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Review article

Strategic decision making in smart home ecosystems: A review on the use of artificial intelligence and Internet of things

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ABSTRACT

In the context of smart-home ecosystems (SHE), this paper reviews the existing literature on the application of artificial intelligence (AI) and Internet of things (IoT) concepts in strategic decision-making. The paper provides insights about this field by identifying main trends, potential benefits, challenges and opportunities of generating new business models related to the creation of SHE. A conceptual framework is presented and analysed according to three sources of value creation: *(i)* AI for strategic decision support; *(ii)* AI for alliances and partnerships; and *(iii)* AI and IoT in SHE. One of the uniqueness of this paper is the fact that the clustering analysis combines the authors' assessment with the results of a machine learning method (non-negative matrix factorization). Our findings contribute to enrich both theoretical and managerial perspectives with new forms of corporate development.

1. Introduction

According to top consulting firms such as Mckinsey & Co. [1] and Bain & Company [2], becoming a relevant player in an ecosystem is one of the top priorities in the coming agenda of many chief executive officers (CEOs). Among the various strategies to achieve corporate growth, CEOs seek to bring a more complete offer to their customers, evolving from the pure core business to an integral value proposal by encouraging different forms of collaboration with players of different industries. In the customers' home ecosystem, this would imply deciding territories to explore (fields of business), partners and types of collaboration, and the role to play (leader or participant) according to its corporate capabilities [3]. Knowing how to tackle this strategic decision implies that CEOs understand the multi-criteria decision problem when deciding whether to expand to one territory or another. The goal is then to design manageable and controllable frameworks using AI oriented to SHE.

By using ecosystem-based business models, digital technologies have enabled companies to compete in new ways. These technologies have changed the nature of collaboration and competition within and across industries [4,5]. Due to an increasing industry convergence, companies are changing their collaborative and competitive behaviour as they take part in ecosystems that include unconventional actors from previously unrelated industries. Co-opetition and co-creation are increasingly common in such ecosystems because of the complex interdependencies between actors [6]. For example, awareness of advances in technology and data prompted Amazon executives to renew the company's business model according to their customers' preferences, moving it from an online bookseller to an ecosystem player including online retailer, publisher and media content organization among others [7]. Also, consumers are increasingly embedding technology within their homes, daily routines and personal interactions, which has

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profound implications for their demands and expectations towards the offerings of and the communications with companies [8]. IoT should be seen as the basis for the transition to a new business model that monetizes the data, in many cases processed through AI systems [9]. Both developments contribute to increased dynamics within industries, in which companies must now compete with an increasing number of competitors from numerous industries and, in some cases, with completely different business models and with a rising number of start-ups. In this context, the main goals of this paper are: *(i)* to provide an updated review on the application of AI and IoT concepts in strategic decision-making; *(ii)* to study the processes of forming new business by applying the ecosystem model; *(iii)* to analyse the use of AI and IoT in the field of SHEs; *(iv)* to offer an holistic framework on the uses of AI, from strategic decision on the different parts of its value chain to the home ecosystems; *(v)* to study both the conclusions obtained by a machine learning method and those provided by the authors' analysis; and *(vi)* to point out the limitations and risk factors of implementing AI in SHEs.

The remaining of the paper is structured as follows: Section 2 introduces the concept of SHE and its relevance in the insurance sector; Section 3 describes the review methodology employed in this paper, which is based both on the authors' judgment as well as on automatic clustering techniques; while Section 4 identifies the main clusters obtained by the authors after analysing the literature, Section 5 provides an alternative analysis generated by a machine learning method (the non-negative matrix factorization or NMF); Section 6 studies the two sets of clusters and, finally, Section 7 highlights the main conclusions and findings of our work.

2. Strategic decision for smart home ecosystems

Following [10], SHE can be defined as "smart devices and sensors that are integrated into an intelligent system, offering management, monitoring, support and responsive services and embracing a range of economic, social, health-related, emotional, sustainability and security benefits". In this sense, [11] affirm that smart devices, specifically IoT [12], are increasingly ubiquitous and, therefore, require AI tools to: *(i)* be properly controlled and allow joint work among them; and *(ii)* correctly interpret their results as well as forecast future results. The rapid adoption of smart devices by households has opened two major debates. On the one hand, the multitude of risks they pose to user privacy [8,11]. On the other hand, the potential improvements in comfort, healthcare, safety, security, and energy conservation that can be delivered to users thanks to the obtained data, both in their homes and at the office [13].

These topics might be of high interest for insurance companies. In effect, the insurance sector is characterized by suffering from the problem of asymmetric information in adverse selection and also in moral hazard [14]. This effect is especially produced in the home insurance market, where a robust evidence of asymmetric information can be found [15]. In this sense, various authors state that new technologies can allow insurers to learn more quickly about the characteristics of their customers, thus reducing risk and information asymmetry, especially the adverse selection. This, in turn, enables insurers to improve the customer experience, to enhance their business processes, to offer new products, and to prepare for competition with other industries [16]. As pointed out by Catlin et al. [17]: "today, insurers win by offering a product; tomorrow, insurers will win by providing access to prevention and assistance services".

3. Survey methodology

One of the aims of this paper is to provide a comprehensive review of the existing literature. In order to do this, first we select the list of papers to be included in the survey. The key concept will be AI and then a combination of it with strategic corporate decisions, creation of ecosystems, smart homes and insurance. Moreover, we will restrict the period to the last 10 years (from 2010–2021) as the "ecosystem" concept is relatively new. Finally, we only select journal articles or articles published in prestigious conference proceedings. The search was carried out in the Scopus, Google Scholar, ScienceDirect and Web of Science databases, using combinations of the following keywords: 'artificial intelligence', 'strategic decision-making', 'corporate strategy', 'business strategy', 'corporate development strategy', 'ecosystems strategy', 'internet of things', 'smart homes', 'insurance ecosystems', and 'AI in insurance'. We will first read the selected papers to be aware of the existing approaches and main trends of the field. Then we need to figure out how to classify the selected papers according to certain criteria. After that, we will also apply the NMF method using the abstracts of all relevant papers. This will generate an automatic clustering of the articles (see Table 1).

Finally, we will analyse the results obtained by the expert analysis with the clusters obtained with the NMF method. This will allow us to extract conclusions with insights and areas of controversy identified from the review.

4. Main clusters identified from the review

In our analysis of the literature, following the expert judgment method proposed by [18], we have identified three main clusters related to AI general applications related to the focus of this paper: *(i)* AI in decision-making for strategic areas; *(ii)* AI in the creation of ecosystems and alliances; and *(iii)* AI and IoT in homes and smart homes. Moreover, a fourth cluster has been included to consider AI specific applications in the insurance sector together with a review of insurance in home ecosystems. In this section we discuss in more detail each of the aforementioned clusters.

Table 1
Methodological process.

Process	Expert analysis	Application of ML (NMF)
Search query combined with filter by knowledge area	Requirements: mandatory AI combined with corporate strategic decisions, creation of ecosystems, IoT, smart home, insurance ecosystems. 10 years Source: Google Scholar, ScienceDirect, Web of Science. Result: 546 publications.	Requirements: AI ecosystem platforms, AI strategic decisions, AI IoT smart home, AI insurance. 10 years. Source: Scopus Result: 609 publications.
Selection of most connected publications	Aim: Select those papers that suits with the aim of the paper: strategic decision making in SHE: application of AI and IoT. Process: Read the abstract and structure of the paper. Result: 56 publications.	
Identification of main topics/clusters	Aim: Identify clusters and understanding of them Process: Read the papers and expert analysis Result: Identify main trends, potential benefits and opportunities in the 4 areas of the analysis.	Aim: Identify value terms and frequency of the main clusters Process: Apply NMF Result: Identify of main concepts in the 4 areas of the analysis.
Creation of the paper	Aim: Create the paper answering the questions to solve Process: Understanding of the analysis and consideration of NMF results Result: Write critical review of the clusters, conclusions, limitations and open challenges.	

4.1. AI in strategic decision-making

In the past decade, many authors have drawn their attention on the application of AI tools to improve business processes. Many aspects of the business value chain have been studied, as it shows the 80 articles found by using the search expression: 'AI' AND 'strategy' AND 'decision-making' AND 'corporate development'. After reviewing these papers, a total of 13 articles have been analysed in detail. Taking into consideration the competitive environment of businesses with vast amounts of data, scarce assets and requirements for velocity in decision-making, several companies have been inspired to implement AI tools. Leading companies are reconsidering the strategic plans for integration of AI tools with the objective of establishing a sustainable performance and a competitive advantage. Researchers refer to AI-related strategy as 'cognitive strategy'.

In their work, Helfat and Eisenhardt [19] identify some major dimensions of corporate strategy, and highlight the potential positive effects of exploring the benefits and costs of sharing, adapting, and transferring resources to create synergies. The growing influence of tech giants is changing from competitive strategies to cooperative ones. Most of the papers and research studies tackled the corporate strategy concept without linking to the potential benefit of introducing technology and, in particular, AI tools. Hence, the following AI subareas have been discussed in the context of strategic decision making: *(i)* machine learning provides the ability to learn through the experience. It also allows us to extract hidden patterns from big data; *(ii)* natural language processing uses AI, human cognition, and linguistics disciplines to learn, understand, and produce human language content [20]. It can help a human expert to diagnose by processing records or to prepare a summary of massive legal documents; and *(iii)* computer vision enables to process images like humans, such as detecting objects from an image and comprehending the image conceptually. All in all, we can identify three driving forces – algorithms, stronger computing power, and massive data – that have made AI a relevant methodology to enhance strategic decision-making, thus providing a competitive advantage. Table 4 shows the main strategic areas where the use of AI concepts can make a difference.

As showed in Table 4, there are five strategic areas affecting the future corporate strategy due to its holistic nature and the need of processing a large and complex amount of data. The area of business model on customer management was covered by some papers in the field of marketing. In particular, Stone et al. [21] did a nice contribution regarding possible aids by AI in marketing decisions. They mentioned that 5% or less of companies have industrialized the use of AI to create a clear enterprise vision based on strategy and competitive advantage. The use of AI aligned with a business strategy to create new revenue streams was covered just by three papers. Blitz and Kazi [22] discussed the use of AI to enable machine-to-machine communication in new business opportunities, but they did not validate their ideas. In contrast, some studies argued that enterprises have received benefits with the development of new products and offering of new services [23,24]. Barro and Davenport [25] studied how AI tools can drive innovation deeper into business, and considered this to be the greatest impact generated by intelligent technologies. Pappas et al. [26] conclude that one further research would be needed on data capacities and availability, including regulations and differences between countries, continents, and cultures towards the creation of unified practices and laws. Authors such as LeCun et al. [27], Davenport and Ronanki [23], or Russell and Norvig [28] point out that some AI technologies need a human expert in the problem domain to establish hypotheses and to select relevant features. In turn, deep learning techniques can extract patterns from data by themselves, but it is hard for humans to understand and to explain the results. Thus, it is important to analyse how leaders formulate strategies to take advantage of the AI potential and to adjust the AI–human equation for generating value to business [29].

4.2. AI in the creation of ecosystems

In the last decade, there is an increasing interest in ecosystems, with more than 18,900 papers published on this topic in 2021. One of the main reasons is because some of the most valued companies base their business models on these concepts. Ecosystems

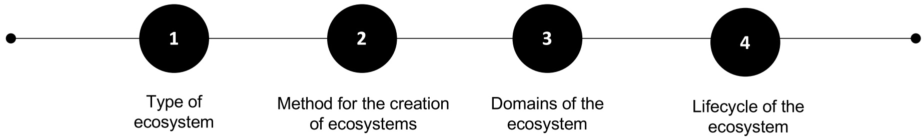

Fig. 1. Factors of an ecosystem where AI could be applied.

are resources that enable value by creating interactions between several partners from other industries and consumers. That means ecosystems connecting users to one another in order to build marketplaces, communication tools, social networks, and online advertising empires. From the initial papers found, for the aim of this study we have selected those that focus on the methodology to create ecosystems and the application of AI to make strategic-decision and enhance those processes. From the resulting 160 papers, it is noticeable that 48.2% of them have been published in 2021 or after. A final selection of 11 papers have been performed, trying to understand how ecosystems departs from traditional companies and leverage their novel features to develop effective strategies based on AI. Business ecosystems are an essential topic for strategy because they shape company decisions about where and how to compete [4]. In recent decades, we have seen numerous companies moving away from hierarchical integrated supply chains and towards these more fragmented networks of strategic partnerships with external entities [30]. Companies need to reconsider how they create and capture value [31] and how to change them in order to sustain competitive advantage [32]. The scope of change often goes beyond the boundaries of the company and entails enabling value creation at the ecosystem level [6]. Ecosystems typically provide three types of values: *(i)* they act as gateways, reducing friction as customers switch across related services; *(ii)* they harness network effects — Google Nest, the maker of an ecosystem of smart home products, provides its customers with a monthly report card that illustrates their energy use and compares it with that of their neighbours to give the numbers context; and *(iii)* they integrate data across a series of services — the Onesait healthcare-data company extracts high-fidelity data from the healthcare ecosystem and applies it to patients' lives to improve human health. Based on the aforementioned values, we propose four factors of analysis in order to understand how AI can be applied in ecosystems (Fig. 1):

The first factor is well developed by Volberda et al. [33], where ecosystems are classified in a matrix depending on their type of change and strategic orientation. Combining the types of change gives us four possible types: *(i)* holistic or "explore and dominate" [34]; *(ii)* facilitated or "explore and connect"; *(iii)* directed or "exploit and improve"; and *(iv)* connected or "exploit and connect". Ecosystems can also be classified depending on the role of the core company: *(i)* in solution ecosystems the network follows an "integral" perspective; and *(ii)* in transaction ecosystems the central role is for a platform with a one-stop shop purpose. We could classify ecosystems of type 1 and type 4 (holistic and connected) with the idea of the transaction ecosystem, while type 2 and type 3 (facilitated and directed) could fit with the idea of the solution ecosystem.

Regarding the second factor, on the method of creation of ecosystems, we have identified 4 phases [35]: *(i)* a market-value and market-segment matrix is created to match products and services to market segments, as well as to identify business units; *(ii)* an analysis is carried out to identify relevant transactions and partners; *(iii)* a matching between transactions and a catalog of generic use cases is performed; and *(iv)* organizational elements are designed — e.g., incentives to motivate partners to form part of the ecosystem, information and data to provide, measurement of revenues, etc.

The third factor of analysis in the creation of ecosystem relates to the use of the service-technology-organization-finance (STOF) tool [36], which provides a multidimensional view: *(i)* service — strategic-decisions on what services determines the value proposition; *(ii)* technology — decisions on the architecture and functionality to offer a complete, on-time and seams-less experience for customers; *(iii)* organization — decisions on the governance of the network and among the partners; and *(iv)* finance — decisions on the generation of revenues and the required investments.

The fourth factor relates to the life-cycle of ecosystems and it is well analysed by [37], who also studied on the threshold between the launch and the evolution phase. There are four phases with specifics jobs to be done: *(i)* in the launch phase, prioritize growth through network effects and set their boundaries to enhance transaction opportunities and innovation complementarities across sides; *(ii)* in the scale phase, the focus is on increasing the loyalty of customers, suppliers and erecting barriers to entry competitors; *(iii)* in the maturity phase, partners alter their boundaries to prioritize profitability and leverage their dominance, expanding the company scope, adding sides to the platform while becoming more selective about who can join the sides and re-calibrating or closing their digital interfaces; and *(iv)* in the evolution phase, the focus is on the expanding offering and on continuing innovating to thrive and survive on the long-term.

4.3. AI & IoT in smart homes

The rapid development of the IoT has led to an increase in smart-home applications, and it could change many companies' business models by modifying the way consumers interact with them and their stakeholders [38]. The smart home 2.0 era allows for the effective combination of technologies such as computers, network communication and electrical appliance control. It integrates technologies for the ease of home life, such as home intelligent control, information exchange, consumer services, auxiliary living, health checks and safety.

During the literature search, there found many papers about smart home, especially with focus on the energy sector, but only a few studies in academia that attempt to investigate smart home ecosystems in terms of strategic-decision for the association of partners or business value network. The first research attempt to 157 papers published in the last ten years of which just 18 add value to the concept of smart home ecosystem and as a result have been analysed in detail.

The smart home market size was valued at USD 98.24 billion in 2020, and it is projected to reach USD 495.15 billion by 2028 [39–41]. Smart homes play a central role in the residents' everyday life. The residents would be able to gather important everyday family information in one place, e.g., to communicate with each other (e-notes), to communicate with their friends (e-mail and address book) and to co-ordinate their activities (calendar). Moreover, smart homes will help them to feel safer (alarms) and to have control over their energy usage. In particular, Jie et al. [42] proposed a solution for integrating many applications into the system through a unified interface. Also, Kadam et al. [43] claimed that consumers are able to use smart devices to ensure security, energy savings, and ventilation, as well as to build smart kitchens and other features. There are two main lines of study: "health and well-being" and "energy and resource management". In addition, the industry expects the most of the economic value to come from the "convenience and comfort" segment. In particular the independence of individuals is a value in the society, and providing that to elderly people is considered as a challenge in this aging society.

Tang and Inoue [40] discussed the impact of ecosystem elements on the consumer perception of value for smart home products based on 595 samples of Japaneses. The results show that consumers appreciate modularity and inter-consumer connectivity. Sandström [44] evaluates the residents' use and benefits of smart homes by: *(i)* evaluating the user expectations' before and right after use; *(ii)* long-term experiences after 3–5 years of use; and *(iii)* issues related to innovation and organization of service delivery. Considering the fact that monetizing value propositions in smart home ecosystem is a strong motivation for corporations, this domain represents a valuable scheme for investigating the sub-elements one by one.

4.4. AI in insurance: Strategic parts of value chain and home ecosystem

While some industries such as banking, healthcare, manufacturing and software development have been investing in AI for years [45], the insurance sector is lagging behind in the worldwide and intersectoral AI movements [46]. Nevertheless, it is likely that AI will have a broad impact along the insurance value chain, from underwriting and claims management over distribution and customer service to asset management. From a research of 149 papers that analyse the application of AI in the insurance sector, a selection of 14 have been systematic assessed. A summary of insurance-relevant AI applications comprise enhanced process efficiency, improved underwriting and product development, reshaped customer interactions and distribution strategies and new business models [47]. Attention has been given to digitization in the insurance industry, with a systematic overview of previous research on the implications to the insurance value chain and its impact on the insurability of risks [48].

Insurance, as many other sectors, is impacted by technology. According to Eling et al. [48] and Eckert and Osterrieder [49], the most relevant technologies for the sector are the following ones: *(i)* Big Data — setting prices in a more accurate way, managing claims in real-time, supporting commercial decisions, etc.; *(ii)* Artificial Intelligence — relating claims and management of post-claims, customer segmentation, prospective buy or churn rates, etc.; *(iii)* IoT — smart homes, connected-cars, smart health, etc.; *(iv)* Cloud Computing — help to create new service delivery models for insurers such as software as a service (SaaS), platform as a service (PaaS), infrastructure as a service (IaaS), and database as a service (DBaaS) [50]; *(v)* Distributed Ledger Technology (blockchain, etc.) — record forgery-proof transactions such as data, contracts, record exchanges, identities, etc. There a numerous papers tackling applications of AI and IoT into the insurance value chain.

The recent proliferation of internet connections have enabled insures to examine the possibilities of new revenue streams, integrate their insurance products into seamless customer journey, new methods of service provision as well as greater opportunities for data collection. Insurers have strong analytics capabilities compared with their peers in other industries because analytics has been a core component of the traditional insurance business model. Hence, insurers can positioned themselves at the centre of an ecosystem of interconnected services, looking beyond their standard insurance products and offering value-added services that address broader consumer and business partner needs. Examples of such value-added services are: *(i)* alerts of smoke, intrusion and leakage monitors for the smart home; *(ii)* telematics sensors for vehicles that can be used to reward good driving or trigger maintenance alerts; *(iii)*health diagnostics and advice; or *(iv)* financial advise and planning. The key question for any insurer is what role it wants to play in the ecosystem economy. This is a strategic-decision, since it affects the potential to reach and attract customers, customers' level of connection to the insurer, as well as the ability to learn from key members of other sectors. Most of the reviewed papers considered that mobility and health ecosystems are those of major potential from an insurance perspective. In the mobility ecosystem, insurance companies face the opportunity to expand their services to areas such as the purchase of vehicles, parking, traffic management and car sharing [17]. Fig. 2 summarizes the main industries and solutions with which insurers could make strategic-decisions in order to create their smart home ecosystems.

5. Topics discovery using machine learning

Advancement in computer and web technology has generated large amounts of digitized unstructured information including articles, books, letters, online forums, mailing lists, blogs, and other communication media. To read and process all these information is simply beyond humans' processing capability. Machine learning algorithms offer support in processing and annotating large archives of documents with thematic information [51]. Some of the mostly used ML methods for topic modelling include the non-negative matrix factorization (NMF) [52] and the latent dirichlet allocation (LDA) [53]. On the one hand, NMF is one of the most popular approaches in topic modelling, and it can effectively extract topics from a collection (corpus) of documents [54]. NMF utilizes methods of dimensionality reduction for 'non-negative matrices', i.e., matrix made up of only positive or zero value

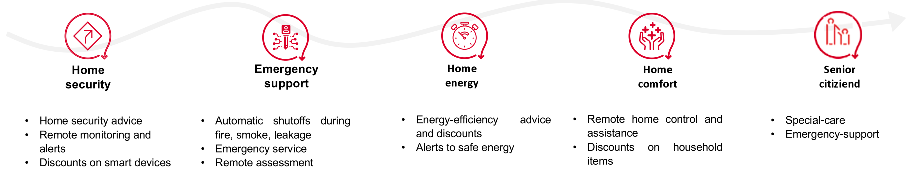

Fig. 2. Main partners for a smart home ecosystem.

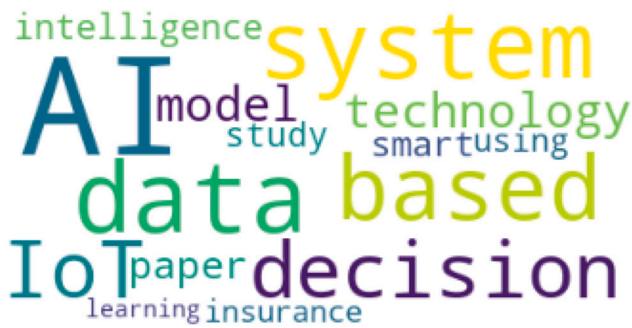

Fig. 3. The 15 most frequent terms.

components. On the other hand, LDA is a generative probabilistic model for collections of discrete data. In LDA, each document is a mix of latent topics, and each topic is a mix of words. LDA represents topics by word probabilities. Once the probabilities are estimated, finding the collection of words that represent a given topic can be done either by selecting the words with highest probabilities or by selecting words whose probabilities are greater than or equal to a predefined threshold value [55].

5.1. Corpus pre-processing and summary

Before applying topic modelling models to a corpus, a set of pre-processing steps is needed to transform raw data into a "clean" and "tidy" corpus. These steps include: *(i)* convert all terms to lowercase, *(ii)* remove all the punctuation marks and digits; *(ii)* remove terms that appear in less than 1% of documents; *(iii)* remove stop words, which are the most common words in any language (like articles, prepositions, pronouns, conjunctions, etc.) and that do not add much information to the text; and, *(iv)* lemmatize all word to its base form.

The title and abstract from Scopus-indexed articles are selected to form the corpus. In particular, 76 articles are selected from the Scopus database using the search keyword 'AI ecosystem platform', 204 articles using the keyword 'AI strategic decisions', 116 articles using the keyword 'AI IoT smart home', and 217 articles using the keyword 'AI insurance'. After dropping duplicated articles, the final number of articles used for the topic modelling is 609. The word cloud in Fig. 3 indicates the 15 most frequent terms in the corpus: 'AI', 'data', 'system', 'based', 'IoT', 'decision', 'technology', 'model', 'paper', 'intelligence', 'smart', 'study', 'using', 'insurance', and 'learning'. The size of the term indicates the value of its frequency. This corpus is transformed into a term frequency–inverse document frequency (TF–IDF) matrix, which provides a measure used in the field of information retrieval to quantify the importance of string representations (words, phrases, lemmas, etc.) in a document of the corpus [56]. Finally, by multiplying these values together we can get a term-by-document matrix containing the TF–IDF values for all the documents.

5.2. Topic modelling

As a final step in our analysis, we employ the NMF and LDA algorithms, already implemented in the Python's Scikit-learn library, to automatically extract the main 'topics' from the corpus. Listing 1 illustrates our topic modelling model developed in Python. Initially, the CSV files containing the title and abstract of the selected articles are read, the duplicate articles are dropped, and every word is lemmatized to its dictionary form by using the function $WordNetLemmatizer$ to form the corpus. Then, a TF–IDF matrix $tfidf$ is obtained from the corpus using the $TfidfVectorizer$ function, considering the stop words, and the minimum frequency of terms in the documents. Once we have the TF–IDF matrix, a NMF and a LDA model with predefined number of topics is constructed. To facilitate the analysis with the clusters identified in the previous section, the number of topics is set to 4. Once the models are constructed, the $tfidf$ matrix is fitted to the models and the topics are extracted. Finally, the top ten weighted words of the extracted topics are printed to illustrate how the topics are composed. Listing 1 in the Appendix offers the code employed in our analysis.

Fig. 4 displays the topics extracted by employing the NMF and LDA models. In our case, the results provided by the NMF model seem to be more consistent with the ones we deduced from our literature review. Therefore, our further comments will be based on the results provided by the NMF model.

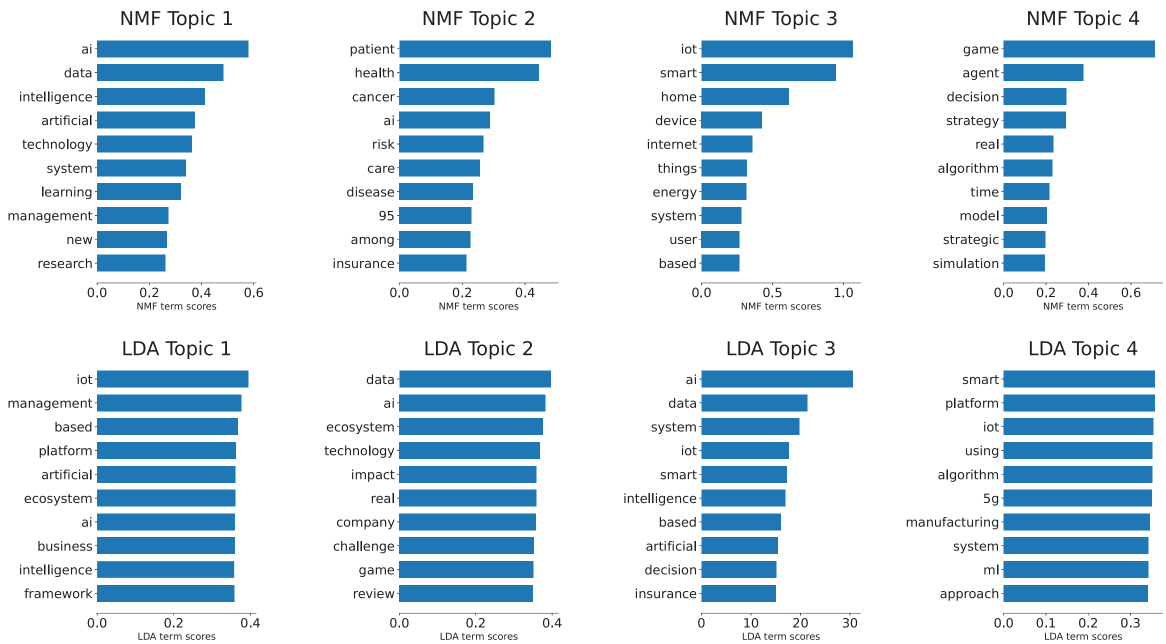

Fig. 4. Topics extracted by employing the NMF and LDA models.

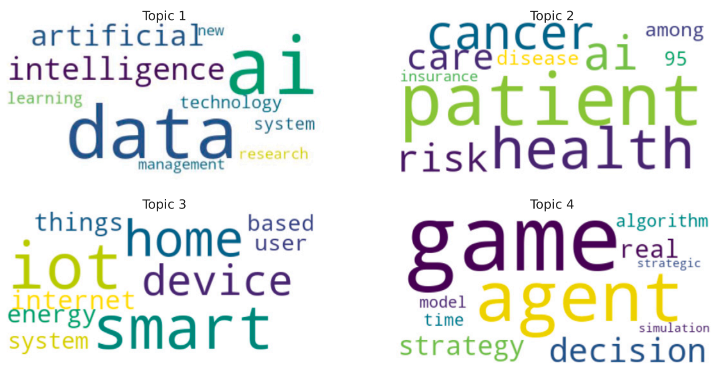

Fig. 5. Topic word cloud.

The ten most weighted descriptors of the four topics identified by the NMF model are: *(i)* Data, AI, and technology in management — AI, data, intelligence, artificial, technology, system, learning, management, new, research; *(ii)* AI and insurance in healthcare — patient, health, cancer, AI, risk, care, disease, insurance; *(iii)* IoT, energy and smart homes ecosystems — smart home, device, Internet of things, energy, system, user based; and *(iv)* algorithms for strategic decision making — game, agent, decision, strategy, real, algorithm, time, model, strategic, simulation. Fig. 5 provides a word cloud for the four topics. The size of the terms in the cloud indicates its weight in the topic.

The scientific literature on the subjects studied in this paper is extremely vast, which makes it difficult to review all the existing works. This paper combines expert judgment review with state-of-the-art topic modelling algorithms that can automatically extract a selected number of topics from a massive amount of manuscripts. To the best of our knowledge, no related study has used topic modelling techniques to analyse the publications related to the use of AI and IoT for strategic decisions in the smart home ecosystem. In contrast, our approach combines filtering, pre-processing, and topic modelling techniques to identify the most relevant topics from a large number of publications. In particular, this paper analysed a total of 609 published manuscripts, which exceeds other reviews that use traditional survey methods and provides a more nuanced and comprehensive understanding of the studied subject.

6. Critical review of the clusters

Regarding the first cluster, on the applications of AI to decision-making for strategic areas, one can notice that the role of AI in corporate strategy is not yet fully developed. There are numerous papers tackling how competitive advantage has changed due to

Table 2
Strategic areas where AI can make sound contributions.

Strategic area	Challenge	AI contribution
Business model and customer relation	Which customers the company wants to acquire, retain, develop, and divest in order to achieve its strategic objectives.	Using machine learning, to assist in "reaching" look-alike audiences. Quantifying and exploring consequences of different business models.
New revenue streams and growth opportunities	Developing revenue by using new ways of introducing a new product or service.	Identifying revenue streams for existing customers and for new markets to accelerate launch. Identifying returns more rapidly and accurately.
Ecosystem management, partnering, outsourcing and value chain redefinition	How companies and partners are organized to ensure that the overall business strategy is developed. Operating in a complex multi-channel, multi-product/service business.	Identifying the most productive parts and gaps in the ecosystem. Obtaining gains from cooperation.
Competitive strategy	How direct and indirect competitors are identified, their strategies discovered and understood. How the company designs strategies to avoid the negative effects of competition.	AI can contribute to identify who are the main competitors, targeting for winning and defense with predictive analytics. It also allows for identifying weakness points in our own and the competitor's strategies.
Value proposition	It can be more closely attuned to target markets, and the engagement of customers with different propositions can be understood more quickly, with iterative changes made and tested for further feedback.	Identifying which propositions work best through customer feedback and testing.

the digital transformation even without a focus on the decision-making process. Moreover, these analyses are mainly qualitative, without providing practical examples. As a result, even if AI offers a great potential to solve strategic challenges, there is a lack of practical implementation of AI in strategic decision making. Likewise, no empirical evidence have been found about the automation of the decision-making effectiveness in strategic areas. This result may be related to the complexity of the interaction between human and AI, which also affects decision-making automation. With respect to the second cluster, research on the evolution of ecosystems over time is still immature. Further empirical research would also be useful in order to clarify the methodology that is required to establish the network of partners, internal capabilities, governance, etc. There is a lack of understanding about how the emergence of the IoT and the creation of ecosystems will impact businesses. Moreover the application of AI in the ecosystem decision-making is still unclear even if the potential is huge. Most of the ecosystems are of digital nature, which allows to track data and analyse it in a natural way.

Concerning the third cluster on IoT and AI in homes, one can conclude that the IoT ecosystem is currently in an emerging phase, i.e., the related ecosystem models are not sufficient enough to capture all emerging actors and the value network among different stakeholders. Finally, and in relation to the fourth cluster on the application of AI in the insurance industry, we can conclude that the majority of existing academic studies are limited to excerpts of digitization in insurance, and thus to specific technologies. Today, the adoption of AI within insurance markets is in its earliest stages and the academic research on the implications of AI on the insurance business model is still limited. However, the topic is attracting increasing attention from practitioners worldwide.

7. Conclusions and open research challenges

The challenge for growth is one of the CEOs imperatives and one of the most relevant focus from corporate strategy. Looking for integral solutions that satisfy customer needs requires a well-defined and well-execute ecosystem strategy that ensembles different industries by alliances and partnerships. In particular, customer needs at their homes is a big field of business opportunity. The incorporation of AI and IoT concepts in the decision making of strategic areas such as for the creation of ecosystems is a topic of major interest, since they are in the foundation of new business models and allow for the creation of competitive advantages. However the current number of scientific publications are still limited with a more qualitative analysis approach and not focused on the strategic decision process supported by real examples or concrete industries, particularly in insurance. As a result of the analysis of the process of forming new business by applying the ecosystems model, we have identified several points where AI can be introduced. Moreover, the application of IoT in home generates the "smart home" concept, which is full of opportunities from a customer perspective as well as for corporations. In particular, insurance firms can take advantage from getting data in order to know better their customers habits, as well as working on prevention of claims and increasing their revenues with new-targeted solutions for them.

One of the greatest difficulties with strategy is human behaviour. Whether consciously or not, it often gets in the way of good choices. This fact is called "the social side of strategy". Biases can lead us to form skewed judgments. Additionally, strategy discussion often become battles for resources, where getting a plan approved is more important than debating strategic assumptions or alternatives (see Table 3).

One of the uniqueness of this paper is the methodological approach enhancing the expert assessment with a ML analysis for the identification of main concepts and trends on the use of AI and IoT for strategic decision making in SHEs. Moreover another differential contribution is the concrete approach of SHEs to the insurance sector. The use of ML analysis allowed us to complement

Table 3
Comparison of contributions from main authors.

Author/Paper	Expert	Machine learning	Other approach	Strategic-decision	Industry case	Real examples
This paper	Yes	Yes	No	Yes	Insurance	Yes
Adner R., Ecosystem as structure.	Yes	No	No	Yes	No	No
Dell' Acqua A. et al. Smart home ecosystems: a model to identify value creation and strategic approaches.	Yes	No	No	Yes	No	No
Gazis A. et al. Smart home iot sensors: principles and applications — a review of low-cost and low-power solutions.	Yes	No	No	No	Mainly energy	Yes
Jacobides M.G. et al. Towards a theory of ecosystems.	Yes	No	No	Yes	No	Yes
Jie Y. et al. Smart home system based on iot technologies.	Yes	No	No	No	Mainly technology	Yes
Langley D.J. et al. The internet of everything: Smart things and their impact on business models.	Yes	No	No	Yes	Mainly technology	No
Lopez C.A. et al. Discovering the value creation system in iot ecosystems.	Yes	No	No	Yes	No	No
Sandström G. Smart homes and user values: longterm evaluation of IT-services in Residential and Single family dwellings.	Yes	No	No	No	Mainly technology	Yes
Stone M. et al. Artificial intelligence (ai) in strategic marketing decision-making: a research agenda.	Yes	No	No	Partially: marketing	No	Yes

the initial analysis made by the authors. In fact, both our initial analysis and the one provided by the ML methods are quite coincidental, which can be seen as a validation of our initial conclusions. Additionally, while a human-based analysis is time-consuming and can only be employed to analyse a relatively small number of documents, the ML approach introduced in our study is fast and can also be employed with much larger sets of documents. In particular, this paper analysed a total of 609 published manuscripts, which exceeds other reviews that use traditional survey methods and provides a more nuanced and comprehensive understanding of the studied subject. To the best of our knowledge, this is the first study that has used ML techniques to analyse the publications related to the use of AI and IoT for strategic decisions in the smart home ecosystem.

Regarding the benefits of the application of AI in corporate strategy for the creation of ecosystems, we highlighted four parts: *(i)* to identify early-stage trends; *(ii)* to identify new growth opportunities; *(iii)* reducing bias in decision-making; and *(iv)* using analytics to anticipate complex market dynamics. The application of AI to strategic decisions, and in particular in the creation and management of ecosystem, gives a sustainable competitive advantage, as it generates strong accountability, better objectivity with data and metrics, and clarifies the governance. As this topic is still an evolving one, there are many aspects to continue studying. In particular, from the bibliographic analysis we can highlight the following challenges and limitations as appear in Table 2:

Ultimately, AI can provide opportunities in strategic-decision making for any organization if it makes the required commitments and investments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Table 4
Challenges and/or limitations of implementing AI in SHEs.

Challenge and/or limitation	Explanation	Bibliographic analysis
Mapping human strategic decisions	There is a big room to specify strategic decisions and mapping them in order to create a method where AI can be applied. The lack of data and information hinders the advance in this field. Another challenging aspect of the AI usage for the strategic decision-making process is responsibility. Only humans can be responsible for their decisions and this challenge leads to the legal regulatory of the AI's strategic decisions.	Dell'Acqua A, Corio A. Smart home ecosystems: a model to identify value creation and strategic approaches. 2018. Stone M. et al. Artificial intelligence (ai) in strategic marketing decision-making: a research agenda.2020.
General data protection regulation	This substantially affects smart homes, as the use of self-tracking data to analyse and price individual risk has several obstacles. Also, the quality of the data gathered, infrastructure compatibility, and privacy constraints also involves restrictions associated with the privacy and security of the shared data. Moreover, one of the main value-added in ecosystems is the sharing and flow of information generated from the different industries that forms it. AI algorithms and other models use multiple data sources and types. Thus, regulatory guidelines should be issued to prescribe insurers to certify the authenticity of the data sources. As the insurance industry is heavily regulated, it has several legal prohibitions that limits the type of personal data that insurers can use to price risk.	Eling M. et al. Technology heterogeneity and market structure. 2022. Pappas et al. Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. 2018.
Competitive regulation	Due to the fact of the newest concept of ecosystems that amplifies traditional sector limits regulation is working on determining where, how and whom would be responsible for them. The European Union is recently creating a law-framework to regulate the interactions on ecosystems and their power. The evolution of the regulation will be relevant to assess the value that can be extracted from some strategic alliances and partnerships of different sectors or industries.	McGrath RG. The end of competitive advantage: How to keep your strategy moving as fast as your business. 2013. Volberda H.W. et al. Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms. 2021
Showing the value creation	This is maybe the most relevant one, as 1205 the profitability or the value creation is one of the key factors to decide where to invest. The lack of empirical results that supports the positives of investing in AI for strategic decision-making is limiting the flow of investments to this field. Moreover, regarding home ecosystem there is also a need to increase the customer perception of the value received.	Eckert C. et al. How digitalization affects insurance companies:overview and use cases of digital technologies. 2020. Dell'Acqua A, Corio A. Smart home ecosystems: a model to identify value creation and strategic approaches. 2018. Lopez C.A. et al. Discovering the value creation system in iot ecosystems. Stone M. et al. Artificial intelligence (ai) in strategic marketing decision-making: a research agenda. 2020. Teece D.J. et al. Business models, value capture, and the digital enterprise. 2017.
Cybersecurity	This is a hot topic that creates limitations for many angles and especially because ecosystems and smart home offers value mainly through the share of information and data among the participants of them. Cybercrime and threats of cybersecurity is much closer to connected home ecosystems futures that ever been expected.	Ruan K. Digital asset valuation and cyber risk measurement: Principles of cybernomics. 2019.

Appendix A

```python
import pandas as pd
from sklearn.decomposition import NMF, LatentDirichletAllocation
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.stem import WordNetLemmatizer
import nltk

# Read and lemmatize the input csv files
lemmatizer = WordNetLemmatizer()
data = []
nltk.download('stopwords') # download stop words
stopwords = nltk.corpus.stopwords.words('english')

d = pd.read_csv('AI ecosystem platform.csv') # the main dataframe
```

```
iot= pd.read_csv(’AI IoT smart home.csv’)
strategic= pd.read_csv(’AI strategic decisions.csv’)
insurance= pd.read_csv(’AI insurance.csv’)
d=pd.concat([d,iot,strategic,insurance], ignore_index=True)
d=d.drop_duplicates(ignore_index=True) # drop duplicate articles
print(’Total number of articles ’, d.shape[0])
for n in range(d.shape[0]):
    singtext=""
    for words in d.Title[n].split(’ ’): # read title
        if words not in stopwords:
            singtext+= lemmatizer.lemmatize(words) + " "
    for words in d.Abstract[n].split(’ ’): # read abstract
        if words not in stopwords:
            singtext+= lemmatizer.lemmatize(words) + " "
    data.append(singtext)

# Get the TFIDF matrix of the input data
vectorizer = TfidfVectorizer(min_df=0.01, stop_words=stopwords, ngram_range=(1,1))
tfidf = vectorizer.fit_transform(data)

# Construct NMF model
nmf = NMF(
    n_components=4, # set the number of topics
    random_state=1,
    beta_loss="kullback-leibler",
    solver="mu",
    max_iter=1000,
    alpha=0.2,
    l1_ratio=0.5,
).fit(tfidf)

# Construct LDA model
lda = LatentDirichletAllocation(
    n_components=4,
    max_iter=10,
    learning_method="online",
    learning_offset=50.0,
    random_state=0,
).fit(tfidf)

# Print the topics
feature_names = vectorizer.get_feature_names()
n_top_words = 10 # number of top weighted words to print

# Input nmf or lda to print the related topics
for topic_idx, topic in enumerate(nmf.components_):
    list_words = []
    print("topic: ", topic_idx + 1)
    topics = topic.argsort()[: -n_top_words - 1: -1]
    print(’ ’.join([feature_names[i] for i in topics]))
```

Listing 1: NMF model in Python.

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