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# Platform-Based Business Models: Insights from an Emerging Ai-Enabled Smart Building Ecosystem

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**Abstract:** Artificial intelligence (AI) is emerging to become a highly potential enabling technology for smart buildings. However, the development of AI applications quite often follows a traditional, closed, and product-oriented approach. This study aims to introduce the platform model and ecosystem thinking to the development of AI-enabled smart buildings. The study identifies the needs for a user-oriented digital service ecosystem and business model in the smart building sector in Finland, which aimed to facilitate the launch of scalable businesses and an experiential and dynamic business ecosystem. A multi-method, interpretive case study was applied in the focal ecosystem, with the leading real estate and facility management operators in Northern Europe as part of a Finnish national innovation project. Our results propose an extended comprehensive framework of the 5C ecosystemic model (Connection, Content, Computation, Context, and Commerce) and the possible paths of ecosystem players in the domain of smart building and smart built environment, both theoretically and empirically. The platform-oriented business models are missing, yet desired, by the ecosystem actors. The value chain and ecosystem platforms imply the quest for new (platform) models. Finally, our research discusses the need for new value-chain- and ecosystem-oriented AI development and big data platforms in the future.

**Keywords:** smart building; artificial intelligence; platform; ecosystem; business model

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## 1. Introduction

"AI is likely to be either the best or the worst thing to happen to humanity".

—Stephen Hawking

Designing and developing a built environment is crucial in providing meaningful engagement and experience for society and all people, regardless of their professions and abilities, to participate in their communities [1]. The use of Artificial Intelligence (AI) technology in the built environment has been extensively researched in recent years in the civil engineering field [2] and the smart building sector [3]. For instance, in smart buildings, the use of expert systems, rule-based systems, knowledge-based engineering, case-based reasoning, neural networks, and machine learning are all investigated to enhance engineering tasks [4].

The rise of AI technology is related to progressive development in the ICT (Information and Communication Technology) industry. Over the past few decades, the world has experienced a sharp increase in computing and information processing power, as [5] estimated. Moreover, the size of computer devices and equipment has decreased and they have become more multifunctional [6].

Today, data collection takes place automatically on the internet via embedded and integrated sensors, e.g., smart mobile devices. "Big data" is distributedly stored in cloud servers over virtual data storage, such as those of Google and Amazon. Analytical algorithms can run and scale on a huge number of central processing units on a 24/7 basis. However, there are new challenges as the digital data volume increases at an exponential speed. In building and real estate industries, construction projects, which were previously carried out only in drawings, are now being digitally modeled and monitored in a continuous manner throughout the projects [7]. According to [3], AI-based techniques have gained popularity due to the ease of use and high degree of accuracy.

Referring to [8,9], the advent of ICT has fostered theoretical and empirical interest in the smart built environments, which refers to "a built environment that has been embedded with smart objects, such as sensors and actuators, with computing and communication capabilities, making the environment sufficiently 'smart' to interact intelligently with and support their human users in their day-to-day activities" (p. 101) [8]. Within smart built environments, the smart building is defined as "buildings (that are) equipped with networked devices providing a safe, productive, and comfortable environment to its occupants while optimizing operational and energy performance" [10]. Smart buildings provide a well-connected environment for the users while making it easy for the sensors and automation solutions to interact with each other [10]. Noticeably, the existing definition of smart building is focused on the use of technology, while the user-centric perspective is missing.

In smart and intelligent building research, intelligent technology has been mainly focused on building energy management and automation. This is not a surprise. The buildings account for almost 30 percent of global energy consumption worldwide [11]. Any effort to reduce the use of building energy can tremendously reduce the planet's reliance on energy globally. As a result, numerous smart building and AI studies have focused on energy use as a part of the intelligent building [11]. The study of [11] suggests, in particular, an in-depth analysis of methods of AI-based building energy prediction, for instance, the Artificial Neural Networks (ANN) and Vector Regressions. Complex models improve the predictive accuracy by integrating different predictive models. However, it is argued by this study that AI's application is beyond just energy management or building automation. The value of the smart building is multi-dimensional and it should not promote a restricted view that only emphasizes the technology advancement in building energy efficiency and comfort creation.

Furthermore, data is another key issue in smart buildings. The digital information flow, digital technologies, such as building information modeling (BIM) and machine learning, lead to enhanced integration between the practices and scales, which are normally considered to be separate. However, the delivery of digital information is currently experiencing limited improvement in time, expenditure, or performance [12]. Thus, new questions emerge regarding the potential for improvement in information utilization in smart buildings and assets. For instance, there are queries regarding the collation of digital information to make portfolios, policies, and operational decisions in smart buildings, as well as the potential for the real estate companies and building operators to use data analysis in new ways to improve the current operation; these questions cannot be answered by pure technical research; they require a multidisciplinary approach. This study addresses this issue of multidisciplinary and focuses on the use of AI in the smart building domain as part of the built environment studies [13]. We apply the ecosystemic business model lens to provide structure for the investigation.

### *1.1. What is AI?*

According to [14], AI can be considered as a general purpose technology (GPT), as it is enabling and empowering numerous other industries, similar to the other GPTs stated by the European Commission (EC) (such as micro- and nano-electronics, advanced manufacturing, advanced materials, photonics, nanotechnology, and biotechnology). The common characteristics of these GPTs are to support product innovation in many industries and they are important for meeting the significant challenges of society.

In the theoretical research setting, [15] defines AI as the research of systems that operate in a manner appearing to be smart and intelligent to an external observer. AI is about developing and utilizing techniques that are based on the intelligent behavior of people and animals for complex problem-solving. This is a hard system perspective, which considers that the systems are the models of the world and can be engineered [16].

According to [17], AI is related to intelligent behaviors in artifacts that comprise perception, learning, reasoning, communicating, and acting in contexts that are complex. The fundamental goal of AI is usually seen with regard to developing the machines that are capable of doing what people can do and even beyond. This can be seen as a behavioral perspective.

It is suggested by [18] that AI technology can tackle diverse categories of problems, such as subtracting, reasoning, problem-solving, knowing how to present, plan, learn, process natural language, movement and manipulation, perception, social intelligence, creativity, and general intelligence. This can be considered as a functional perspective.

An empirical case example is the Deep Blue computer from IBM that beat Garry Kasparov in 1997 [19], which is a historical event and it can be considered as a major breakthrough in the advancement of AI. The idea is that computers need to represent knowledge as symbols and utilize different types of rules and reasoning to infer new knowledge [19].

Furthermore, AlexNet, as an extremely large neural network, demonstrated its capability to recognize different images in 1000 different categories in 2012. This approach later became known as deep learning [19,20]. Today, AI technologies (e.g., machine learning, deep learning) are utilized and deployed on a very large scale by organizations, such as Google, Facebook, YouTube, as well as Tesla [14,19].

Regarding the use of AI in smart buildings, academic scholars have investigated AI techniques to predict energy usage. Numerous statistical and AI techniques for reverse modeling of heating and cooling buildings have been developed [21–23]. Researchers combined ANN with a quasi-physical description to forecast the annual space heating demand for numerous buildings [24]. Support Vector Regression (SVR), which is a variation of Support Vector Machine (SVM), has been widely utilized in prediction and regression [25]. Existing research evaluated the use of SVR to predict energy consumption in tropical regions [21]. Generally, existing smart building literature demonstrates that AI algorithms provide satisfactory results in predicting energy performance in the buildings [23]. However, a majority of the research work and effort has used narrowly focused algorithms and models.

### *1.2. Research on the Ecosystem Business Model and Platform*

Business model is a multidisciplinary and boundary-spanning unit of analysis [26] that addresses the theoretical discussion regarding opportunity exploration and exploitation [27,28], value perspective (e.g., value proposition, value creation, and value capture) [29–32], and competitive advantage [33,34]. In the work of [27], they summarize the business model as "the content, structure, and governance of transactions designed so as to create value through the exploitation of business opportunities". Furthermore, the business model conceptualization can be used to approach the duality of technology and economics [35] in platforms in the aspects of architecture, governance, and environmental dynamics [36]. From an architectural perspective, literature provides that business models can be designed as a product-based model [37] as well as an ecosystem-based model [34,38].

Building on the ecosystem and business model theories, the study of [39] has proposed a conceptual framework that connects the (digital) business model and ecosystem. There are five elements in the framework: namely, the value proposition, the interface, the service platform, the organizing model, as well as the revenue model. The purpose of the framework is to show how the business model can be investigated in the context of the evolving and ever-changing digital business ecosystem. Notably, the fundamental logic of [39]'s framework is in several folds: First, the underlying assumption in the ecosystem view of a business model is that the value creation and capture in the (digital) ecosystem is beyond the focal company, and are in concert with competitors, complementors, customers, as well as the ecosystem's community. Therefore, a closed, control-oriented mentality and approach does not fit the development of an ecosystem [40].

Second, business ecosystems are constantly evolving at a fast pace. It is particularly challenging for companies in the digital ecosystem driven by rapid technological change as well as intensive competition [41]. Therefore, numerous digital business ecosystems are created and organized in a way that digital services are being created and delivered through digital platforms, like the empirical examples of Amazon [42] and Google [43] demonstrate.

Third, digital business ecosystems also have the characteristics of turbulence, which can be understood as the mixture of the environment as well as the complex interconnectedness among ecosystem actors [44]. As the success and failure of the actors in the ecosystem are intertwined and inter-connected in the digital ecosystem, different actors (even competitors) have to collaborate together in "coopetition" (simultaneous existence of cooperation and competition) to establish common technical standards and platforms. As such, continuous interaction leads to the co-development and co-evolution of the business models and digital innovations [39].

Overall, from the value perspective, one of the key issues to address in a digital ecosystem is the balance between value creation, value conversion, and value capture [39,45]. Additionally, issues related to the ecosystem governance, orchestration, and architecture design (open versus closed) are seen as important in various literature [46,47]. As addressed by [39] at the conceptual level, the development of effective and viable digital business models for the different actors in an ecosystem context is emerging to become a critical challenge for all actors in the ecosystem to tackle, which also demands the paradigm shift from a focal company-focused logic to an ecosystem-focused logic [48].

In an empirical context, accompanied by the advent of digital technology, the building and real estate sector is experiencing a paradigm change in business operations and business models. Referring to [49], in traditional construction, the logic of business is simple and similar to the value-chain thinking of a conventional product business. Business models and revenue models at different levels of the value chain combine the output of previous stages of the value chain in an aggregated product or system, and the added value is rarely achieved in the process. Thus, the building and real estate industry has a very traditional cost-plus -price model. It is important to note that the price difference by performance and the added value have not traditionally had much space in the value chain of buildings.

It is further argued by [49] that the most basic requirement for transforming the construction industry into sustainable development is to change the prevailing business model from a product-oriented business model to a service-oriented model, or a model in which the prices and profits are truly diversified by the new value created, delivered, and realized by the customers and society. Evidently, this paradigm shift from product logic to service logic requires both a change in the building industry's structure as well as a change in the way customers and stakeholders in the real estate and smart building industry perceive and appreciate the new value generated in smart building.

### *1.3. Research Gaps Addressed in This Study*

The first research gap tackled in this study revolves around the need for a more holistic framework for the integration of AI in the smart building and real estate sector. From a system architecture perspective, a majority of the existing studies has focused on the individual AI implementation in specific techniques or applications, but it does not provide a system view of larger AI systems that are often needed in practice. For instance, it is argued by [4] that the extant of smart building research has often focused on narrow and specialized technical subtasks rather than on the larger and more integrated systems. In addition, the "building as a product model" is mainly how smart building has been developed. The above discussion shows that this is a gap in both technical and business model aspects of the smart building studies.

The second research gap is concerned with the integration of the user perspective in smart building research. The literature review shows that a user-centric view can help with the development of the coherent framework for the built environment; in the context of this study, it is the framework for the smart buildings that are empowered by AI.

The theory of environmental determinism in the built environment indicates that the physical environment affects human behavior [50]. This theory is built on a comprehensive study of environmental psychology [51,52] and it provides tangible results in the context of physical well-being [53,54], territory [55], and usability [56,57]. These can then be utilized to assess the user's satisfaction. However, as argued by [58], the theory of environmental determinism does not recognize social aspects as an explanatory factor for user satisfaction [50]. Another stream of research uses the theory of constructivism [58] in buildings where society is defining the space and influencing people's behavior [51]. Constructivism is based on cultural and social standards as well as learned behaviors. However, the weakness of this stream of the theory is that the measures are difficult to quantify, with little support for construction designers, and the theory does not take into account the environmental impact on human behavior [50,58].

The user-centric approach is developed by [58]. The approach is grounded in user-centered theory for the built environment/buildings. The theory of user-centrism on the built environment (e.g., smart building) connects the two opposing theories, the constructivism theory and the environmental deterministic theory. Environmental determinism and constructivism both explain the effects of human behavior on user experiences with the building [55], while the user-centered theory dwells between the other two theories at different ends.

Extensive user-centric research has been carried out to investigate the factors that affect user experience, with conventional research focused on comfort [53,59–61]. However, according to [58], there is no direct correlation between knowledge, comfort, and behavior. As such, one cannot generalize that designing for comfort will provide a more user-friendly experience, and that important environmental features, such as resilience and adaptability, are taken into account [62].

According to the suggestion of [58], the user-centric view outlines the user's experience and defines it, not only in physiological terms and psychological comfort, but it also substantially addresses social and behavioral aspects of the buildings. This study suggests that the factors mentioned in the user experience can be helpful in determining how to improve and successfully support the users in the smart buildings. Overall, this study is built on the user-centric approach to address the use of AI in smart buildings in a more holistic framework, from the tech stack to the user stack.

The third research gap that is addressed by this study is related to the missing ecosystem perspective in smart building research. It is suggested by [63] that there are multiple stakeholders that are involved in the smart building industry: the building owners, the building operators, and the building designers that drive building operation and interaction decisions. Evidently, it is argued that the building and real estate industry and business have complex social and technical process [64], in which a wide range of stakeholders have to build and communicate high-quality design spaces [65]. However, this conventional approach creates a gap between the tasks of the users and the construction input factors (e.g., conditions, operational parameters, and user preferences). Furthermore, as explained by [8], in the context of a smart building, the building users are not limited to the occupants of the facilities, but they should also include other relevant groups, such as the building's owners, operators, as well as facility managers. Thus, from an ecosystem perspective, the smart building and related technology development (such as AI solutions) need the participation of multiple stakeholders and actors in the ecosystem, which is rarely addressed in extant research.

A potential way to address restricted technical research in the smart building space is the adoption of the ecosystemic approach for developing next-generation smart building business. In light of the emerging ecosystem thinking, the ecosystemic business model is one that is raised as a topic of interest in the studies of business models (e.g., [46]). Existing research [32] suggests a paradigm shift from viewing the digital platform as a pure technological platform to deeming it as a business ecosystem with its resources, assets, and actors. It is suggested by [66] that "The business ecosystem concept helps to think about how to respond to the dynamic and changing business environment, and how to move towards dynamic and adaptive business ecosystems".

Thus, this paper proposes research on the platform-based business model in the context of a digital ecosystem that is enabled by AI. The targeted outcome of the study is to provide insight into the emergence of AI-based platform within a smart building ecosystem coordinated by multiple actors. The development of a digital platform and its ecosystem adapts to the user behavior and preferences with AI technology. In this article, we examine to what extent the business model and ecosystem thinking apply to AI-based environments and what is needed for designing an AI-based business model.

The article presents and discusses a novel approach that is utilized by the smart building industry in Finland, which shows how far the industry is from achieving better smart building performance as well as user experience and value in parallel. The principles, applications, and value of such AI-based business models are presented in the research. We expect this to be of general interest as such cyber-physical techno-ecosystems emerge for common use. In addition, we will discuss future directions for the study of methods predicting the use of energy with AI.

The following part of the paper is organized, as follows: Section 2 discusses the typology of the platforms from both technology and economic perspectives. Subsequently, it introduces the 4C-ecosystemic framework and improves the framework further by incorporating AI and computation as a new layer within the framework. The overall conceptual framework and the research method are also presented in the same section. In Section 3, the results of the research are presented and discussed. Section 4 dives deeper into the refined results. The last section of the paper provides discussion, conclusion, and future research directions.

## 2. Materials and Methods

This section presents the core concepts, frameworks, materials, and methods of the study. We start the discussion with platform thinking and business model concept and summarize the theoretical discussion with how the business model components are layered.

### *2.1. The Integrated Typology of the Platforms*

As proposed by [67], existing research regarding the concept of the platform can be segregated into two major views: the technology and engineering view of the platform [68–70] and the economic view of platform [14,71–73].

In the technology view of the platforms, engineering design scholars were the first to develop the platform concept. The term is used in the literature that focuses on the development innovation of new products. The engineering literature tries to investigate the consequences of the so-called "design hierarchy" [74] to industrial processes (e.g., product development), which gives rise to the concept of product platforming and stressing the particular selection of product architecture designs [75] that could support the companies to create product families [76] and rapidly develop new innovations.

From a technical standpoint, the platforms are interpreted as a deliberate technological architecture that facilitates innovation. The perspective essentially sees the platforms as structurally stable: innovation takes place on modules, within the framework of stable systems architecture and facilitated by the interfaces. It is suggested by [67] that the technology view that in design and utilization of platforms can help companies to achieve economies of scope, design, and innovation. The technology platform thinking is often associated with the dyadic components of “core” and “peripherals” [67,77]. As such, “a platform architecture partitions a system into stable core components and variable peripheral components” [77].

At a more detailed level, this study argues that the traditional system elements of digital platforms, i.e., components and interfaces, should be complemented with two new elements, algorithms and data when discussing platforms that are enabled by AI [78].

In regard to the economic view of the platform, a stream of the industrial organization economics literature has established the theory on platform thinking and designs that have been referred to as “two-sided markets”, “multi-sided markets”, or “multi-sided platforms” [42,78–80]. Economist-perspective platforms are particular sorts of markets that play the role of facilitators of trade between customers that could not otherwise transact with each other. Researchers [73] define two-sided markets as “markets involving two groups of agents interacting via ‘platforms’ where one group's benefit from joining a platform depends on the size of the other group that joins the platform".

In short, the economic theoretical perspective suggests that a platform can create or generate value by facilitating the connection or transaction of two different groups of customers who would not be able to interact with each other with no platform. In this way, the platforms produce value by coordinating the economic activities of the different groups of customers.

Building on the different streams of platform literature in both technical and economic fields, [67] proposes an integrated typology of the platforms incorporating both the engineering and economic perspectives. Essentially, the platforms are perceptible at different levels of analysis and organization levels, such as within companies, supply chains, and industrial ecosystems.

Depending on the degree of abstract and conceptualization, the platform can be classified as 1) a company and its internal units, or the internal platforms; 2) the network of a company and its suppliers or the supply chain platforms; and, 3) an ecosystem keystone actor and its supplement actors in a technology or business ecosystem, or the ecosystem platform. As claimed by [67], such a common architecture and typology of the platforms is therefore consistent across all platforms and cuts through all organizational forms, which is aligned with the holistic approach of this study and it is adopted as part of the conceptual framework of the study.

### *2.2. The 5C Layers of the Business Model*

Regarding the conceptualization of a business model, a review of the literature provides the insight that there are normally three key aspects that can connect the business model to different business contexts. The first aspect is related to opportunity exploration and exploitation. The second is the value aspect that focuses on value creation and capture. The third aspect is tied to the strategy and management literature that is concerned with establishing (competitive) advantages [32,81,82]. Going more in-depth, this paper focuses on the concepts of the platform and ecosystemic business model.

First, the platform business model describes the mechanisms of coordinating the interactions, activities, as well as transactions through the establishment of the network effect; the value of the platform can dynamically change or shift depending on the platform participation rates [83]. The network of participants can explore and/or create opportunities and help to optimize the costs and revenues for the efficiency of the platform. As mentioned before, Amazon [42] and Google [43] are empirical examples of platform business models.

Second, the platform business model also embodies the ecosystemic thinking that expands the organizational boundary of a firm 1) to co-create and co-capture value with external organizations and other companies [84]; and, 2) facilitate connection and interaction among different organizations, communities, as well as the individuals for the joint innovations, especially in the context of an ecosystem [85]. In this vein, the 4C framework for digital ecosystem has been utilized to empirically research the various phenomenon of digitalization, for instance, the 4C framework has been employed in studies related to large and complex industries, such as energy and telecommunication [32,86,87]. The framework is adopted and further improved in this research by integrating the AI aspect.

The 4C framework describes the typology of a business model based on four categorical value propositions or aspects: the Connection, Content, Context, and Commerce (as shown in Table 1). The four categories of a business model are formed as layers, where lower-layer business models act as catalysts or enablers for the business models in the upper layers. When dynamically placing the layered business models, one can obtain more advantage and achieve better benefits and values in terms of developing innovative and differentiated (digital) business models within the ecosystem. In the focal research project of the paper, the 4C ecosystemic framework is identified as a key tool or approach for supporting the service dynamics, experience-based automated provisioning, and utilization on an AI platform for smart buildings. The 4C framework also facilitates the business model value co-creation and co-capture [32] within the ecosystem.

**Table 1.** The 4C ecosystemic business model and value framework (adapted from [32,87]).

| Layer | Description |
|---|---|
| Commerce | Digital services and solutions that provide all stakeholders with an application or marketplace for trading alternative connectivity solutions, content, or context data. |
| Context | Digital services and solutions that provide data and information-related contextual-based services. |
| Content | Digital services and solutions that provide any data, information, and content that users would want or need. |
| Connection | Connection technologies and solutions to connect one or more networks. |

In the 4C framework, the content and context layers are particularly relevant to the field of AI as data, and context-aware services from these two layers are primarily enabled and supported by the underlying technical infrastructure. As such, different types and sources of data (the proprietarily copyrighted data, the data that is co-created or system-generated) can be utilized to create new predictive analytics and on-demand digital content and functionality for the smart buildings to deploy contextualized services.

Furthermore, grounded on the 4C concept, this study introduces an additional layer as the fifth "C", or the computation layer of the ecosystemic business model. From the technology perspective, the computation value of a digitalized ecosystem is realized through the integration of AI technology and algorithms into the existing ICT systems. The AI algorithms are developed and trained through various frameworks (e.g., Tensorflow) and hardware and software computation resources. AI algorithms are trained to build meaningful models to enable the execution of the automated tasks at scale building on top of the establishment of network connectivity and the extraction, collection, and storage of data. From the economic and business model perspective, AI and computation as a new layer do not only support and enable the creation of other types of value in the smart building and real estate ecosystems, but also serve as a stand-alone technology stack for other application verticals.

Overall, the conceptual framework development that was employed in this research is demonstrated in Figure 1. In the horizontal direction, the three major types of platforms at different scales are provided; while in the vertical direction, the 5C layers of the ecosystemic business model are placed and overplayed with the typology of the framework. This integrated framework will be employed in the later section to analyze the smart building and real estate ecosystem in Finland that is enabled by AI technology with multiple-use cases.

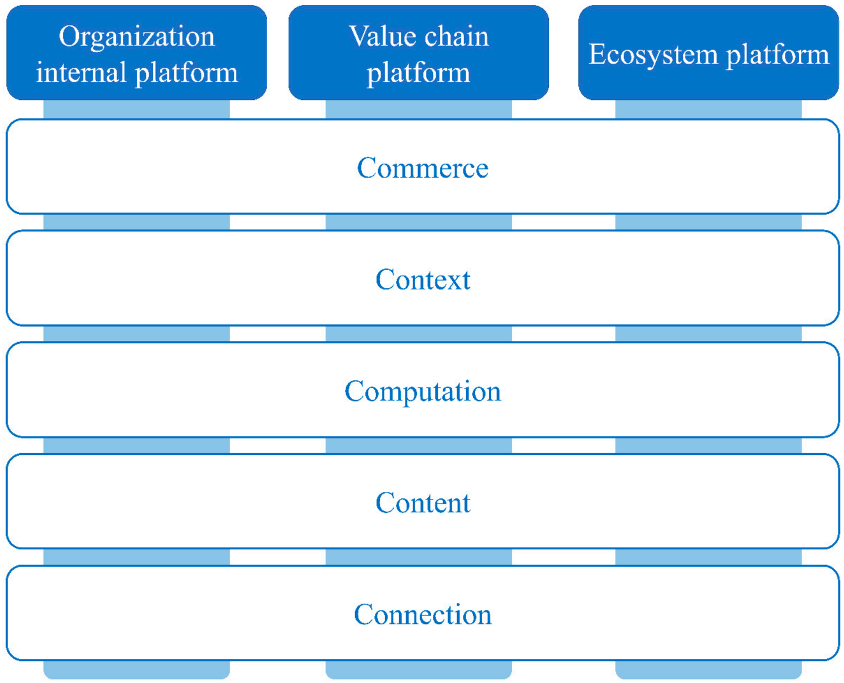


**Figure 1.** The overall conceptual framework of the study.

### *2.3. The Methodology*

The research adopts the multi-method and interpretive case study approach [88]. The AI platform and its ecosystem come from the VirpaD research project. The research is a Finnish national digital service and innovation project. The smart building ecosystem that is involved in this study is jointly established through industry-academia collaboration. The entire project consortium consists of over ten companies (large international companies and smaller local players) as well as four universities. The ultimate goal of the project is to co-create and co-develop multiple digital and value-added services for the real estate and facilities business and the smart building end users.

As the architects of the digital platform and the ecosystem, the keystones or leading actors of the platforms need to take action regarding designing, managing, and modifying the ecosystems as the external environment conditions shift. This is an extremely complex task, while taking into account the breadth of the related stakeholders, the numerous features of such ecosystems, as well as the high uncertainty. The leader or the orchestrator of the platform acts in a world of market failures due to the inadequate information and data that can affect the effective decision making. This is especially the case in a connected digital platform and ecosystem, where highly dependent decisions are required due to the presence of interdependent network effects.

We are investigating the AI-enabled platforms through multiple AI use cases from 10 prominent companies in AI, big data, and smart building and real estate ecosystems. There are both large multinational firms and fast-growing Small and Medium-sized Enterprises (SMEs) in this sector. The study also includes the leading property asset management company in North Europe, with over one million square meters of buildings and properties under its management. Our findings are integrated into a broader emergency framework, which allows for us to contribute to the discussion on the pros and cons of changing the main business model or running parallel side business models (e.g., [89,90]).

We follow an ecosystem approach to engage and involve key players and stakeholders in the ecosystem, including public and private partners. Such an approach is similar to the mass solution systems [91] proposed by the ecosystem system approach to complex problem solving from different backgrounds and heterogeneous contributions of partners. Therefore, the benefits of such systems are to create alternative or complementary solutions.

The key activities for the development of the digital platform are conducted in four so-called “mini-ecosystems” of the project. The main focuses of the activities involve the following: first, value-added services with a data-driven approach; and second, data collection, data refining, and data analysis. The data are collected from the actual building users with the purpose of promoting and advocating for well-being in smart buildings. Through effective data collection and data utilization from multiple data sources and ecosystem actors, the project creates and develops innovative business cases and new value for future smart buildings. This study has focused on researching the narrative reality [92] of the actors within the focal ecosystem. The research incorporates the entanglements of the technology on one side and the user experience on the other side, especially in the ecosystem setting in which the narratives [92] can convey.

In regard to the data collection, the study collects the empirical data through three face-to-face interactive ecosystem actor workshops during the period of 2018–2019. To study an emergent ecosystem like the selected case, the research utilizes the organizational ethnography [93] as well as the interpretive case study methods. Referring to [94], there is an entanglement of both human and non-human aspects (e.g., technology, business models) intertwined in complex situations like the ecosystem. In the context of AI-based platforms and ecosystems, interactive activities affect and shape each individual agent, which can include AI technologies, human users, and other agents. The agents can have a shared momentary view of the ecosystem. However, individual agents might not comprehend the whole picture due to their positions and limited perspectives in the ecosystem [64,94]. Through an interactive process, the agents can shift their perspectives on the ecosystem, and in turn change the ecosystem. Overall, the study of the smart building ecosystem involves researching the narrative reality [92] of the ecosystem actors. In addition, the study is supported and supplemented with additional evidence, including secondary materials (e.g., industry data, market reports and company documents).

## 3. Results

Building on the review of the extant literature, as well as the empirical results of the research, our results support the argument that the 5C framework is a viable tool for studying AI-based platforms and ecosystems. It expands the prior 4C ecosystemic framework in the existing digital business literature. Most importantly, it allows adapting to the advent of AI technology due to the fact that AI is becoming a GPT that penetrates many sectors and verticals of the digitalized industries.

We present the empirical findings from the mapping of AI use cases in smart building and real estate ecosystem below.

Figure 2 shows the overall results of the research. We identified five categories of business models in the AI-based smart building and real estate ecosystems of the study, which are the traditional product-oriented business models (non-AI), traditional platform-oriented business models (non-AI), AI-based product-oriented business models, AI-based platform-oriented business models, as well as the future potential models that are still missing in the investigated ecosystem.

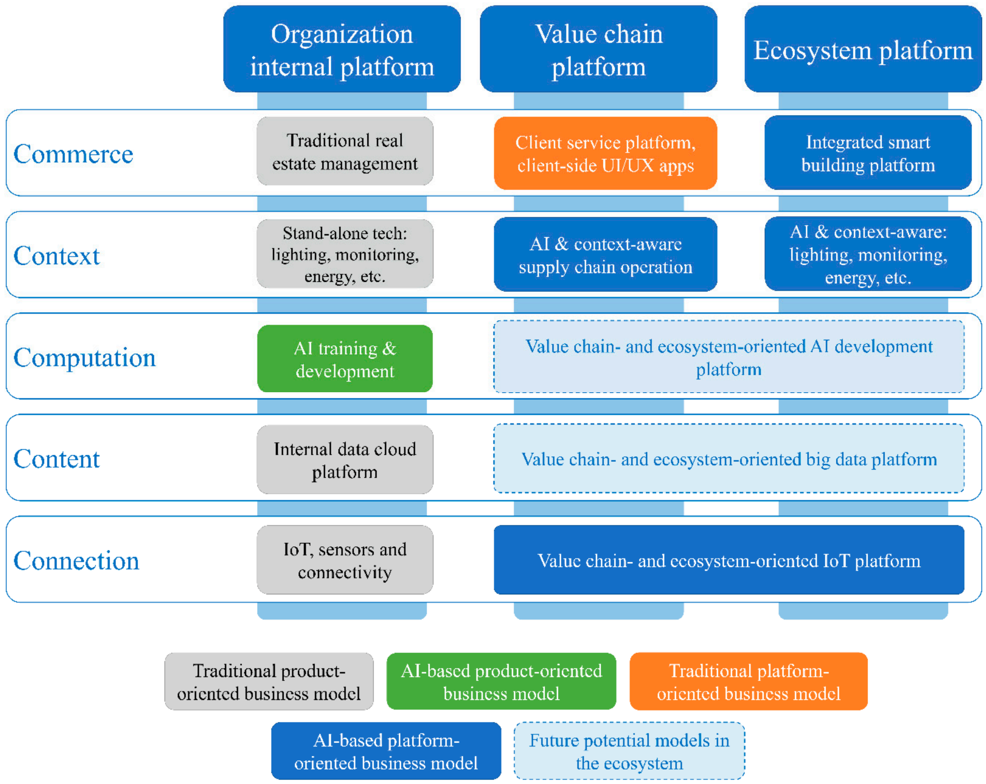


**Figure 2.** Overview of the research results.

### *3.1. AI in the Internal-Oriented Platforms*

From the category of organizational internal platforms, many companies still utilize product-oriented logic in terms of the business model and business operation. Unsurprisingly, the building and real estate industry has been a traditional sector and the inertia of space and volume-based model is dominant in the industry. Thus, the ecosystem surrounding the incumbent companies mainly focuses on the development of un-connected stand-alone products and services across most of the layers in the ecosystem, products, such as lighting systems, security, video surveillance, building energy management, IoT (Internet of Things), and the cloud. In the light of gradual adoption of ICT technology, the relatively innovative companies have introduced the digital systems and platforms into the organization and business operation. However, many of these systems are used in internal development or serve as an addition to the existing product offering with limited options to capture the additional value that is created.

Noticeably, the AI technology partners within the project have been developing the AI platforms internally, such as video processing and emotion recognition. The concept of technology and engineering platforms can be applied here, since AI is the internal technology platform for continuous AI training and development with the organization.

### *3.2. AI in the Value Chain-Oriented Platforms*

When examining the value chain platforms that were identified in the project, the platform-oriented business models start to become visible. In the connection layer, the digital platform that supports the integration of building IoT devices are being developed to establish a digital infrastructure for the creation and delivery of new digital services. AI-enabled building management can support the supply chain of the property management companies that are gradually becoming smart building operators. Sensors can inform of material supply shortages and ad hoc services that are needed in a smarter and more user-centric built environment, which can eventually increase the satisfaction of the building users.

At the same time, there are non-AI, platform-oriented business models at the commerce layer. For instance, real estate management companies can build a Wikipedia-like digital platform for their clients to browse and select the ideal properties based on their preference and criteria. On the one side, such a platform invites the building owners to the platform to supply relevant building data and information; on the other side of the platform, the potential building customers are attracted to use the data and information that were made available by the building owners and the real estate management companies. Such a novel use of the platform-based business model is very similar to the economy view of the platform as discussed above, although without the incorporation of AI technology.

### *3.3. AI in the ecosystem-oriented platforms*

Moving into the category of ecosystem platforms, multiple so-called businesses, and technology innovations have taken place. Building on top of the IoT integration platform, one company has developed user-centric and integrated platforms that enable the integration of third-party smart building applications within the ecosystem. From the technology perspective of the platform, such a keystone action can provide open APIs (Application Programming Interface) to enable smart digital services at a broader level and with greater scalability. Real-time visualization of the building use data can enhance user experience. Such a platform can integrate with the AI algorithms, models, and applications for different use cases. Moreover, the integrated platform can enhance the economic and commerce aspect by connecting and facilitating the transaction between the potential customers of the smart buildings and third-party technology providers.

In the context layer, new businesses and solutions are emerging, which are only made possible by AI. For instance, the AI-enabled lighting solutions can enhance the productivity and well-being of the smart building users, creating personalized value and unique customer experience when people interact with digital systems and services. According to the Cambridge English Dictionary (2018), context means "the situation within which something exists or happens, and that can help explain it". Originally, the context business is proposed by [86] in a study that focuses on classifying typologies for the digital business models. In the study of [86], the context-focused businesses and business models make use of the structured data and information that are existing or generated in internet activities. The companies who adopt the context-focused business model can combine online data and information with a strong personalization [86].,Through empirical data and observation, this study identifies that the context business is made possible mainly by context-aware technologies like AI, just like the connectivity business was merely a concept until the development of telecommunication technology makes it possible for the public.

In addition to the above findings, the use of the more comprehensive framework of this study allows for us to see that AI is still an emerging field in the domain of smart building and smart built environment, both theoretically and empirically. In the categories of the value chain and ecosystem platforms, it becomes obvious that new and potential (platform) models are needed to be developed in the future. In both content and computation layers, the platform-oriented business models are missing yet desired by the ecosystem actors.

New AI techniques, such as deep learning, require a huge volume of data to improve the accuracy of the model. Data cleaning and pre-processing is another pressing issue, as the data collected in a real-life environment are quite often not ideal to be used directly as input data for the AI models. It is worthy to note that certain AI techniques do not require a large volume of external data (such as deep re-enforcement learning). However, such techniques still have limited use cases and they need to be further explored. Thus, this study envisions that the value chain- and ecosystem-oriented AI development platforms and big data platforms can be the emerging new areas of development. Such platform types have already been introduced in other fields, such as Dialogflow for natural language processing, which was acquired by Google.

## 4. Discussion

Further analysis of the research outcomes that are presented in the previous section leads us to a new proposition of the AI ecosystemic development paths and emerging new quadrants. The creation of the quadrants is derived through the refinement of the use case mapping results above.

Through the analysis of AI business models and use cases in the focal ecosystem of this research, the study further develops the AI ecosystemic development path quadrants to help enhance our understanding of the AI-based and non-AI business models, serving as a further finding of the research.

As illustrated in Figure 3, the AI development quadrants of the study are formed with two dimensions: the first dimension is the business model archetype dimension and the second is the AI-enablement dimension. The quadrant starts with the traditional product-based quadrant, where the conventional product-logic prevails in the smart building and real estate industry. In this quadrant, not only is the dominant logic the traditional value chain thinking, but AI technology is also not incorporated or adopted in the building operations and management, which is quite similar to the status quo of the industry today. Extending from this quadrant, the adoption of AI in technology and business models can have five potential development paths that are supported by the research data and finding of this study. The first path is typical in numerous industries that have had or are undergoing the digital transition. For instance, Airbnb originally used a non-AI approach towards the conventional type of platform business model in the hotel and accommodation industry, which is a relevant case for the property business. This path demonstrates the emergence of the platform-based models with the ecosystem thinking as the cornerstone.

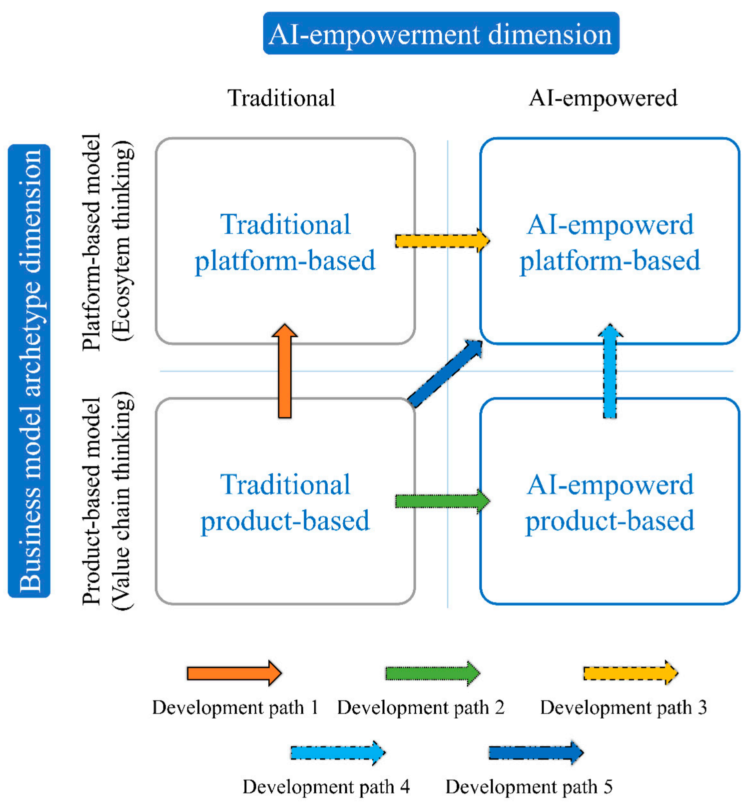


**Figure 3.** The AI (Artificial Intelligence) ecosystemic development path quadrants.

The second development path is the shift from traditional product-based business models to the AI-empowered product-based models. This can be a relatively straightforward path for the industry incumbents to incorporate AI technology as part of the existing product and service portfolios. It can also be suitable for the AI startups that have just developed MVP (minimum viable product) AI products with the core features and functions [95,96].

The third path is to move from the conventional platform business model to the AI-empowered platform. Existing research shows that a typical digitalized business can be defined by the 4C ecosystemic framework [32,87], where connectivity and data are integrated as the new technical stacks for the existing business and organization operations. The addition of a computation layer that is powered by the algorithms means that the traditional platforms can be transformed into AI-empowered platforms. Like the previous example of Airbnb, the company today is using deep learning to enhance the search function and experience for its over five million property listings [97].

Development path four is a more futuristic vision for the "Born AI" companies who are focused on developing AI products and services for the smart building industry (as well as other industries). These companies fit well with the 5C framework of this study by having the computation (algorithm) layer at their inception. However, empirical data shows that, on the commerce layer, many of the AI startups are still utilizing the more traditional product logic for its business model. Thus, a potential development path for these companies is to navigate towards the AI platform model through "ecosystem thinking".

The fifth development path can be a significant leapfrogging from a product-first company to an AI-first company while transforming the fundamental logic of the business model and operations to the platform and ecosystem thinking. Such a transformation is particularly challenging for the companies based on the evidence and company narratives from the research. However, the empirical example shows that the possibility still exists. In 2017, Google's CEO, Sundar Pichai, officially announced that Google strives to become an "AI-first" firm by having a new and strong emphasis on the utilization of contextual information, machine learning, and AI technologies to enhance the user experience of Google's digital platforms [98]. This is nearly two decades after Google was initially founded in 1998.

## 5. Conclusions

By using the integrated conceptual framework that developed from the study, we see that AI-enabled smart buildings are not restricted to the technology development in a few narrow and restricted technical applications, but AI can be a key for facilitating the transition of the building and real estate industry, (1) from product-orientation to user-orientation, (2) from a volume-based business logic to a performance and value-based business logic, and (3) from stand-alone product development to platform and ecosystem development. These all require a paradigm change in operational practices, business model designs, and practitioner mentalities.

In this context, the customers and operators of the smart buildings have a potentially important role to play in the transformation of business models and the transition of the smart building industry towards AI enablement and empowerment. For instance, the business model can change from space and volume-based business model to being based on the willingness-to-pay for performance. In this setting, the customers of the smart building and real estate industry can have the power to set ambitiously high-performance targets and thus encourage the smart building operators to challenge both its facilities and the way that it works and the established business practices.

From the use case perspective, the paper sees that the smart building as an emerging concept can be connected with the related domains of smart city and smart home by looking at the empirical cases. For example, the AI intelligence can provide context-specific and diverse user experiences for the public premises (e.g., office buildings, educational institutes, and other smart city facilities) and private premises (e.g., residential home). Across these contexts, the key elements of an AI platform (e.g., components, interfaces, data, and algorithms) can be observed at the systemic level. Nonetheless, such an observation requires further investigation.

From the system's perspective, the paper contributes to the smart building research at three levels: At the upper level, the theoretical discussion has been focused on the energy management on a larger scale, such as in a smart city energy management platform [99] or a smart decision support system that supports emergency management in city traffic [100]. The management platform (e.g., energy, water, building usage) emerges as a focal interest in the research project that utilizes the AI algorithms for more accurate resource and usage prediction and optimized building maintenance operations. This paper argues that the applications of AI in a broader context of a "smart built environment" is a relevant and important topic also at a higher level (such as taking a city as a unit of analysis). Research that focuses more on the development of smart cities can tackle the utilization of AI at this level.

At the middle-ground level, existing research has investigated the energy usage and scheduling among interconnected residence buildings [101]. Furthermore, the management of energy at the district level [102], as well as the decentralized and distributed energy networks that enable the energy management (e.g., DSM (demand-side management) at the local energy network level, have been conducted. Aligned with this line of research, this study provides the proposition of an AI platform that can optimize the operations of smart buildings, for instance, operations, such as energy efficiency and energy-saving management. Reflecting the earlier literature discussion, a digital platform that facilitates the delivery of the product and service empowered by an ecosystem-oriented business model and approach is identified as a feasible approach in this research project. The different ecosystem actors can integrate their technical solutions at different layers of the 5C framework to co-create and co-capture value through an AI-enabled platform with integrated interfaces and operating modes.

At the lower level, the majority of the existing studies has been focused on narrow AI applications in the management of a single smart building [103], smart home [104], and optimization at the user level [105]. The research identifies that the empirical situation of AI development in the smart building sector is in line with what has been described and discussed in literature that focuses on respective technical domains. However, empirical research also shows that there is a need to develop platform architecture at the system level. On the technical side of the platform, an important issue is how different AI technologies can have better integration in a connected manner. On the economic side of the platform, it is crucial for the AI developers and other ecosystem actors to collaborate and identify the appropriate operating model of the ecosystem to enable value creation, value capture, and value sharing within the ecosystem.

In summary, the paper provides a number of contributions: First, it extends the AI technology in the domain of smart buildings by providing, organizing, and analyzing the AI use cases in a more systematic manner. Second, the research introduces the platform thinking from engineering design and industrial economic literature to construct a more holistic framework to help understand the potential development of AI in both technology and business model perspectives. Third, the study promotes user-centricity and ecosystem-orientation to the existing smart building studies, addressing that user-side development is a new front for the adoption, integration, and deployment of AI technology and systems in the smart building sector. For instance, the paper presents the context-aware AI use cases that emphasize the user-centric thinking for the development of future AI technology and business models. Fourth, the study refines the existing theoretical frameworks in digital business with an improved version of the ecosystemic framework and proposes AI ecosystemic development path quadrants to support and guide the future development of AI at the ecosystem level with the platform as a new and novel architecture of the technology and business model. The existing smart building owners, facility management companies, and building product and service providers are primarily the immediate recipients or beneficiaries of this study. Furthermore, the technical developers, such as AI, software, and embedded system developers, can also benefit from the results of the paper.

Overall, this study is exploratory research in AI's potential development in the emerging research domains of smart building and smart built environment. The study is constructed through a techno-economic approach. Looking forward, the research sees that, along with technology and the business model, regulations can also affect the ongoing development of AI in the smart building sector. For example, data privacy is a significant factor in Europe. The General Data Protection Regulation (GDPR) is an established legal requirement and regulation in the European Union (EU) law on the privacy of data and the appropriate protection of individual data in EU member states. Therefore, future research can consider the regulatory aspect of AI technology development for the smart building sector. Additionally, future studies can incorporate more empirical smart building use case and ecosystems to test and apply the framework of this research on a larger scale.

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