‘Cognitive facility management’: Definition, system architecture, and example scenario

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Abstract:
Prevailing facility management (FM) discourses have recognized the importance of efficient facilities to improve the quality of life and the productivity of business. Advanced technologies have elevated facilities from ‘brick and mortar’ to ‘intelligent beings’. To date, facilities have become more anthropomorphized, imbued with cognitive capability akin to humans, e.g., able to perceive, learn, and act. However, the development of ‘cognitive FM’ remains in its infancy. This paper attempts to put forward the concept of cognitive FM by providing a working definition and articulating its key elements, including perception, learning, and action. An eight-layer system architecture is proposed to facilitate the implementation of cognitive FM. Following that, a demonstrative scenario called ‘Event Manager’ is utilized to showcase the potential applications of such cognitive FM. The paper contributes to the body of knowledge by advancing the stagnant FM discourses defined and subsequently confined by the smart/intelligent building language three decades ago. It opens a new avenue for both researchers and practitioners to better investigate and value FM as a cognitive system.

Keywords: Facility; Facility management; Cognitive system; Cognitive facility management; Proactive intelligence

1. Introduction

A facility is an asset that is built, installed, or established to serve our social and economic activities (Kaplan et al., 2004). Facilities include different types of physical infrastructures (e.g., bridges, roads, and stadiums) and buildings (e.g., hospitals, shopping malls, and housing). The growing complexity of modern facilities increases the responsibilities and importance of

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management. The International Standard Organization (ISO) (2017) defines facility management (FM) as an organizational function which integrates people, place and process within the built environment for the purpose of improving quality of life and productivity of business. Drion et al. (2012) asserts that FM is a management function that focuses on how to develop, maintain and improve the physical assets needed to support and add value to the business processes of organizations, as well as create and maintain a physical workplace that provides optimal support to the people and work of the organizations. One of the legitimate scopes of FM is to facilitate resources use, enhance organizational effectiveness, and improve our living and working environment for social and economic activities (Rondeau et al., 2012). Compared with other phases in a facility's life cycle, FM can last for a relatively longer period, roughly thirty to fifty years if not longer (Atkin and Brooks, 2015). FM must be well conducted to realize a facility's designated functions. The efficiency and effectiveness of FM significantly affects operation cost (Teicholz, 2013), energy consumption (Bilgen, 2014), indoor comfort and in grander scheme global climate (Nielsen et al., 2016). The importance of FM is underpinned in Winston Churchill's famous quote (Cited in O'Toole and Lawler, 2007), "*We shape our buildings, thereafter they shape us*".

Over the last three decades or so, smart facilities and their management captured the basis of FM discourse, especially concerning the lasting and heated discussion around smart building and intelligent building. Adding automation and intelligence features to tradition, standard, physical and largely dumb 'brick and mortar' renders them 'intelligent', providing more efficient, responsive, and environmentally friendly services to occupants. Advanced technologies, software, and systems directed at FM stimulated a boom in 'intelligent' initiatives and innovations. Examples of such systems include the widely adopted CMMS (computerized maintenance management system), CAFMS (computer-aided facility management systems), BAS (building automation system), CAS (communication automation system), SAS (security automation system), FAS (firefighting alarm system), pervasively discussed BIM (building information modelling) technology, and smart public transportations system.

Nevertheless, current FM practices, be they routine maintenance or *ad hoc* event management, are largely backward and characterized by a low level of automation and intelligence (Pärn et al., 2017; Wu et al., 2014). Only able to operate on preset conditions, they cannot adapt to complex scenarios. They often perform passively and in an isolated manner (Lau et al., 2013). Different FM systems (e.g., CAS, BAS, FAS, and SAS) do not share information with each other. Decision-making involved in current FM relies heavily on manual input, setting and operation, which can be fallible due to the limited computation capacity and bounded rationality of human beings (Niu et al., 2016). Moreover, current FM generally pays scant attention to the differentiated and changing requirements of occupants in a facility. Therefore, it is not uncommon that a facility fails to provide satisfactory services to people, organizations, and businesses it serves (Wang et al., 2018). These predicaments are resulted from the passiveness of current FM systems. Various passive FM systems are pre-programmed, which cannot respond to complicated, flexible, changing situations in real life. FM needs to be updated with intelligence to a higher level akin to human beings' cognitive capability (e.g., to perceive, to learn, and to act). Although some recent research efforts have explored the application of cognitive capability to FM, none have been able to provide a detailed, systematic account.

This study aims to take the very first step to define a new concept, cognitive FM, which empowers cognitive capability into traditional facilities and their management. It tries to answer the following research questions: (1) what is cognitive FM? (2) what are its key elements? (3) what is its system architecture? and (4) how does it influence FM? The remainder of this paper is organized as follows. Section 2 reports related work on concepts related to cognitive FM and cognitive computing, and emerging computation technology. Section 3 discusses the definition, key elements and enabling technologies of cognitive FM. The proposed system architecture of cognitive FM is illustrated in Section 4. Section 5 proposes an application scenario of cognitive FM. Discussion and conclusions are made in Sections 6 and 7, respectively.

2. Literature review

2.1 Concepts related to cognitive facility management

Smart facilities and their management form the crux of FM literature and practices, especially as relates to contentious concepts like the smart home, ambient intelligence, smart building, and intelligent building. A 'smart home' constitutes a residence able to anticipate and respond to the needs of its occupants, enhancing their comfort, convenience, entertainment, and security with the support of technology (e.g., Information Communication Technologies [ICTs] or Internet of Things [IoT]) in the home environment and connects to the world beyond (Harper, 2006). A wealth of research and development has been dedicated to smart electronic devices and home appliances for smart homes. However, smart homes, by and large, can only react to given requirements and conditions. They cannot effectively perform functions outside their programmed range.

'Ambient intelligence' characterizes an environment embedded with technologies but in natural surroundings. Sensitive, adaptive, and responsive to the presence of people and objects, it exploits smart non-explicit assistance to augment activities (Weber and Rabaey, 2005). Using sensors or sensor networks, ambient intelligence perceives the state of a setting, situation and the people within them. Ambient intelligence can greatly influence people's lives through applications such as health monitoring assistances, emergency services, and intelligent workplaces. However, ambient intelligence systems have to interact sensibly with users in a variety of sophisticated ways to learn their preferences, intentions, and needs, which brings intervention, privacy and security challenges (Cook et al., 2009).

‘Smart building’ and ‘intelligent building’ are often used interchangeably. Smart buildings integrate and account for intelligence, enterprise, control, and materials and construction as an entire building system, with adaptability, for building progression (Buckman et al., 2014). Whereas intelligent building refers more to a dynamic and responsive architecture that provides every occupant with productive, cost-effective and environmentally approved conditions through a continuous interaction among its basic elements, i.e., structures, systems, services and management, as well as their interrelations (Ghaffarianhoseini, et al., 2016). These definitions suggest that the two terms share similar vision. Their implementations are more on the updating of hardware and the adoption of ICTs, and still largely rely on passive control by human beings.

It is difficult to trace the origin of the phrase ‘cognitive building’. In 2016, IBM applied it in relation to machine learning, which makes it more of an industry concept than a scholarly defined one. Cognitive buildings exhibit an integrated approach to the deployment of technologically advanced solutions. They turn data into actionable insights via cognitive computing and comprehensive facilities management capability to better manage buildings (Ploennigs et al., 2018). Though the concept has propagated widely, no theoretical concepts, foundations, or framework have been proposed to formalize it. Nor does the ‘building’ adage differentiate unique types of facilities from one another.

A brief review of the concepts related to cognitive FM helped develop the Venn diagram shown in Figure 1 illustrating the relationship between these concepts. Smart home is a subset of smart building and intelligent building, which has large overlap between each other (Ghayvat et al., 2015). Cognitive building shares a similar scope with smart and intelligent building, but with more consideration for people and more intelligence in the loop (Pasini et al., 2016). Ambient intelligence, focusing on the ambient environment, somewhat overlaps with the four other concepts, but does not solely operate at the home and building level (Hui et al., 2017). FM covers smart home, smart building, intelligent building, cognitive building and a large part of ambient intelligence (Fairchild, 2019).

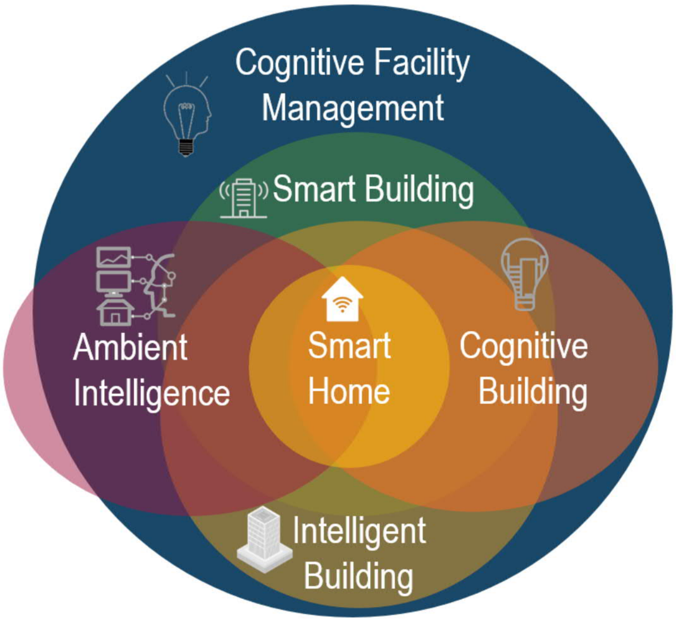

Figure 1. The relationship between advanced technologies related to cognitive FM

All these initiatives are stimulated by and rooted in the advancement of IoT, ICT, and the growing power of computing. Adopting advanced technologies at the home/building/facility level of intelligence succinctly falls into three purpose categories:

(1) Using data sensing technologies such as sensors, sensor networks, laser scanning and photogrammetry to capture the status data of buildings or facilities (Wong et al., 2018). They imitate the five senses of human beings, i.e., touch, sight, hearing, taste and smell. Typically non-destructive technologies, they collect environmental parameters like temperature, humidity, luminance, and air quality (Wu et al., 2016), estimate occupancy (Candanedo and Feldheim, 2016), detect events (Sixsmith and Johnson, 2004), and so on. Laser scanning and photogrammetry are widely used to access a built environment's geometric information. Furthermore, the information they collect help fabricate as-built BIM reconstructions for existing buildings and facilities (Chen et al., 2018).

(2) Using advanced ICTs such as WiFi, Bluetooth, Zigbee, and NFC (Near Field Communication) to report the status of home appliances and control them remotely. Via Bluetooth or WiFi, smart devices like mobile phones, watches, or computers can connect with televisions, sound devices, air conditioners, lights, refrigerators, and washing machines to check their condition (e.g., on, off, operating at certain mode) in real time and change that condition (e.g., turn on/off, set to a new mode) with a tap or click (Robles and Kim, 2010). With these technologies, users can monitor the utilization status, energy consumption, or environmental conditions of buildings or facilities nearly instantaneously. Moreover, humans and the machines can interact with each other naturally through text, voice, gesture, motion, even emotion (Jaimes and Sebe, 2007).

(3) A clear trend is to develop various smart applications and integrate them into various BIM systems/platforms (Lu et al., 2018). The Architecture, Engineering, Construction and

Facilities Management (AEC/FM) domains rely heavily on BIM technology (Liao and Teo, 2019). It involves digitally constructing an accurate virtual model of a building via BIM technology (Azhar, 2011). The model can help improve the performance and productivity of design, construction, operation, and maintenance (Love et al., 2013). For new buildings or facilities, their BIM models can be created via BIM software in the design stage. While for existing buildings or facilities, their BIM models are generated from measurement data (e.g., 2D images or 3D point clouds) captured by cameras and laser scanners, respectively (Volk et al., 2014). BIM-enabled platforms are increasingly integrating smart applications into their features.

Although the concepts of smart home, ambient intelligence, smart building, intelligent building, and cognitive building share some similarities, they also have several obvious differences. First, the scopes of FM and smart/intelligent home/building, cognitive building are different. FM focuses on not only buildings but also other types of facilities such as highways, utility grids, and municipal pipelines. Second, smart/intelligent home/building, cognitive building, and ambient intelligence are more from the perspective and ownership of residents, while FM consigns the decision-making and control with the facility manger on behalf of clients, occupants and tenants. Third, smart/intelligent building/home, allows the automation of building systems, ICTs, and security systems separately (Chen et al., 2014) through emerging pervasive technologies, while FM emphasizes the integrated management of entire facilities. Nevertheless, all these concepts place a solid cornerstone for cognitive FM for this paper to explore.

2.2 Cognitive computing and related technologies

Cognitive science is the foundation of cognition-related studies including cognitive FM. Encompassing psychology, epistemology, linguistics, computer science, economics, and the social sciences more generally, cognitive science is the interdisciplinary study of brain cognition and its information processing mechanisms (Simon, 1980). Human cognition has three accepted main components including perception, action, and learning (Fuster, 2003; Haykin, 2012). A cognitive system can reason, use represented knowledge, learn from its experience, accumulate knowledge, explain itself, accept directions, be aware of its own behavior and capability, as well as respond in a way that loosely mimics the process of cognition in the human mind (Sheth, 2016). Cognitive systems have been tested in construction engineering and management fields such as construction safety management (Saurin et al., 2008) and intelligent business information management (Ogiela and Ogiela, 2014).

Merging human cognizance with computing machines breeds cognitive computing (CC), which basically enables cognitive systems the fuzzy computing ability. An interdisciplinary product, it combines cognitive science and computer science to mimic the human thinking process in a computerized environment. Cognitive computing manages the low power, small volume, mind-like function, and real-time performance of the human brain (Preissl et al., 2012). It is trained, rather than programmed, to forecast future events with purpose and estimated strength (Marchevsky et al., 2017). It has the capability to extract concepts, emotions, objects, keywords, and relationships from massive unstructured data, and use artificial intelligence and enhanced machine learning algorithms to process analytics, make predictions and hypothesize in a scalable way (Dessì et al., 2019). With cognitive computing, a cognitive system can quickly learn and improve as it discovers knowledge and acquires profundity in complex environments.

Cognitive computing is permeating and evolving into such scopes as machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision (CV), and artificial intelligence (AI) (Capuano and Toti, 2019). Machine learning concerns technology that can learn from examples and teach itself how to solve problems without being programmed manually (Stanescu et al., 2018). Deep learning, the forefront of ML, constitutes simple but non-linear modules that each transform the representation of raw inputs into a representation at a higher, slightly more abstract level (LeCun et al., 2015). Natural language processing converts human written or spoken language into a formal representation easy for computers to manipulate (Hirschberg and Manning, 2015). Computer vision is the transformation of data from a still or video camera into either a decision or a new representation (Bradski and Kaehler, 2008). AI is defined as the simulation of human intelligence onto a machine, so as to make the machine proficient at identifying and applying the right piece of “Knowledge” at a given step to solve a problem (Konar, 1999). The Venn diagram shown in Figure 2 displays their relationships according to the ascertains: DL is a subnet of ML which is a subnet of AI (LeCun et al., 2015); NLP and CV are also subnets of AI while using some ML and DL techniques (Jordan & Mitchell, 2015; Young et al., 2018); AI falls into a significant part of CC (Chen et al., 2016). Embodying the major natural intelligence behaviors of the brain such as thinking, inference, learning, and perceptions, cognitive computing is an intelligent technology past the imperative and automatic (Wang et al., 2010).

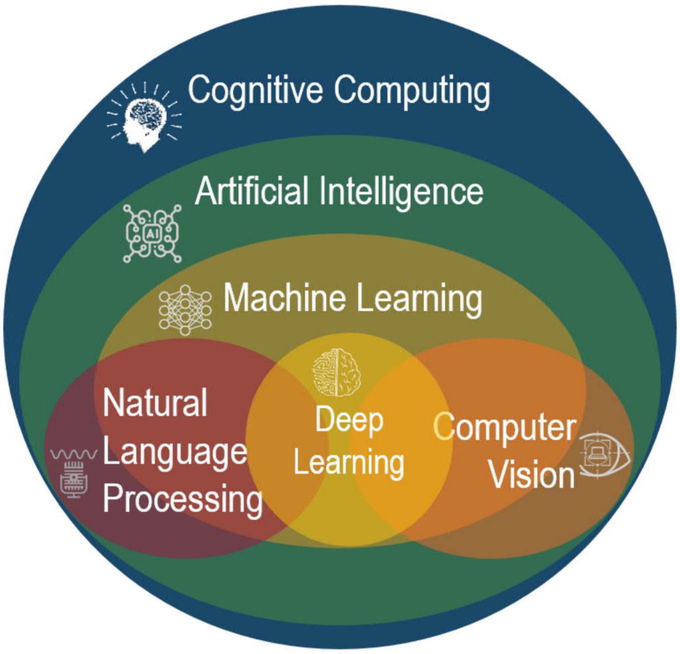

Figure 2. The relationship between advanced technologies related to cognitive computing

A critical review of various concepts discovered that current developments in smart FM have stagnated. Passive intelligence, which can only deal with given problems based on pre-defined rules, repeatable patterns, and pre-programmed algorithms, remains the norm. FM nowadays has to face complex and dynamic situations affected by energy, information, the external and internal environment, and occupants' changing requirements. An elevation in FM is highly advantageous and desired from its current state of passive intelligence to one of cognitive capability. The advances in cognitive computing provide a strategic opportunity to pursue such cognitive FM. However, little research makes up this emerging field, demanding a clear definition of cognitive FM and a theory or theoretical framework behind the new concept. Espoused by the theories of cognition and FM, this paper aims to fill the gaps by putting forward the concept of cognitive FM, presenting a potential system architecture, exemplifying an application scenario, and exploring its prospects and challenges.

3. Cognitive facility management

3.1 A working definition

Based on current FM predicaments, emerging technologies development, and the theories borrowed from cognitive system, the idea of 'cognitive FM' is sprouted. It aims to advance the stagnant FM status and add advanced active intelligence that mimics the mechanism of human brain information processing to FM. Perception, action, and learning are the primary elements in a cognitive system to allow for active intelligence, as illustrated in Figure 3. There are two parts in the system architecture, the core system and the external environment that the system was contextualized in. Sensors and actuators bridge the system and the environment. Sensors take in perceptions of environment and communicate the signals to performance element which is responsible for selecting actions based on perceptions and evaluation component. The evaluation component takes performance standard as input and gives out feedbacks to the learning element, which forms the most important distinction between a cognitive agent and other general agents. It is responsible for making improvements using feedback from the evaluation component on how the system is doing to solve application problems and determines how the performance element should be modified to do better in the future (Russell and Norvig, 2016). To sum up, perception and action are the two primary components which bridges the environment and the system itself. Learning element is the core component which connects application, performance, and evaluation.

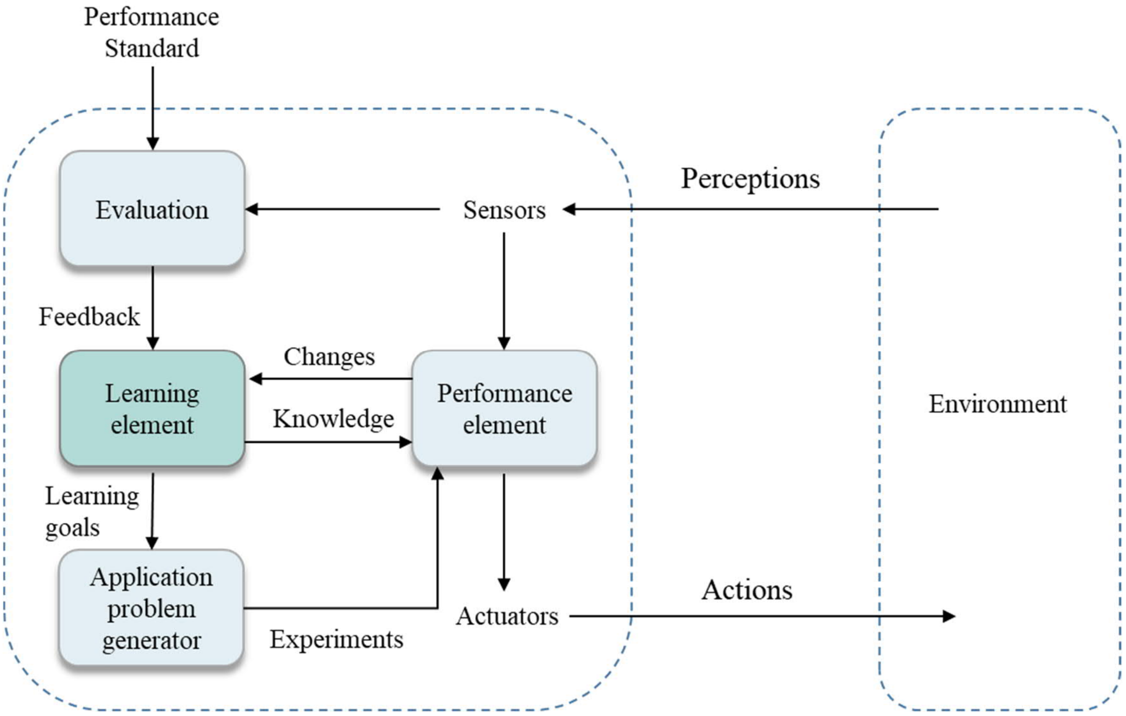

Figure 3. The architecture of a learning agent in cognitive system (Adapted from Russel and Norvig, 2016)

Based on the theories of cognitive system and facility management, 'cognitive FM' is defined as:

> *The active intelligent management of a facility, which have the ability of perception through cognitive systems, learning in the manner of human cognition with the power of cognitive computing, and adaptive, adaptive, and efficient action via automated actuators, to improve the quality of people's life and productivity of core business.*

There are many elements of cognitive FM, but *perception*, *learning* and *action* are argued as the three key definitional characteristics of the new concept.

3.2 Key characteristics of cognitive FM

3.2.1 Perception

Perception is an active process involving the recognition and interpretation of stimuli which register senses made to the environment (Rookes and Willson, 2005). It requires a form of expectation, of knowing what is about to confront us and preparing for it (Ratey, 2001). Perception provides a system with information about the world it inhabits by interpreting sensors (Russell and Norvig, 2016). Perception can be empowered by Cognitive IoT, which supports cooperation and interaction between IoT and human beings. Wired or wireless sensors, cameras, Auto-IDs, and GPS, smart devices and their connected utilities are the 'things' that sense the status and environments of facilities. Wireless sensor networks (WSNs) in buildings, utilities, and transportation systems can enable real-time collection of sensory data (Huang and Mao, 2017). Videos or images captured by cameras are extensively used to gather movement and behavioral information for health, safety and security. They are also pervasive sources of spatial and geometric data that can help reconstruct digital models of in-use facilities. Auto-IDs such as 2D barcode and RFID make real-time localization, tracking and navigation available at facility managers' fingertips (Xue et al., 2018). Capable of collecting different types of data, like the ambient environment and user behavior patterns, smart devices have proved vital sources of information.

3.2.2 Learning

Learning is the accumulation of information in memories, the acquisition of access routes for its retrieval, and the discovery of knowledge based on it (Russell and Norvig, 2016). In a cognitive system, learning helps recognize objects, categorizations, relationships, events, procedures for executing actions, new actions and action sequences to accomplish new tasks (Franklin et al., 2014). It provides an enormous source for variation, adaptation, and evolution in system action. For example, learning from historic data of indoor temperatures, air conditioning controls, and weather helps the system realize occupant preferences and anticipate the outside forces that disrupt equilibrium. Disruptions can be natural or human, for example an individual changing a room's temperature controls one time to suit a unique and short-term situation. A passive system would stay in that new condition indefinitely. Learning is achieved through four approaches, i.e., observation, experience, feedback, and reinforcement (e.g, through watching other's performance and imitating, concluding experiences and recognizing patterns, reflecting feedbacks and discovering knowledge, and reinforcing by punishment or rewards, respectively) (Illeris, 2004). In real cases, learning is a multimodal process which integrates various approaches and mechanisms. Multimodal integration learning combines multiple sources of sensory information such as vision, sound and movement to help a cognitive system achieve enhanced perceptual clarity and reduced ambiguity regarding its environment (Noda et al., 2014).

3.2.3 Action

Action in human cognition instantiates in the brain as motor planning and representation (Immordino-Yang, 2008). Action in cognitive FM may include decision-making, sending alerts, recommending action, analyzing or visualizing statistics, reconstructing models, service provisioning, device actuating, and a combination thereof. Simply being in action can facilitate perception of affordances, i.e., what the environment affords the individual, because actions provide information about the dynamic capability of the facility (Franchak et al., 2010). In cognitive FM, action executes in three ways, i.e., passively, semi-actively and actively (Casciati et al., 2012). Passive action aims to assist people to make decisions with an optimum action plan based on the real-time situation it perceives. A typical example would be issuing an alert that demands a response from facility managers or workers. Semi-active action is an action cooperated by humans and machined via human-machine interaction. Active action can actually execute the optimum action plan via the facility itself without requiring humans to be in the loop. For example, controlling the lights of a room based on occupancy, natural light condition and the type of activity in the room is active action. Realization of the action, especially semi-active and active action, is dependent on cognitive computing and automatically controlled through actuating devices. Automatically controlled actuating devices comprise motorized built-in controllers and robotic actuators, and as this technology matures, they become more affordable.

3.3 Interrelationships of the three key elements of cognitive FM

In cognitive FM, three key elements have direct and/or indirect influence on one another as regards a constantly changing environment and requirements from users. Figure 4 shows the details and relationships between these three key elements. Perception and action intricately connect. Perception provides the requisite information for selecting and guiding actions adaptively (Franchak et al., 2010). Action in turn has concurrent effects on perception (Hecht et al., 2001). They form a perception-action cycle through connections between sensory and motor structures (Fuster, 2003). The perception-action cycle governs the cognitive interactions of a system, be they animate or artificial. This interactive cycle is the basic principle that characterizes the dynamic adaptation of the organism to its environment (Fuster, 2003).

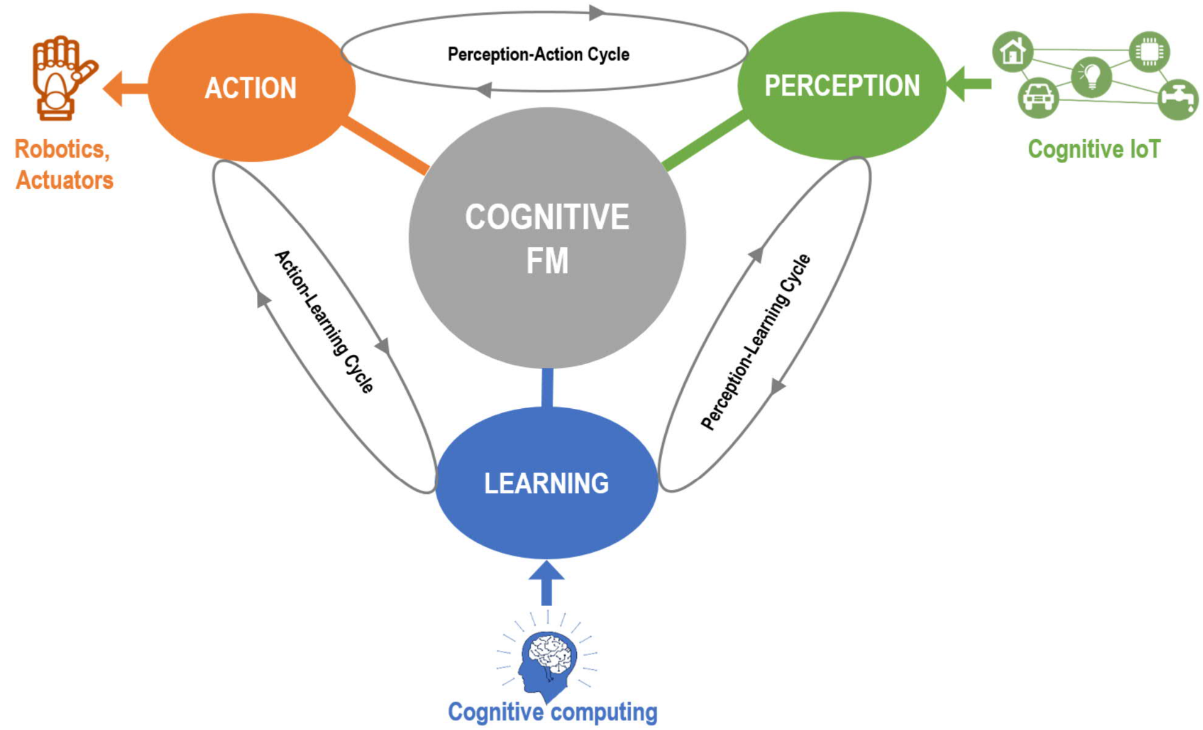

Figure 4. The interrelationships between the key elements of cognitive FM

What hides behind the perception-action cycle to make a system cognitive is learning. Learning helps the system improve its performance on future actions after making perceptions about the internal and external environment (Russell and Norvig, 2016), as well as adapts perception modes to the found patterns of actions, reducing sensing, computing, and memory consumption (Noda et al., 2014).

Learning from perceptions empowers reasoning and knowledge discovery about changes in the internal and external environment, and in turn shapes the way a system perceives, forming a perception-learning cycle (Fiser et al., 2010). This perception-learning cycle facilitates a cognitive system's predictive perception, i.e., ability to predict what an incoming signal might mean, respond, or adjust the perception modes. Predictive perception is what differentiates a cognitive system from a traditional artificial intelligent system, which perceives based on pre-set rules or reinforced learning (Otsu et al., 2017).

Learning from a collection of actions and perception-action cycles enables the system to predict actions and select the most appropriate one for a new perception. Learning can also facilitate action selection and execution of the system in order to adapt to uncertainties and make decisions that maximize the benefits while minimizing the risks (Arashpour et al., 2017). The action-learning cycle enables a cognitive system to alter its strategies and behaviors according to an ever-changing environment and requirements (Lee et al., 2018). This cycle embodies the proactive intelligence and automation of a cognitive system by learning from its own experiences. Robotics can realize and perfect proactive intelligence and automation being able to both read conditions, take actions and learn from experiences (Lee et al., 2018).

In FM, perception, learning and action form a stable triangle that helps a facility to accurately, effectively, and proactively adapt to dynamic environments and various user needs. This triangle empowers the proactive intelligence and automation of a facility to better serve users in a manner more acceptable to human beings.

4. System architecture of cognitive FM

Figure 5 illustrates a system architecture for cognitive FM according to the definition of cognitive FM and the interrelationships of its three key elements. Its eight-layer structure consists of an (1) environment layer, (2) perception layer, (3) data layer, (4) communication layer, (5) computation layer, (6) application layer, (7) action layer, and (8) evaluation layer. Each layer is elaborated as follows:

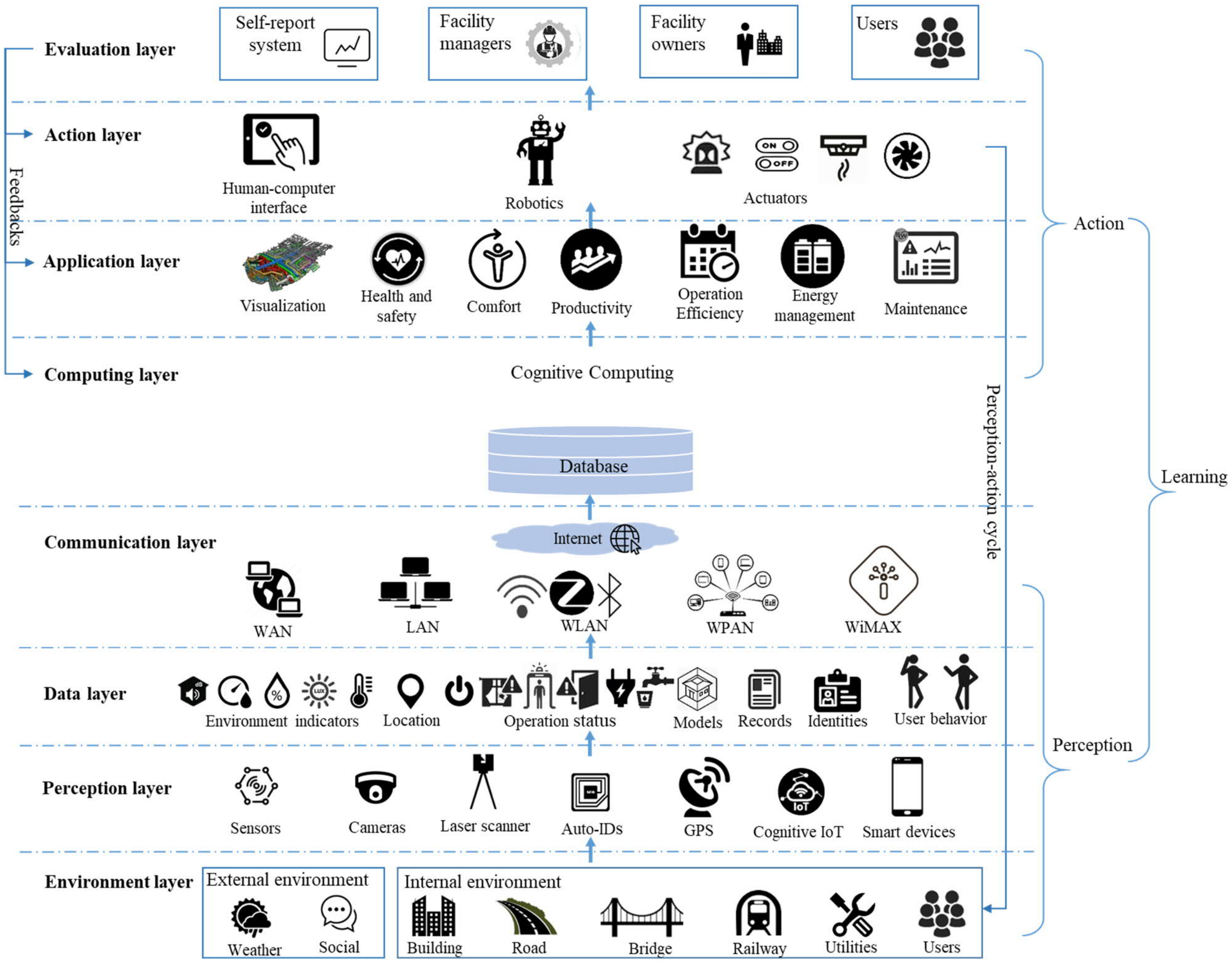

Figure 5. The system architecture of cognitive FM

(1) The environment layer entails the internal and external environments of a facility. The external environment, including natural and social components, forms the context which the facility is positioned in and exposed to. The facility as a whole is the object of cognitive FM, therefore its internal environment is the utilities and users within the facility. It is the layer where all commercial, residential, and social activities take place, and also the layer the system needs to perceive.

(2) The perception layer consists of various sensing devices that operate in a connected fashion to capture the features of the environment layer. Perceptors (e.g., sensors, cameras, LiDAR, Auto-IDs, and GPS) sense the environment by processing the incoming stimuli and feeding observations to the upper layer (Jung et al., 2019). They can detect the status or characteristics of different objects. The information collected by the perceptors is interpreted by the cognitive computing behind.

(3) The data layer denotes various data types generated after perception, including environmental indicators, such as temperature, humidity, luminosity, air pressure, or particulate matter density. It may also comprise pictures, video or 3D point cloud data of a facility or area, the identities of building components, furniture and users, location, operation status, user behavior, and other characteristics.

(4) The communication layer helps upload the sensing data to the database, which acts as base memory. Different types of communication protocols may be used. Local and wireless communication protocols offer a lot of current applications as well as promise for future growth (Tolman et al., 2009). Emerging personal networks (e.g., WPAN) as well as new interoperable networks (e.g., WiMAX) will likely popularize as social communication happens more and more virtually. BIM is increasingly becoming the hub of this communication layer (Chen and Lu, 2019).

(5) The computation layer effectively analyzes the sensed data from the lower layers to generate decision support information through cognitive computing. This essentially embodies behaviors like reasoning, interpreting, inferencing, and learning in uncertain, fuzzy and complex environments with the help of ML, CV, NLP, SA and NN discussed in Section 2.2.

(6) The application layer uses the information and knowledge abstracted from the lower layers to enable multiple or even massive interactive agents (e.g., facilities or users) to reason, plan, and select the most suitable action to support corresponding FM applications.

(7) The action layer is where actuators proceed to facilitate the applications, control the objects and change the perceptron via human-machine interface, robotics, or actuators. The actuators directly control the facilities in the object layer, issuing alerts or guidance to facility users or managers. Robots with caring, operation or maintenance abilities can also execute actions.

(8) The evaluation layer shares import interfaces with social networks, in which on-demand service provision can be shared by facility managers and users to social networks. Novel performance metrics are designed to evaluate the services provided. Moreover, the

evaluation results feedback to the application layer to reset the application variables and objectives, or to the computation layer to adjust the computing algorithms.

The eight-layer system architecture of cognitive FM helps recognize and explain its key elements, i.e., perception, learning, and action. Cognitive FM energizes multi-sourcing and cognitive computing power to support various applications. Through cognitive FM, data sensing informs users, facility managers/owners, and facility manufacturers/designers, enabling more profound information analysis, decision-making, and application execution. Meanwhile, many tedious choices and actions can been performed automatically. The system architecture can be put into the complex real-world FM scenarios.

5. Example scenario of applying cognitive FM

This section presents an applied scenario of cognitive FM called “Event Manager”. Such “Event Manager” is especially important for public and commercial buildings, where events bring considerable people flows within a short time, leading to periodic but rapidly growing needs from certain facilities (e.g., elevators). Efficient scheduling and utilization of these facilities aligned with events is crucial to sustainability, productivity and safe facility operations. Through cognitive FM, the “Event Manager” can perceive data (perception ability) including facilities operations processes (e.g., elevator traveling to a certain floor), the number of people and their status (e.g., in a hurry, anxious, or claustrophobic), even their intentions (e.g., turning the thermostat down) with cognitive IoT and other technologies at the perception layer. Such data and information will be automatically uploaded into the database via the Internet. Learning from experience, best practices, and current information empowered by cognitive computing helps attain an optimal schedule plan, which represents the learning ability of cognitive FM system. The facilities at a specific place will automatically schedule and take actions to satisfy the requirements of users at that time and location (active action). Moreover, the digital model will display the real-time statistics on a dashboard or APP for users and facility managers to better visualize the data, these applications can intelligently guide users to better plan and conduct work, as well as for their evaluation.

To further illustrate how cognitive FM works, an “Event Manager” of a campus building with three elevators is presented. In this scenario, the general system architecture in Figure 5 is specified to the one as displayed in Figure 6 (a). The elevators and users belong to the environment layer (Figure 6 (b)). A UWB (ultra-wideband) local positioning system serves as the perception layer (Figure 6 (c)). The system tracks the real-time location of the users by UWB with a precision to 20cm. By installing UWB anchors in the building, the locations of the UWB tags can be tracked (Ruiz and Granja, 2017). With the Users’ IDs attached to the UWB tags allocated to them when they register the event, the location of the users can be tracked. Once a user walked into the area of the building, the UWB tracking system can detect his/her location. The most important inputs at the data layer include the event schedule of the building (e.g., at what time a significant number of people will attend or exit an event on a given floor), users' location, elevators' features, and floor function. The four major types of entities in the system database and their relationships are shown in Figure 6 (d). All the information items are connected in the database for the perception of the event and further computing. The user location will be communicated via WLAN while elevators' status can be communicated to the database through LAN. The "Event Manager" in the elevator system works following the rationality shown in Figure 6 (e). Finally, with the data in the database and the memory and fuzzy computing ability, the "Event Manager" can better serve the users with cognition by considering the lead time of the elevators to travel from floors to floors, the distribution of users' location and arrival time from short-term memory, and the user behavior pattern from long-term memory. The "Event Manager" will take actions by calling the elevators in advance for the users and automatically taking the users to their destinations. It will optimize the performance of the facility by considering three objectives, i.e., shortening the waiting time, improving the operation efficiency of the elevators and building, and saving energy through learning. A visualization interface will also show the location of the users and elevators as illustrated at Figure 6 (f). The actuation layer is the controlling system of the elevators, see Figure 6 (g). The system can generate daily self-report for evaluation; users may also provide their experience comments as feedbacks for future improvement, as illustrated by Figure 6 (h). This cognitive change, albeit minor, can provide privileged services for the users and upgrade the performance of the facilities.

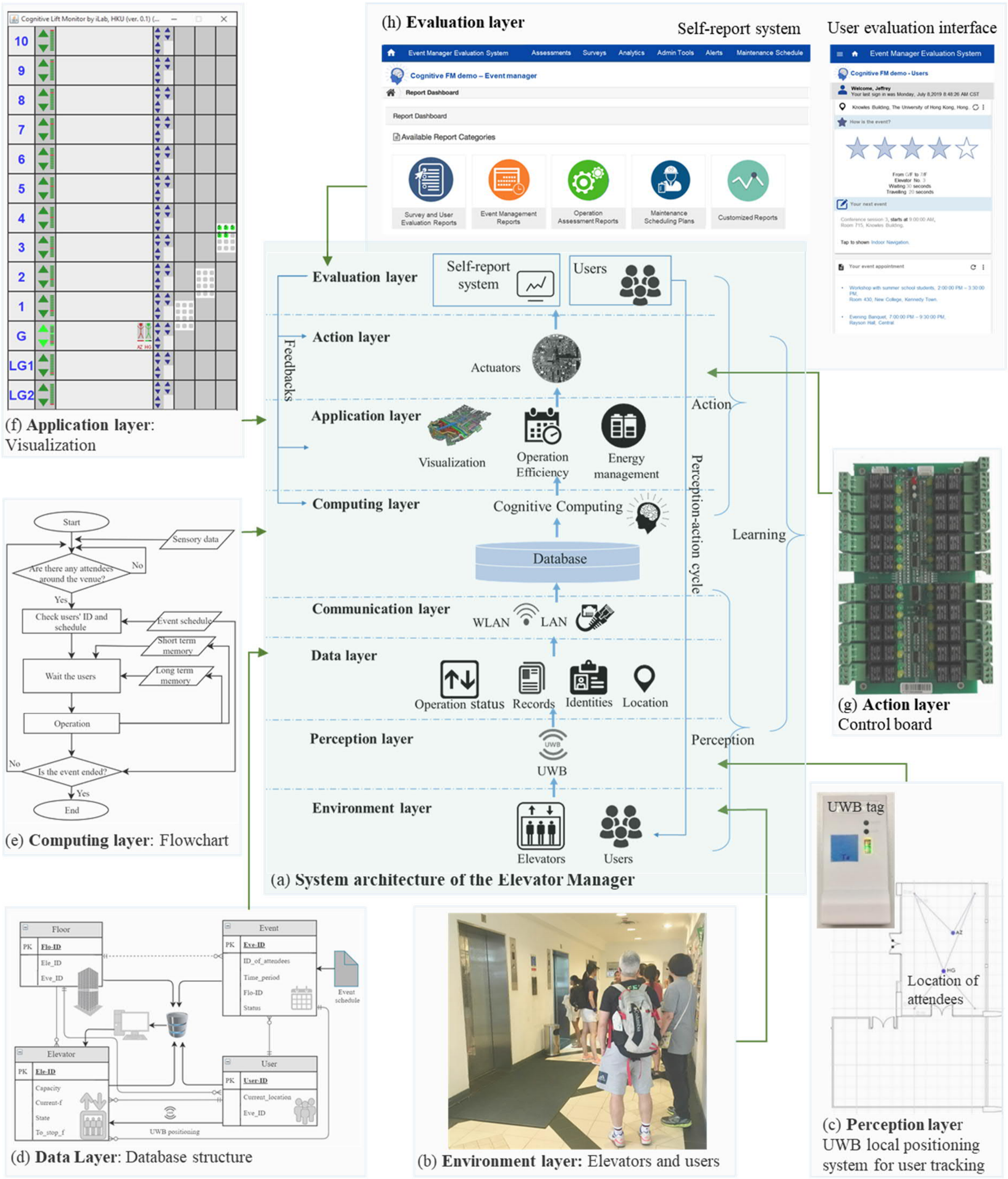

Figure 6 Elevator management system of the “Event Manager”

It should be pointed out that the “Event Manager” as illustrated above is just one of the very primitive scenarios of cognitive FM. Future studies are encouraged to develop other scenarios. The system architecture proposed in this study provides a general guideline by following which other more sophisticated scenarios can be developed. New developments in different layers, particularly perception, data, communication, computing, and actuating technologies will provide unlimited opportunities to realize cognitive FM. Due efforts should be paid to validate such system architecture. The key to this validation work is to develop a real-life cognitive FM system and define their key performance indicators, including both tangible (e.g., energy saving, time saving, or system reliability) and intangible ones (e.g., users satisfactory, ambient environment, or productivity enhancement).

6. Discussion

This paper put forward a bold proposition – cognitive FM – in the inert body of FM literature. It provided the working definition of cognitive FM, and articulated its three key definitional characteristics, i.e., perception, learning, and action. A system architecture of eight layers provides a cognitive FM framework for the structure and operation of human-like proactive intelligence in FM. The highlighted interrelationships and the real-world case, i.e., the 'Event Manager', were presented in an attempt to illustrate how cognitive FM could push boundary of both FM theory and practice. Beyond the 'Event Manager' example portrayed, readers of this paper should note the wealth of other compelling scenarios such as customized service provision and predictive maintenance which fall under the realm of cognitive FM that can be explored in the future.

The advancement of new technologies provides boundless challenges and opportunities to realizing cognitive FM. The technologies on the perception layer, e.g., sensor networks, camera, Auto-ID, smart devices, and cognitive IoT are developing in an unprecedented pace, which allows quickly capturing numerous and various 'big data' (known for its 3V, namely, volume, velocity, and variety) related to facilities and their occupiers and managers with an affordable cost. The communication technologies such as WAN, LAN, and particularly recent fifth generation (5G) cellular network, allow quick communication of the facility big data between the data layer and the computing layer. Quick development of computing technologies such as GPU and clouding computing enables the harness of the power of big data to realize perception and learning capability, while the advancement of human-computer interface, robotics, and other actuating technologies will allow the realization of autonomous actions of cognitive FM. Not only the individual technologies developed (e.g. emerging pervasive technologies (Niu et al., 2019)), but also the new system integration philosophies (e.g., edge computing (Shi et al., 2016), smart construction objects (Niu et al., 2016)) make the bold proposition of cognitive FM feasible than ever. Information and industrial manufacturing conglomerates like Schneider, Siemens, and IBM continuously offer more and more cognitive building services (e.g., Watson IoT for Buildings and IBM TRIRIGA), which integrate the physical and digital worlds.

This research deems FM remained dormant and without a literature base to elevate the discipline to the science it should be, especially given the new technology and capacities available to it. Challenges and opportunities also exist in the development of cognitive science, which is the interdisciplinary study of cognition in humans, animals, and machines (Norman, 1980). Despite the great achievements in cognitive science, very limited actually we know about our cognitive capability and process. Cognitive capability such as perception and learning exclusively possessed either innate or learned by human beings are now facing the challenge to be anthropomorphized to facilities to realize cognitive FM. The resurgence of Artificial Intelligence (AI), and the technological advancement as exhibited above, all underpin the best time to pursue cognitive FM. Research and academia should provide more solid science and technological foundation for promoting cognitive FM as a discipline of science.

While this paper so far has mainly explored the benefits of cognitive FM, its potential drawbacks should not be neglected. For example, the benefits (e.g., convenience) that cognitive FM brings to occupants should never be achieved at the cost of their security and privacy. If we take the pioneering modernist architect Le Corbusier's view that 'a house is a machine for living in' in 1923 (Kornberger and Clegg, 2004), now the machine/facility is of human's cognitive capability of perception, learning, and action, all the ethics issues related to human dignity, transparency, accountability, or unintended consequences would surface from this new domain of FM. Cognitive FM can join the ever-heated debate on AI and robotics ethics to gain a better understanding of its domain specific ethics issues.

Ultimately, development of cognitive FM is determined by the changing dyadic relationship between us and the facilities we built. Man has never stopped exploring such relationship. Le Corbusier's view in the 1920s represented the industrialization era where humans have started to massively engage machine in production, life, and other activities. We built buildings as a machine to serve us. The sociotechnical systems coined at Tavistock Institute (1966), referring to the interaction between society's complex infrastructures and human behavior, provides a perspective of the dyadic relationship between facilities and humans. The facilities, be they machines or intelligent/smart buildings, are alien to us. They have never been treated as a part of mankind. Humans never stop trying to make them as cognitive and intelligent as possible to free us from routine work and regular decisions. We imbue facilities with cognitive capability. We treat a way humans taking care of each other is the way humans need from facility services. It reaches to the level that Churchill has seen it, i.e., facilities can shape us. The issue is whether humans are ready for it, will allow it happen, or can stop it happen.

7. Conclusion

With all due respect, the researchers of this paper are unsatisfied with the stagnant FM discourses that have been demarcated by smart/intelligent building for already three decades or so. To this end, they put forward the concept of 'cognitive FM'. Inspired by human cognition systems, the definition of cognitive FM was given as actively intelligent management of facilities within the built environment, where a facility perceives through a cognitive IoT, learns in the manner of human cognition with the power of cognitive computing, and acts actively, adaptively, and efficiently via automated actuators to improve the quality of life or productivity of business. Unlike passive, pre-setting, and nonreciprocal intelligence of smart/intelligent building, cognitive FM proposes an active, adaptive and naturally interactive way to give intelligence to facilities through three key characteristics, i.e., perception, learning, and action.

An eight-layered system architecture comprising of environment, perception, data, communication, computation, application, actuation and evaluation was developed for better realization of cognitive FM. This architecture puts most of the advanced technologies of information, communication, computation, and action together in an organic and dynamic fashion to realize the cognitive capability of perception, learning, and action. To better illustrate what cognitive FM is and how the architecture can guide its implementation, an illustrative scenario called 'Event Manager' was elaborated. The case study showed that cognitive FM can enable human-like cognition, enhancing the value of facilities, and ultimately, better serving our health, economic activities, and social behaviour. Other than the 'Event Manager', there are other compelling scenarios of cognitive FM awaiting researchers and practitioners to explore.

Cognitive FM tries to imbue existing facilities with human-like cognition in order to deliver their designated functions (e.g., keep us warm/cold; save energy; make us comfortable; keeping us secure; keeping us healthy; improving quality of life; and enhancing productivity of our business). The facility can know what its users want and need, understand their needs and preferences, learn and give feedbacks, catch the details the users might miss, distinguish between different users, interact with and serve for them like an experienced but agile manager with the ability of perception, learning, and action. The definition of cognitive FM, its system architecture, and the pervasive supporting technologies as presented in this paper would open up a new avenue to empower the traditional FM in the era of AI resurgence. Our understanding towards facilities has evolved from the 1920s when Le Corbusier perceived them as machines for living in, to intelligent/smart building 30 years ago, and to this cognitive system akin to human now. Technological advancement provides unlimited possibilities to realizing cognitive FM. But whether a cognitive facility can be a human-like one, or whether we human want it to be indistinguishable from us, are the philosophical questions to be answered on this journey to develop cognitive FM.

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