spatial, social or environmental phenomena over time. Multiple maps can be superimposed to consider aggregated spatial, social, and environmental phenomena over time [69]. The PI previously used data-maps to describe people density, congestion, noise propagation [45] as well as contact-related infection risks [70].

The numerical data log and data maps will be analyzed based on Key Performance Indicators of space utilization, operational efficiency, and people experience developed in collaboration with hospital stakeholders in WP1. They may include hard and soft criteria. Hard criteria are quantitative, measurable performances, such as patients and staff walking paths and distances, patients’ length of stay, overall throughput, congestion, and utilization of space, equipment, and human resources. Soft criteria are typically qualitative, based on subjective perceptions, such as social and psychological elements, including patients’ perceived density, privacy levels, and sense of control. Hard and soft criteria will be evaluated using a combination of numerical approaches and human-in-the-loop analyses that rely on human experience to extrapolate key insights from data visualizations generated via simulation [71]. For each simulation scenario, the measured KPIs will be compared to predefined threshold measures or relative to one another. A preliminary list of KPI considered in this project includes (a) the percentage of time a space is being used or left unused, (b) staff walking distances, (d) spatial congestion, and (e) patients’ turnaround and waiting times. These KPIs have been identified as critical to evaluating the performance of healthcare environments [52], [53], [55].

A tradeoff mechanism will balance competing KPIs, which may be valued differently by different stakeholders. In fact, to create a building-wide management system it is necessary to consider the relative merits of each KPI and combine them into an aggregated overall objective [72]. The tradeoff mechanism can choose to optimize one performance characteristic over others or strike a balance in the degree to which any performance criterion is achieved, assuring that overall performance is maximized. Several scenarios testing alternative workflows and resource allocation strategies will be compared to identify the one that achieves the best performance goals.

A ‘horizon effect’ parameter will control the number of time steps in the future that the model will consider. This will prevent the system from recommending strategies that provide optimal outcomes in the short term, but detrimental outcomes in the long term. While ideally, the system should consider the maximum possible horizon effect, this comes at the cost of computational efficiency. During this research, I will explore tradeoffs between the horizon effect and the computational efforts to run simulations. The far-reaching implications of chosen operations strategies at a broader spatial scale (i.e., the hospital level) instead of at the unit level will be considered in future work.

Preliminary work of the PI involved simulating the implications of selected alternative solutions to a spatial conflict involving two patients competing for a single bed in a holding area within a catheterization lab (Figure 5). Expected outcomes of this WPinclude (a) a recommendation engine to explore intelligent building adaptation strategies, (b) an open-source release of the developed software, and (c) a scientific paper in a peer-reviewed journal (Q1 ranked) in the field of Building Operations Management, such as *Facilities* or *Intelligent Buildings.*

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**Figure 5.** Preliminary experiment to simulate the implication of a specific conflict resolution strategy in a catheterization lab

**WP4: Iterative Model Verification, Validation, and Evaluation**

This WP will aim at calibrating the proposed framework against real-world data and exploring its capabilities to provide valuable insights for hospital stakeholders.

**Verification & Validation*.*** Algorithmic approaches will be used to verify the correct implementation of the simulation model by automatically identifying anomalies in the generated data. For example, tests will be run to confirm that people are always engaged in a Narrative, the profile of people and spaces are correctly updated over time, and data logs that record the location and activities of people over time are correctly generated. A combination of three complementary strategies will be used to validate the accuracy of the model in a selected number of mockup scenarios [74]: (a) *Face Validity*: experts from the partner hospital will be asked to assess whether the model output is reasonable through a survey; (b) *Historical Data*: part of the data collected in the hospital will be used to develop the proposed simulation model and represent the current state of the hospital environment, while the remainder of the data will be used to validate the predictions of future states of the hospital. (c) *Parameter variability and sensitivity analysis*: values of the model including the space layout, number of patients or staff members and operational workflows will be systematically changed to determine if the output of the model is reasonable. Prior work of the PI involved using face validity and sensitivity analysis to validate human behavior simulation models [45].

**Evaluation**. A series of experiments will be conducted in collaboration with staff members of the Rambam Institute for Pain Medicine to compare the proposed recommendation system against more traditional decision-making processes based on human experience and intuition. Five to eight participants including the deputy director of the institute will be asked to predict and evaluate the implications of alternative resource allocation strategies in a series of selected mockup situations. In some situations, the participants will be required to use their own experience and intuition, while in others they will test the proposed recommendation framework. The decision outputs will be compared, and a survey will be distributed to investigate the potential benefits and limitations of simulation-powered decision-making processes.

The expected deliverables of this WPinclude (a) insights on the model validity and the role of simulation to augment the decision-making process of hospital stakeholders, and (b) at least one scientific paper in a peer-reviewed journal (Q1 ranked) in the field of Simulation and/or Building Operations Management, such as *Facilities* or *Intelligent Buildings or Automation in Construction*

**6. Research Personnel and Supporting Infrastructure**

The project will be managed by the PI, assisted by a Ph.D. and MSc students trained in Computer-Aided-Design (CAD), Building Information Modeling (BIM), simulation, and spatial analytics. Dr. Amir Minerbi, the Deputy Director of the Rambam Institute for Pain Medicine, will provide access to his medical unit. Field observations will be performed with five (5) undergraduate students who will be trained for this task by the PI, who has previously managed field studies in hospitals. Prof. Efrat Eizenberg will help collect data using interviews and field observations. Prof. Avigdor Gal will help analyze the collected data and mine it to inform the simulation model development. The Ph.D. and MSc students will be responsible for analyzing the collected data and developing the components of the proposed approach under the supervision of the PI, who has prior experience in modeling and simulating behavior patterns in healthcare environments. The PI established a new lab at the Technion and secured funding to recruit personnel, including students, a technician, and a postdoc, who may be selected to contribute to this project. Additionally, the PI secured funding to buy equipment that will support this research, including (a) a laptop for the PI, (b) tablet computers that will be used by the undergraduate students for data collection in the hospital setting, and (c) occupancy sensors and wearable devices which could be deployed as additional sources of data collection if approved by the hospital management.

**7. Expected Results and Pitfalls**

Expected results include a framework for dynamic building management at the intersection of architectural design, social science, computer science, and operations research that will integrate theoretical models of the relationship between human behavior and built environments, such as the theory of Place, with concepts and methods from Building Information Modeling (BIM), Internet of Things (IoT) and human behavior analytics. This approach holds promise to spark exciting new research opportunities in real-time space and people management and the development of next-generation smart and networked environments. I expect to explore the capabilities of the proposed management system in collaboration with one or more Units at the Rambam Healthcare campus and possibly other hospital partners.

A potential pitfall may be the quality of the data collected using the hospital’s IT systems, which may require additional processing to be incorporated into the simulation model. To mitigate this, I budgeted the work of an undergraduate student from computer science or industrial engineering who will be able to process the data and prepare it for the simulation. Besides, to overcome the risk of relying on a single hospital partner for collecting data and gathering experts’ insights, I will explore potential collaborations with additional hospitals to test and calibrate the model in different settings and thus prevent the risk of overfitting the predictive models to a specific context.

**8. Impact**

Exploring a novel approach for transforming buildings from static containers into active participants in the life of a built environment could bring a transformational impact on the way buildings are conceived. While building design and operation management have been typically considered two independently developed areas, the proposed framework considers them fundamentally intertwined and mutually responsible to enable efficient building utilization patterns that satisfy the dynamic needs of the building occupants. As IT-enhanced buildings become more pervasive, more and more building utilization data will be collected, providing a solid base to integrate more information in the proposed framework and power the model with smarter decisions.

The design of dynamic and responsive environments will likely require stakeholders with diversified expertise (e.g., Operations Research, Artificial Intelligence, Social Sciences, Environmental Psychology, Healthcare, and Electrical Engineering) to collaborate and coordinate the responses of a ‘living’ machine [75]. In this way, they might be able to design integrated human experiences in which the digital and the physical are interwoven to achieve the best match between operational efficiency and people experience. At the same time, responsive environments equipped with autonomous decision-support capabilities may spark new research in the field of human-machine interaction to explore the ethical implications of technological failures, trust issues towards automated systems, and implications of lack of compliance with system recommendations.

From a practical perspective, advancements in simulation-powered operations management in smart hospitals could mark a departure from existing approaches that are heavily based on human intuition. It could potentially account more closely for the implications that operational decisions may have on space utilization patterns and evaluate tradeoffs between alternative strategies to identify the solution that best balances the outcomes for the involved stakeholders, including patients, visitors, and staff members. Intelligent and adaptive environments capable of continuous operational awareness and data-driven actionable recommendations hold promise to help the overall healthcare delivery system adapt faster and better to rapidly changing spatial, operational, and staffing needs. More broadly, the proposed approach could provide a framework for reducing the gap between the expected performance of a facility and its actual use using quick decision-making cycles that do not require long, expensive, and environmentally damaging architectural design renovations.

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