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Zooming in and out the landscape: Artificial intelligence and system dynamics in business and management

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ABSTRACT

Organizations are increasingly leveraging the ability of artificial intelligence to analyze and resolve complex problems. This can potentially reshape the interdependencies and interactions of complex systems, leading to our research question: To what extent and in which direction is the literature on Artificial Intelligence (AI) and System Dynamics (SD) converging within the business and management landscape? We conducted an extensive literature review using bibliometric and topic modeling methods to address this question. Through a bibliometric analysis, we identified the areas in which academic papers referred to both SD and AI literature. However, bibliometrics do not show a clear path towards convergence. The top modeling analysis highlights more details on how convergence is structured, providing insights into how SD and AI may be integrated. Two trajectories are identified. In the "soft convergence," AI supports system dynamics analysis and modeling more deeply characterized by social interaction. In the "hard convergence," AI shapes innovative ways of rethinking system design, dynamics, and interdependencies. Our analysis suggests that while soft convergence is more visible in the business and management landscape, hard convergence may well represent a new frontier in studying system dynamics with the potential to reshape the landscape.

1. Introduction

Socioeconomic systems have become increasingly complex, also because of the simultaneous globalization of value chains and innovation networks, fostering innovative outcomes' nonlinearity (Russel and Somorodinskaya, 2018). Such complexity represents the central interest of two academic disciplines, one concerned with "system dynamics" (SD) and the other with "artificial intelligence" (AI). Given their focus on complexity, academic papers in both SD and AI are commonly referenced in various subfields of business and management literature. Nonetheless, the intersection between SD and AI within the business and management landscape remains largely unexplored. This is surprising as the integration of SD (with its focus on system complexity) and AI (with its focus on big data analytics and deep learning) would bring a wider perspective to the analysis and evolution of technological processes and decisions (Zhao et al., 2018; Sterman et al., 2015; Liu et al., 2015; Gruetzemacher et al., 2021; Mendoza et al., 2014). This leads to the question addressed in this study: To what extent and in which direction is the literature on AI and SD converging within the business and management landscape?

This study leverages recent advancements in bibliometrics and topic modeling techniques to address this question. Our aim is twofold: First, through bibliometric analysis, we focus on the literature landscape to analyze the shape and intensity of convergence between SD and AI. This part of the analysis is concerned with the "how much" and "what for" questions concerning convergence. We also analyze the academic networks through which SD and AI converge. Second, through topic modeling, we zoom out the landscape to identify topics in which artificial intelligence and system dynamics will become more entwined.

The business and management landscape encompasses two major and interconnected literature streams on systems; one revolves around system architectures, while the other concerns "system dynamics." The "system architecture stream" focuses on the managerial implications of modular design upon coordinating innovative agents. Henderson and Clark (1990) unearthed a deep relationship between modularity, architectural knowledge, and innovation by showing that incremental

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innovation in peripheral modules might lead to architectural innovation, that is, a nonlinear and unforeseen change in the interdependencies among modules in a given product/process architecture. Along the same stream of thought, other authors focused on the relationship between modularity and outsourcing strategies (Baldwin and Clark, 2000; Baldwin and Lopez-Gonzalez, 2015). More recently, the modular system theory (Tiwana et al., 2010; Jacobides et al., 2018) has informed the analysis of innovation ecosystems and technological platforms around issues of coordination/integration of dispersed innovative actors (Gawer, 2014, Cusumano et al., 2019, Gawer, 2020).

The "system dynamics" stream focuses on how systems behave in specific contexts. As such, the SD literature spans different fields from engineering to business, management, and economics (Kogan and Lou, 2003; Lee et al., 2011; Reddi and Moon, 2011). In particular, the system dynamics approach has proven fruitful to various business forecasting functions, from technological substitution (Sharif and Kabir, 1976; Kabir et al., 1981) to market forecasting (Lyneis, 2000). The SD literature is also concerned with system viability, that is, how system architectures and communication modes should be designed to build preconditions for systemic viability (Barile et al., 2016). However, landscapes are becoming increasingly complex, with system dynamics increasingly shaped by nonlinear behaviors (Zhao et al., 2018). Therefore, developing an analytical approach based on systemic thinking requires considering the nonlinearity of system dynamics and outcomes (Russel and Somorodinskaya, 2018; Zhao et al., 2018). This calls for better integration of system dynamics with data analytics in organizational practices and academic research. Regarding organizational practices, recent research underscores the misalignment between the complexity of system dynamics and actual data analytics capabilities (Garbero et al., 2021). While organizations usually embed data collection and storage in their structures, data are often only partially utilized and analyzed or are fragmented and not available to strategists and policymakers systematically. Artificial intelligence, machine learning, and big data analytics should become increasingly relevant to system dynamics for better analyses of dynamics and more precise forecasting, as we will try to explain further in this paper. Indeed, AI is believed to carry high transformative power in various industries such as traditional manufacturing and digital services (Collins et al., 2021). However, it is not yet clear how and in what direction AI will be integrated into other disciplines relevant to business and management. This warrants our analysis of the relationship between system dynamics and artificial intelligence through bibliometrics and topic modeling.

While our empirical results substantiate the poor integration of system dynamics and artificial intelligence literature, they also show emerging convergences and help frame future reflections for academics, practitioners, and policymakers.

Our analysis focuses on three overarching themes within the business and management landscape: technological forecasting, knowledge elicitation, and decision-making. In terms of contributions, our analysis provides evidence of the convergence between SD and AI. More importantly, it shows two distinct convergence trajectories that we call "soft" and "hard" convergence. By soft convergence, we mean that SD and AI are used (or referred to) in academic papers that analyze socio-technological systems more deeply characterized by social aspects. Soft convergence is most common in marketing, knowledge management, entrepreneurship, and service management, especially when academic publications are concerned with our three overarching themes (i.e., technological forecasting, knowledge elicitation, and decision-making). In contrast, "hard convergence" underscores the power of AI to reshape innovative ways to rethink system design, dynamics, and interdependencies, for example, through emerging process-based views such as process mining. We detected a hard convergence in operational research, complex system designs, robotics, and digital platforms. Again, we detected hard convergence in these topics, especially when the academic papers were concerned with three overarching themes (technological forecasting, knowledge elicitation, and decision-making).

Our analysis suggests that while soft convergence between SD and AI is already visible in the business and management landscape, hard convergence between SD and AI is underrepresented in our sample and, therefore, can potentially reshape the landscape. In particular, the literature currently engaging in such a "hard convergence" between SD and AI revolves around two distinct elements: a) using data analytics system diagnostics and troubleshooting. This approach does not question the assumptions underpinning system design. Therefore, it is not apt to evidence any embedded bias stemming from an incorrect perception of how things are happening within organizations; b) the use of data analytics for systems reengineering and structural assumption redesign. In this case, machine learning is used to question the assumptions and reshape the bias. The emerging literature highlights the use of data analytics and machine learning such that the underlying model of the system can continuously (and potentially autonomously) change assumptions and redefine bias (Fan et al., 2021; Badakhshan et al., 2020; Azadeh et al., 2014; Alinasab et al., 2022; Krenz et al., 2014; North and Kumta, 2018).

The emergence of hard convergence between SD and AI is the main theoretical implication of this study. While SD is more concerned with questions of causation, AI is concerned with questions of correlation, and clearly, the two fields and approaches can be integrated fruitfully in the future. Such a theoretical development may also require a deep reflection on the relationship between autonomous AI learning and human agency in system dynamics. Implications for practice are mostly related to the soft convergence between SD and AI, as practitioners and policymakers may have to consider the possible impacts of datafication, especially in socioeconomic contexts driven by digitization, with implications on regulation and data-related issues.

The remainder of this paper is structured as follows. The next section addresses the theoretical background of our investigation, followed by a methodological section. We then analyze system dynamics and artificial intelligence integration in the business and management literature through bibliometric analysis. The next section addresses topic modeling to identify topics most likely to witness future integration between system dynamics and artificial intelligence. Discussion, implications, and conclusions are reported at the end of the paper.

2. Background

This section presents the theoretical background and historical development of the System Dynamics and Artificial Intelligence fields. The following section describes these two fields of knowledge, focusing on their analysis of technological forecasting, knowledge elicitation, and decision-making. These three topics are used later to deepen the discussion of the retrieved results, which have gained attention from the research community and published literature.

2.1. System dynamics

System dynamics has been recognized as an approach to technological substitution forecasting since the 70s, when Sharif and Kabir (1976) proposed a multilevel forecasting methodology based on system dynamics and the "principle of substitution." The authors concluded that the SD-based approach can incorporate various time-dependent parameters as exogenous factors that can influence the course of substitution, which is depicted as an S-shaped curve. Kabir et al. (1981) further explored the model proposed by Sharif and Kabir (1976), who used a multilevel SD model structure to forecast the size of the market and the share of each competing technology or product under various assumptions regarding market growth.

In the early 80s, Martino (1980, p. 31) described system dynamics as a "new technique with considerable potential for technological forecasting". Martino further elaborated on this, arguing that besides SD being a completely deterministic modeling technique, it could also be helpful in uncertain contexts for events and impacts (common for technological forecasters) because it allows the introduction of stochastic events.

In addition, system dynamics has been seen as a forecasting approach suitable for several contexts, scenarios, and varying levels of analysis. In its origin, SD was used for dealing, in a systemic perspective, with challenges and planning interventions within business management (Forrester, 1961), urban management (Forrester, 1969), and worldwide challenges (Forrester, 1971) levels. These were seminal works in the SD field, which proved to be a proficuous approach for dealing with planning, forecasting, and evaluating different complex socio-technical scenarios and challenges over time.

More recently, several other authors have exploited SD for several forecasting scenarios. For example, Maier (1998) assessed new product diffusion models and showed how to extend traditional innovation models to incorporate competition while considering the substitution process among successive product generations. Lyneis (2000) used an SD model for market forecasting in the commercial jet aircraft industry to demonstrate that system dynamics provides more reliable short- to mid-term trend forecasts than statistical models, with an endogenous focus on understanding the causes of the industry's observed behaviors.

Several authors have demonstrated how SD can be used to forecast natural resource usage/demand, improve management of its usage, and not compromise the environment, such as in water management (Winz et al., 2009), waste management (Dyson and Chang, 2005), energy transition (Moxnes, 1990), and the electric power industry (Ford, 1997).

Despite many previous studies using SD to forecast the specific future conditions of particular variables, Forrester (2007) argued that SD could face some barriers owing to its fundamental nature. However, Forrester (2007, p. 364) added that the "emphasis on forecasting future events diverts attention from the kind of forecast that system dynamics can reliably make; that is, the forecasting of the kind of continuing effect that an enduring policy change might cause in the behavior of the system."

Several studies were conducted not to forecast or predict a single future state, condition, or event but to promote better understanding and improve decision-making related to complex socio-technical systems. There is a vast bibliography and comprehensive knowledge base for deploying the system dynamics approach for knowledge elicitation, scenario evaluation, and supporting decision-making.

Concerning knowledge elicitation, system dynamics models usually leverage multiple information streams, including quantitative data, written records, and information in the mental models of individuals and groups (Vennix et al., 1992). Vennix et al. (1990) and Vennix and Gubbels (1992) argue that eliciting relevant knowledge from stakeholders' mental models is critical for creating SD models. To this end, they proposed combining different techniques for knowledge elicitation (i.e., how to obtain the necessary knowledge from a group of people) to overcome problems arising from high-time investments and low performance. They then evaluated their proposed method in a public healthcare system case study.

Ford and Sterman (1998) stated that knowledge-intensive processes are usually driven and constrained by mental models; thus, it is difficult to elicit and represent expert knowledge to develop valuable models. Ford and Sterman (1998) proposed an elicitation method that could improve the model's accuracy and credibility and provide tools for improving the development team's understanding of problems. Vennix (1999) explored how group model building, in which stakeholders are deeply involved in the model-construction process, can tackle an ill-defined or messy problem arising from divergent opinions and understanding.

The knowledge elicitation phase is usually a predecessor activity to build a shared understanding of the problem to be addressed, the structure responsible for this undesired problematic behavior, and to develop a simulation model to mimic real-world problems that can later be used to evaluate scenarios and to support and improve decision-making processes.

Decisions apply inference rules from mental models to conditions perceived in the real world. The difference between good and poor decisions lies in the gray area between the information-gathering process and action implementation. It is based on how a small relevant fraction of all available information is selected and effectively processed (Forrester, 1992) to set up actions (or make decisions) to achieve a specific objective.

When making decisions, the human mind is limited by the availability of the very same information, its cognitive limitations, and the available time to process information and make a decision; hence, it cannot achieve the ideal "objective rationality" (make the most optimal decision possible, given the information available) and is destined to have a lower level of the intended rationality (Simon, 1955).

System dynamics on decision-making topics has gained attention among policymakers and the academic community. Morecroft (1988) referred to SD as an approach to create 'microworlds,' which captures decision-makers' mental models and could be used to trigger richer debates and discussions that produce a consensus for action. These microworlds include knowledge, information, theory, maps, debate, and the interplay of these factors, and can be used to assess candidate intervention policies and their potential impacts.

Rouwette et al. (2004) conducted a literature review of dynamic decision-making to identify the various factors that could influence it. The authors found strengths connected to SD that could improve decision-making performance, such as better awareness of delays, increased feedback strengths, model transparency, decision information, and clear long-term goals. Richardson (2011) added that understanding the "endogenous point of view," that is, the endogenous sources of complex system behaviors (or the dynamic behavior that arises from the system's internal structure), is a crucial foundation in system dynamics. Thus, it should be the starting point for hypothesizing, testing, and refining endogenous explanations of system changes and then used to guide policy and decision-making.

Ghaffarzadegan et al. (2011) argued that using a small system dynamics model could overcome the frequent failures arising from public policy implementation, which fail to achieve their intended results because of the complexity of the environment and policymaking process. According to the authors, these small models helped promote accessible and insightful lessons for policymaking arising from the endogenous and aggregate perspectives of the SD approach.

2.2. *Artificial intelligence*

Artificial intelligence (AI) is a branch of computer science that seeks to create intelligent machines capable of simulating human cognitive functions such as learning, problem-solving, perception, and decision-making. The field of AI originated in the 1950s and has evolved significantly over the decades with advancements in computational power, algorithms, and the availability of large amounts of data (Patterson, 1990). This section presents an overview of AI's historical development and its contributions to these areas.

One key application of AI is technological forecasting. AI techniques such as machine learning have been used to analyze large amounts of data and generate predictive models for various domains (Dwivedi et al., 2021), including finance (Goodell et al., 2021), healthcare (Jiang et al., 2017), manufacturing (Zhang et al., 2018), and industrial marketing (Martínez-López and Casillas, 2013). AI-driven forecasting models have proven effective in technology adoption (Hengstler et al., 2016), and innovation management (Haefner et al., 2021).

Another important application of AI is knowledge elicitation. AI techniques such as natural language processing and expert systems have been used to extract, represent, and store knowledge from various sources, including human experts, documents, and databases. This knowledge can then be used to support decision-making and problem-solving in various domains (Duan et al., 2019) and has been a topic of growing interest in the past few decades. Aamodt and Nygård (1995) emphasized the importance of clarifying the distinction between data, information, and knowledge and proposed a unified definitional model. They explored case-based reasoning in decision support systems and argued that focusing on retaining and reusing past cases could facilitate the transition from an information system to a knowledge-based one. O'Leary (1998) examined the use of AI in knowledge management systems, focusing specifically on knowledge bases and ontologies. The Author studied how knowledge management is practiced at three major professional service firms, highlighting the dependence of AI-related technologies on specific settings. The role of AI in knowledge management was further emphasized by Liebowitz (2001), who argues that it is a key building block in advancing the field of knowledge management. Liebowitz discussed the emergence and future of knowledge management and its link to AI, asserting that many practitioners and theorists have overlooked the importance of AI in the development of knowledge management systems. The early 2000s saw growing interest in decision support systems (DSS), with Nemati et al. (2002) proposing a knowledge warehouse (KW) architecture as an extension of the data warehouse model. The authors suggested that the purpose of DSS should be expanded to knowledge improvement and that future DSS effectiveness can be measured by how well it promotes and enhances knowledge and improves decision-making. By the 2020s, the integration of AI in various sectors became even more apparent, with a strong surge of literature on the theme. Malik et al. (2021) explored how a large multinational enterprise used AI-mediated social exchange in global talent management strategies. Their findings revealed that AI-enabled talent applications improved individual experiences, job satisfaction, and commitment, reducing turnover intention. This illustrates the potential of AI to transform knowledge sharing and management in an increasingly globalized world. Finally, Fridgeirsson et al. (2021) investigate the potential impact of AI on the project management profession, specifically focusing on ten categories of project management knowledge areas defined by the Project Management Institute (PMI). The findings of this study indicate that AI could be an integrated part of future project management practices, particularly affecting cost, schedule, and risk management. However, AI was found to have less of an impact on areas that require human leadership skills, such as team development and stakeholder management.

AI has made significant contributions to decision-making. AI techniques such as multi-agent systems, game theory, and optimization algorithms have been used to model complex decision-making processes, support collaboration among multiple decision-makers, and find optimal solutions to challenging problems (Scherer, 2015; van de Poel, 2020; Core et al., 2006). The study of artificial intelligence (AI) and its application to decision-making has been significantly influenced by understanding human cognition and decision-making processes. Kahneman's seminal book, "Thinking Fast and Slow" (2011), proposed that the human mind has two systems of decision-making: System 1, which is fast, implicit, intuitive, and imprecise, and System 2, which is slow, meticulous, and requires logic and concentration. The division of labor between these systems allows the human mind to balance speed and accuracy, learn and execute tasks, and adapt to various situations. Inspired by this concept, researchers have sought to develop AI systems that can mimic and complement human decision-making capabilities by incorporating System 1 and System 2 models.

In healthcare, Bennet and Hauser (2013) developed a computational framework that combines Markov decision processes and dynamic decision networks to learn from clinical data and develop complex plans by simulating alternative sequential decision paths. The framework has demonstrated the potential to improve patient outcomes and reduce costs compared to traditional treatment-as-usual models.

More recently, Jarrahi (2018) emphasized the complementarity of humans and AI in organizational decision-making processes, typically characterized by uncertainty, complexity, and equivocality. Although AI systems can extend human cognition when addressing complexity, humans can offer a more holistic and intuitive approach to dealing with uncertainty and equivocality. This perspective aligns with the intelligence augmentation concept, which advocates designing AI systems that augment rather than replace human contributions. Shrestha et al. (2019) explored the impact of AI-based decision-making algorithms on organizational decision-making and developed a novel framework outlining how human and AI-based decision-making can be combined to improve organizational decision-making quality optimally. The framework proposes three structural categories for combining human and AI-based decisions: full human-to-AI delegation, hybrid human-to-AI and AI-to-human sequential decision-making, and aggregated human-AI decision-making.

AI and system dynamics share many similarities as both fields are concerned with modeling complex systems, understanding their behavior, and predicting future outcomes. In recent years, efforts have been made to integrate AI and system dynamics approaches to enhance the capabilities of each field.

3. Materials and methods

3.1. Data

The Web of Science, a highly authoritative bibliographic database, was used to construct the database. The research strategy involved using the author's keywords related to "system* dynamic*" and "artificial intelligence" and focusing on business and management scientific categories. This approach allowed for a more focused investigation, avoiding the potential inclusion of unrelated articles. The query returned 2590 references, including 1765 articles, 810 proceedings, and 86 review articles. There were 1254 references for system dynamics and 1336 for artificial intelligence.

Fig. 1 presents a graphical representation illustrating the trends in scholarly attention towards system dynamics and artificial intelligence over time. The graph shows that interest in system dynamics research has remained relatively stable over the years, indicating consistent focus in this area within the academic community. In contrast, the graph highlights a significant surge in interest in artificial intelligence research over the last five years. This increase in scholarly attention can be attributed to rapid advancements in technology, growing awareness of the potential applications of artificial intelligence, and the increasing demand for AI-driven solutions in various industries. The escalating interest in artificial intelligence research underscores the growing importance and potential of the field in shaping the future of technology and society.

Fig. 2 compares the presence of system dynamics and artificial intelligence research in academic journals. It provides valuable insights into the relative prominence of these two fields in academia. The data shows that both fields have distinct representations in academic literature, with only seven journals featuring articles from both domains. Although there is some overlap, system dynamics and artificial intelligence tend to be treated as separate disciplines with unique research focuses.

The European Journal of Operational Research and Technological Forecasting and Social Change stands out as the two journals with a more balanced representation in both fields. This suggests that these journals may focus on interdisciplinary research or welcome contributions combining system dynamics and artificial intelligence methodologies and perspectives.

The full query is provided in the Supplemental material to ensure reproducibility.

3.2. Methods

We utilized a dual approach combining bibliometric analysis and topic modeling to comprehend the methodologies, application areas, and emerging trends in the two research domains thoroughly (de Vasconcelos Gomes et al., 2018). This integrated methodology enabled us to

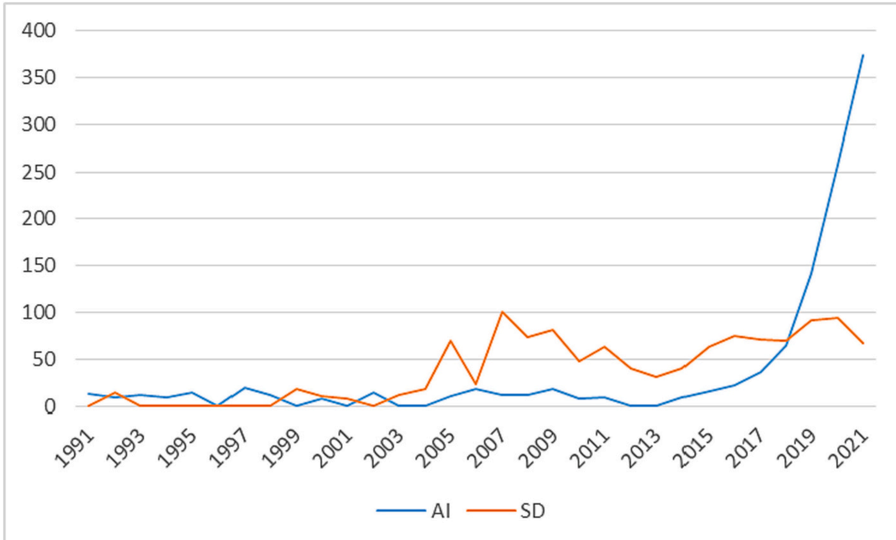

Fig. 1. Trend of Scholar's attention to the two perspectives over time.
Source: Authors elaboration.

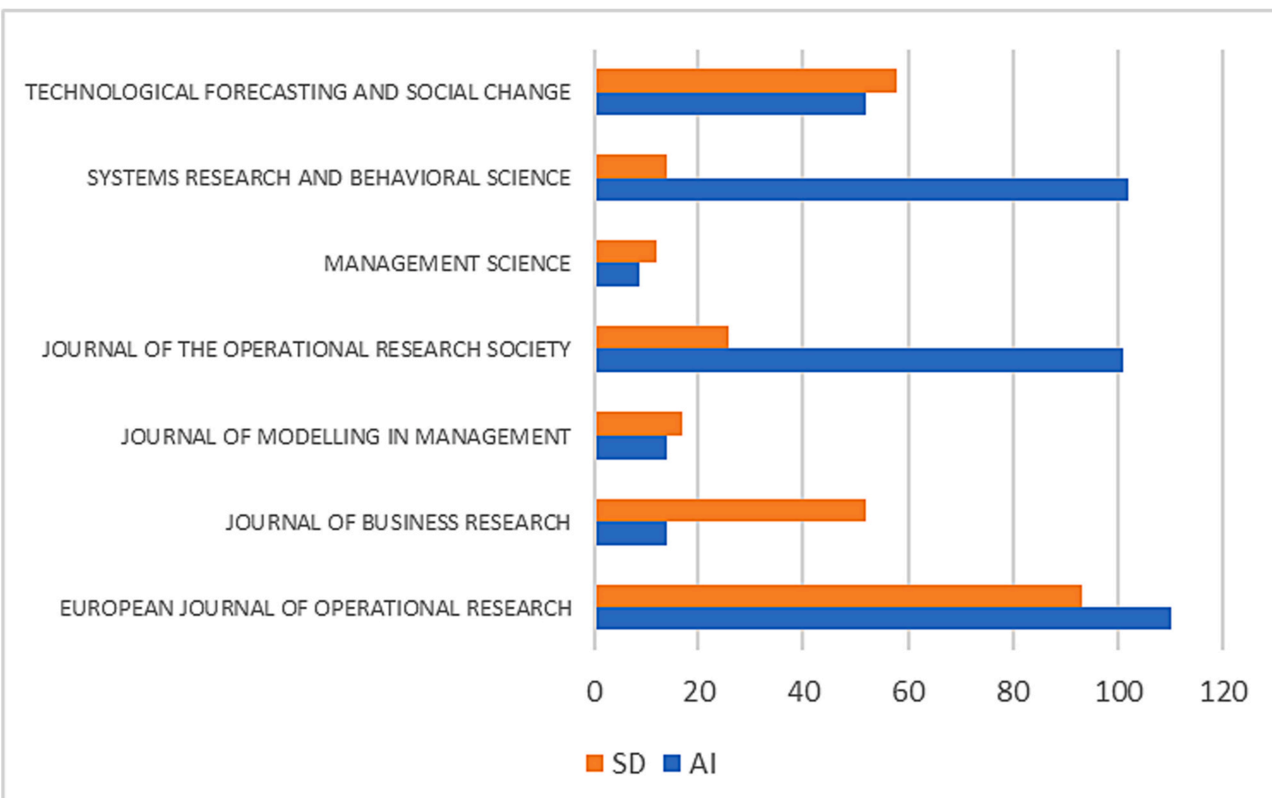

Fig. 2. Comparative analysis of system dynamics and artificial intelligence research presence in academic journals.
Source: Authors elaboration.

explore the subtleties of research domains and derive significant insights. Bibliometric analysis is crucial in demonstrating the distinction between the two research domains (van Eck and Waltman, 2010, 2011, 2017) by evaluating metrics such as author keyword usage and contribution coupling based on author keywords. This examination provides a quantitative viewpoint on the disparities in methodologies and application areas, emphasizing each research domain's distinct features and focal points (Huang et al., 2021). Conversely, topic modeling allowed us to discern and monitor evolving trends and subjects of interest within each research domain. By scrutinizing the distribution of topics in a research corpus, we can assess the connections between concepts and ideas, pinpoint potential gaps or neglected papers, and observe changes in the field over time (De Solla Price, 1965; Antons et al., 2016). Topic modeling facilitated the discovery of thematic structures of the research domains and presented a qualitative perspective on their progression and expansion. The fusion of bibliometric analysis and topic modeling proved an effective strategy in our investigation, enabling a more refined understanding of the research domains. By implementing both techniques, we captured the unique methodological and thematic disparities between the research domains and revealed their individual trajectories and growth areas.

3.2.1. Bibliometrics

The method used in this study is a variant of the traditional bibliographic coupling method that focuses on coupling contributions based on shared keywords (Kessler, 1963; Marshakova, 1973). As in bibliographic coupling, the relatedness of documents is determined by the number of shared references. Coupling contributions by keywords means that "N" documents ($N > 1$) are coupled if they share at least "m" keywords ($m \geq 1$). Therefore, coupling considered the overlap in the list of keywords in the examined publications. The more keywords two publications have in common, the stronger the link between them. This variant allows classification across the entire timespan in which contributions have been published, as keywords are always theoretically available. The traditional bibliographic coupling method should ideally be restricted to a short period so the available bibliographic references can be considered homogeneous.

3.2.2. Topic modeling

Topic Modeling is a statistical technique that captures word correlations in textual documents through a low-dimensional multinomial distribution set called "topics." Latent Dirichlet Allocation (LDA), a probabilistic approach to topic Modeling, has become the standard method (Jelodar et al., 2019). The basic idea behind LDA is that documents are represented as a random mixture of underlying topics, where a distribution of words characterizes each topic. The model outputs the probability distributions of words for each topic and the topic distributions for each document. This procedure was introduced by Blei in 2003 (Blei et al., 2003) and subsequently improved by Blei (Blei, 2012). For each document and word in the document, the procedure calculates: a) a term-topic matrix that contains information on the distribution of terms across the identified topics. In the matrix, each row represents a term, each column represents a topic, and the values in the matrix indicate the weight of each term in each topic, which has been used to interpret and label the topics based on the most relevant terms; b) a Topic Distribution matrix, which contains information on the distribution of topics across the corpus of documents, each row represents a document, and each column represents a topic; the values in the matrix indicate the proportion of each topic present in each document; c) Topic Trend matrix which contains information on the distribution of topics over time: in the matrix, each row represents a year, each column represents a topic and the values in the matrix indicate the weight of each topic in that year. The robustness of the method (the reliability of the probabilities brought about by the matrices) primarily depends on the number of topics, which requires pre-determination by an analyst, thereby introducing subjectivity. In this regard, various methods have been used to determine the optimal number of topics based on the size (total number of words) and diversity (number of unique words) of the text corpus being analyzed. This technique is useful for literature reviews, as it can reduce the time needed to read and identify relevant papers. Hannigan et al. (2019) provided an overview of the use of Topic Modeling for literature reviews in business management, discussing its benefits and offering guidance on selecting and using appropriate algorithms. Several studies have demonstrated the potential of using topic Modeling for literature reviews, such as Kitanaka et al. (2021), Park et al. (2018), Talafidaryani (2021), Guerreiro et al. (2016), and Arroyabe et al. (2022) who successfully applied this technique to analyze various aspects of their respective research domains.

4. Findings

4.1. Bibliometric analysis

Bibliometric analysis shows that there is a clear separation between the fields of system dynamics (SD) and artificial intelligence (AI) owing to their distinct methodological and applicative developments (Figs. 3 and 4). AI-related research focuses on advanced computational methods for modeling and analyzing complex systems by employing neural networks, negotiation support systems, system dynamics, and fuzzy reasoning. SD-related research centers on systems thinking, operational research, and management science. It explores topics such as mutual knowledge, accumulation, control theory, information sharing in supply chains, innovation systems, simulation in manufacturing and business, quality erosion in the service industry, and diffusion dynamics. Despite this separation, areas of common interest are shared by both fields, including decision-making, project management, knowledge management, forecasting, supply chain, risk management, and learning. Preliminary bibliometric analysis findings suggest potential areas of integration between AI and SD, especially in applying AI technologies, such as neural networks, fuzzy reasoning, and genetic algorithms, to support decision-making, negotiations, and forecasting.

The contributions of the cluster of articles related to AI (in red) involve using advanced computational methods to model and analyze complex systems. Neural networks can be used for forecasting and prediction, negotiation support systems for multi-criteria decision-making, system dynamics for simulating related diversification strategies, and fuzzy reasoning for evaluating tax policies to reduce CO2 emissions. All these applications require sophisticated mathematical modeling techniques to represent the behavior of the underlying systems being studied accurately (Tam, 1992; Huang and Rust, 2018; Das and Chen, 2007; Wirtz et al., 2018; Kaplan and Haenlein, 2019; Fethi and Pasiouras, 2010; Zhang et al., 1999; Davenport et al., 2020; Jarrahi, 2018; Jiang and Wen, 2020).

The articles belonging to the cluster related to SD (green) discuss different aspects of systems thinking, operational research, and management science. They explored topics such as mutual knowledge, accumulation, control theory, information sharing in supply chains, innovation systems, simulations in manufacturing and business, quality erosion in the service industry, diffusion dynamics, and multiagent approaches. This cluster shows how these areas are interconnected and how they can be used to understand better the complex problems related to dispersed collaboration (Hekkert et al., 2007; Cramton, 2001; Swaminathan et al., 1998; Dejonckheere et al., 2003; Rahmandad and Sterman, 2008; Jahangirian et al., 2010; Oliva and Sterman, 2001; Fiala, 2005; Mingers and White, 2010; Cronin et al., 2009).

The preliminary findings of the bibliometric analysis also showed some areas of integration between the scientific fields of artificial intelligence and system dynamics. In particular, studies have discussed the use of AI technologies such as neural networks, fuzzy reasoning, and genetic algorithms to support various activities such as decision-making, negotiation, and forecasting (Adya and Collopy, 1998; Lambrecht and Tucker, 2019; Gary, 2005; Lustig and Puget, 2001; Espinasse et al., 1997; Nag and Mitra, 2002; Redmond and Baveja, 2002; Prentice et al., 2020; Kunsch and Springael, 2008; Wirth, 2018).

4.2. Topic modeling

Using Topic Modeling techniques to analyze scientific literature (as well as any collection of texts) requires imposing some topics to disaggregate the collection of documents under analysis. Despite the vast literature on this topic, there is no definitive answer to how many topics should be included in a topic model (Zhao et al., 2015). To find the optimal number of topics, we used the R package "ldatuning" (Nikita and Chaney, 2016), generally accepted as robust (Ballester and Penner, 2022), by applying the criterion followed by Kunc et al. (2018) for which

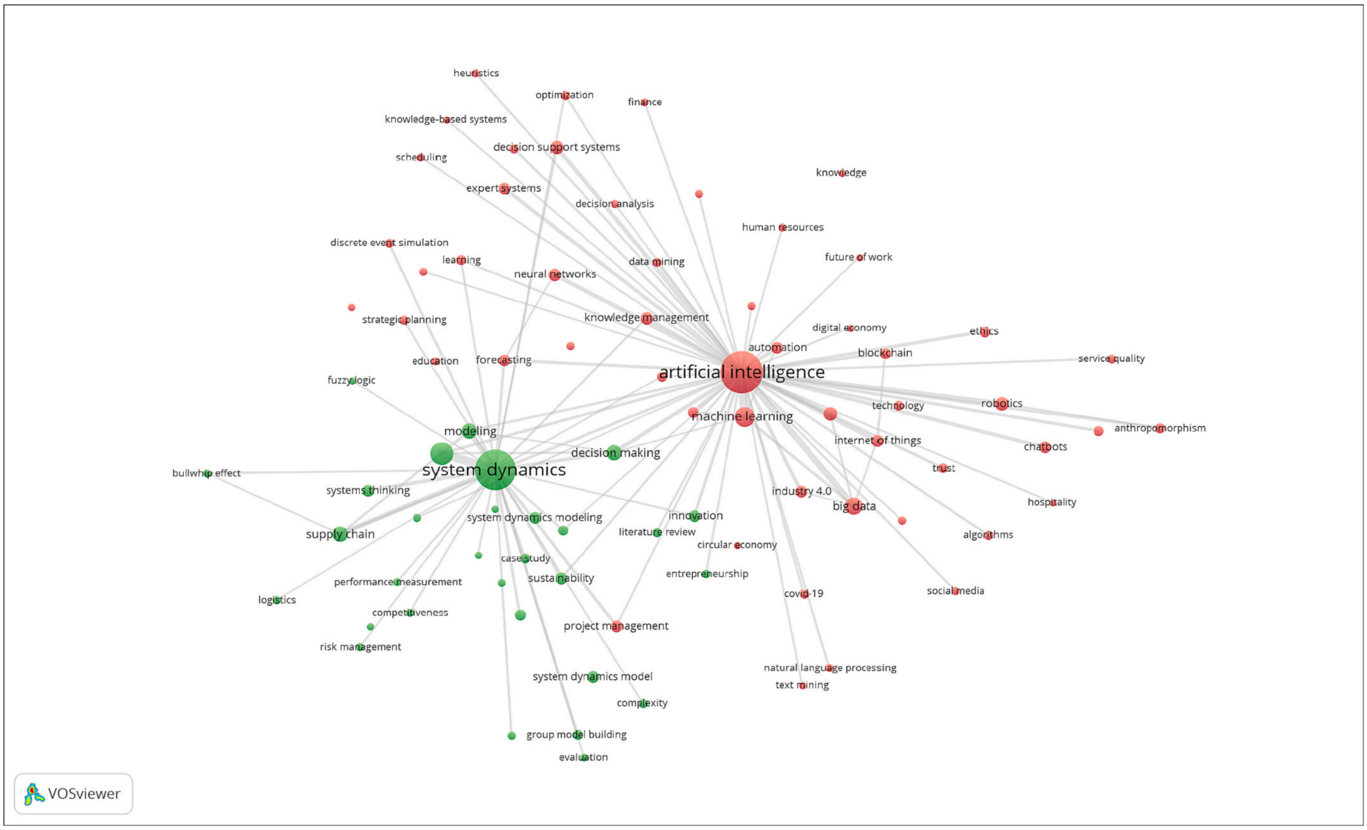

Fig. 3. Author keywords co-occurrence (https://bit.ly/3Fk1vTn).
Source: Authors elaboration in Vosviewer.

the point of intersection of two metrics to be maximized [in our case those of Griffiths and Steyvers, 2004 and Deveaud et al., 2014] indicates the optimal number of topics to consider for the chosen number of terms considered.

The analysis was conducted considering 25 topics. The topic Modeling findings are summarized in the Supplemental material.

Fig. S.1 Distribution of topics over the complete collection.

Fig. S.2 Trend of topics popularity among Scholars over time.

For conciseness, the list of the first six words in order of probability is omitted in this paragraph and presented in the following paragraph, with the labels assigned to each of them and the procedure indicated in that paragraph.

5. Labeling and characterizing topics

5.1. Labeling

For each identified topic, we selected a representative sample of the top 20 articles based on their probabilistic index, which is the likelihood of an article belonging to a specific topic as determined by Latent Dirichlet Allocation (LDA). The process of defining labels for the topics was as follows: a) each author independently assigned a label to the identified topics, reflecting the core theme or concept they believed the topic represented; b) the authors convened as a group to discuss their individual labeling choices, comparing their perspectives; c) in cases of discrepancies, the authors engaged in a thorough discussion to reach a consensus on the most accurate and appropriate label for the topic in question. The outcomes of this collaborative labeling process are detailed in Table 1, which presents the final set of topic labels determined by the authors through careful deliberation and agreement. This method ensured that topic labels accurately reflected the underlying themes and concepts of the research areas, providing a clear and concise overview of the topic structure for further analysis and interpretation.

Building on the results obtained through topic modeling, we extracted a strategic topic map showing the density and centrality of the topics using the root of keywords as the base, as shown in Fig. 6. The trends depicting the changing popularity of topics over time are presented in Fig. S.2 in the Supplementary materials, using regression analysis to identify prospective future topics.

5.2. Characterizing

From a procedural point of view, each article retrieved in WoS (Web of Science) with either of the two queries was labeled “SD” or “AI,” and this label was retained in the processing of the Topic Distribution Matrix. Fig. 7 associates each obtained topic with the subsets of documents retrieved in WoS with their respective queries “system* dynamic*” and “artificial intelligence,” limited to the first 20 works in terms of probability of belonging to each topic (topic distribution matrix). Based on the number of articles, it is clear that some are mainly addressed through system dynamics analysis (i.e., the upper rows of the table) and others through AI-based analysis (i.e., the bottom rows). A few topics were addressed by both the SD and AI analyses, as represented by the middle-range rows in Table 1.

Based on the distribution between the two domains of the works with the highest probability, the obtained topics were collected into three clusters: 1) topics most connected to SD, 2) topics most connected to AI, and 3) topics addressed by both approaches.

The top five articles with the highest probability (calculated following the LDA method) of being part of the topic were analyzed, and relevant papers were searched in lower positions, regardless of the source’s popularity in terms of citation numbers received. For each topic, the articles grouped were analyzed to identify how the two approaches were used to address the topics. Subsequently, the abstracts of

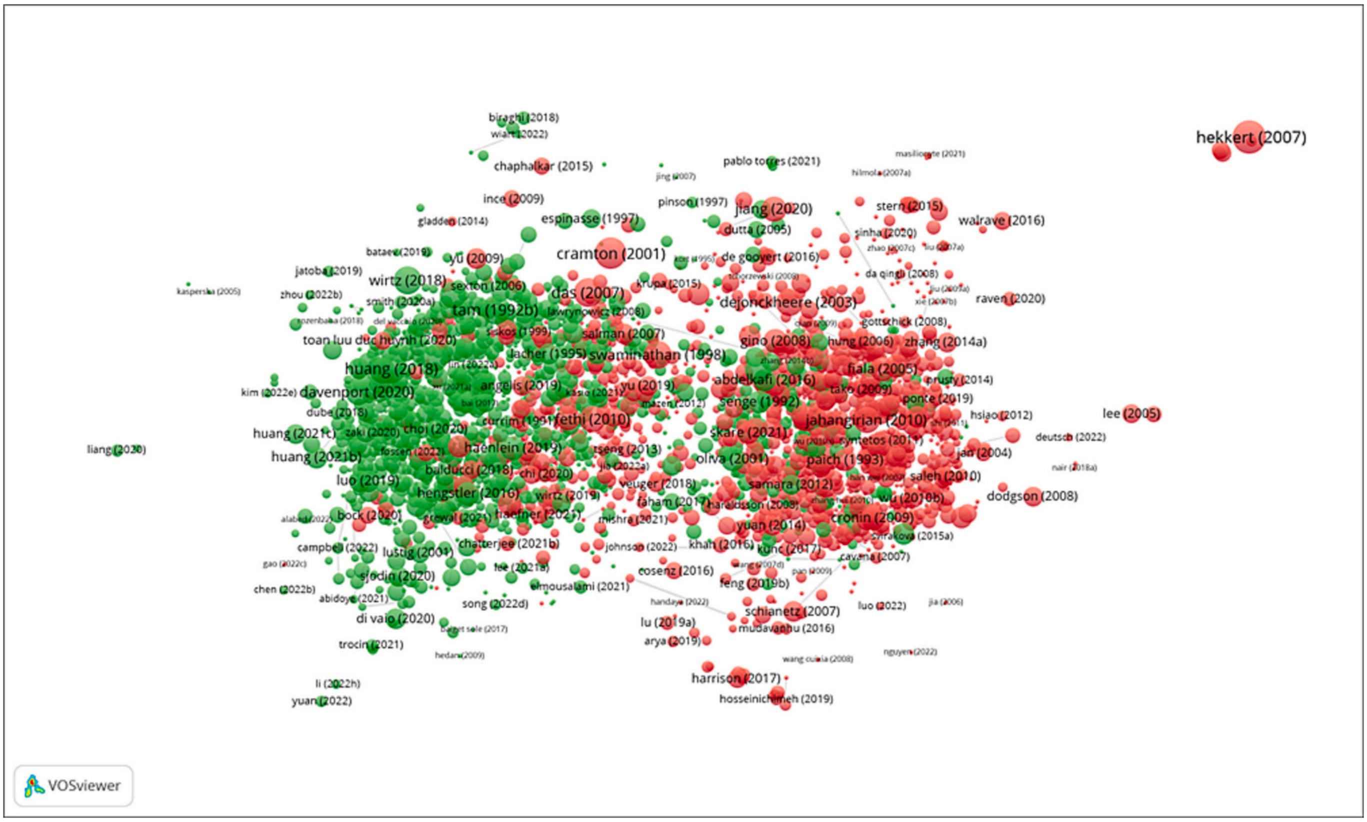

Fig. 4. Matching contributions based on author keywords.
Source: Authors elaboration in Vosviewer.

Table 1
Words per Topic.

Topic	Label	Root of keywords					
#1	*Supply chain (SCM)*	*supply*	*chain*	*system*	*demand*	*product*	*inventory*
#2	*System dynamic*	*system*	*model*	*dynam*	*polic*	*simul*	*sd*
#3	*Ecological & Socio-Economic Systems*	*develop*	*system*	*model*	*product*	*resourc*	*polici*
#4	*Project management*	*project*	*construct*	*model*	*manag*	*factor*	*perform*
#5	*Transportation*	*logist*	*transport*	*vehicle*	*game*	*traffic*	*cost*
#6	*Healthcare*	*health*	*care*	*healthcare*	*patient*	*system*	*crisis*
#7	*Risk management*	*risk*	*factor*	*invest*	*manag*	*enterpris*	*model*
#8	*Innovation*	*innov*	*industri*	*model*	*diffus*	*develop*	*technolog*
#9	*Energy*	*energ*	*power*	*electr*	*generat*	*emiss*	*wind*
#10	*Soft modeling*	*system*	*model*	*dynam*	*manag*	*simul*	*develop*
#11	*Price control*	*market*	*price*	*hous*	*estat*	*invest*	*trade*
#12	*Knowledge*	*knowledg*	*manag*	*capabl*	*team*	*organ*	*process*
#13	*Business & enterprise*	*busi*	*perfor*	*firm*	*compani*	*strategi*	*manag*
#14	*Workforce/labor force*	*chang*	*labor*	*level*	*work*	*sustain*	*countri*
#15	*Market knowledge*	*market*	*framework*	*understand*	*role*	*literature*	*practic*
#16	*Education*	*educ*	*univers*	*student*	*school*	*learn*	*skill*
#17	*Human resource management (HRM)*	*employe*	*ai*	*technolog*	*adopt*	*job*	*organ*
#18	*Decision making (DSS)*	*decision*	*inform*	*system*	*tool*	*process*	*agent*
#19	*Service management (CRM)*	*literature*	*review*	*ai*	*tourism*	*manag*	*framework*
#20	*Data bias*	*data*	*inform*	*sale*	*machin*	*market*	*learn*
#21	*Sentiments/emotions*	*servic*	*custom*	*robot*	*qualiti*	*bank*	*experi*
#22	*AI pathways*	*ai*	*intellig*	*technolog*	*data*	*busi*	*develop*
#23	*Algorithms/optimization*	*problem*	*algorithm*	*solut*	*program*	*search*	*time*
#24	*Forecasting/prediction*	*model*	*network*	*data*	*forecast*	*predict*	*techniqu*
#25	*Role of AI in consumer aiding tasks*	*consumer*	*ai*	*intent*	*brand*	*trust*	*product*

the articles were subjected to content analysis. For each topic, the articles grouped were analyzed to identify how the two approaches addressed the topics.

5.3. Topics mostly connected to SD

Four topics were formed solely based on studies that employed system dynamics-based approaches to address supply chain (SCM) issues, system dynamics, ecological and socio-economic systems, and project management. Other topics included some works from the AI field, but we decided to start considering a topic as effectively dealing in a hybrid way with both SD and AI, only starting from a minimum of five works in each topic.

As expected, the **system dynamics** topic (#**2**) contained only SD-based or derived approaches and was composed of articles that proposed complementary methods of using this modeling and simulation paradigm. Schwaninger (2006) provides an overview of the role of SD in the evolutionary context of system movement and how the evolution of both SD and system movement are intimately linked and intertwined. Kwakkel and Pruyt (2015) showed how system dynamics modeling could be combined with exploratory modeling and analysis to address societal challenges. Oliva (2003) argued that SD model calibration could be seen as a rigorous test of a hypothesis, linking structure to behavior, and then proposed a framework to use calibration as a form of model testing. Kampmann and Oliva (2008) argued that theory building cannot be based on pure simulation and model building alone, and they proposed approaches for strengthening the SD analytical foundation. Hovmand et al. (2012) described an approach for documenting group model-building (GMB) scripts and how documented GMB scripts can be used to design more effective sessions that address cultural and ideological barriers to collaboration.

Within the **supply chain** (**SCM**) topic (#**1**), there was a tight connection among the samples of the retrieved articles, as almost all studies had a probability above 80 % of being part of the topic. The highest-ranked works regarding the probability index explored the volatility and oscillatory behaviors in supply chains (usually known as the bullwhip effect) from a systemic and endogenous perspective using system dynamics simulation models to investigate the structural sources of oscillations and evaluate policies to reduce or eliminate them (Barlas and Gunduz, 2011; Hwarng and Xie, 2008; Kim and Springer, 2008). Some analyzed this volatility problem using SD simulation models but presented a context-specific analysis within reverse logistics (Wang and Ding, 2009) and healthcare supply chains (Clay et al., 2018).

The articles retrieved from the **project management** topic (#**4**) sought to analyze challenges during the project life cycle. Akkermans and van Oorschot (2016) explored the effects of concurrent engineering on complex aircraft development projects and argued that counterintuitive decisions can positively affect project completion and subsequent sales. Other studies have employed SD simulation models to explore the effect of project cycle iteration duration on project performance (van Oorschot et al., 2018), elicit and map the causal relationships that could account for the effects of rework and delays on project performance (Williams et al., 1995), and model the complex interrelated structures of different factors affecting labor productivity and project performance (Nasirzadeh and Nojedehi, 2013).

Some studies were grouped within the **ecological** & **socio-economic systems** topic (#**3**), which used SD to tackle, for example, the interrelation of agriculture and natural resource management (Nyam et al., 2022), and food production systems (Nicholson and Kaiser, 2008).

Regarding **transportation** topic #**5**, most studies used SD to deal with issues related to people transportation within urban scenarios, such as the challenges of electrical vehicle adoption (Hein et al., 2012; Harrison and Thiel, 2017; Liu, 2018), and traffic congestion (Suryani et al., 2021).

The **healthcare** topic (#**6**) was mainly composed of articles that used system dynamics simulation models to assess public health policies on some more broad and governance-related contexts (Brailsford et al., 2004; Maliapen and Dangerfield, 2010) and other more context-specific, such as stroke management (Bayer et al., 2021), analysis of the effectiveness of Chlamydia screening (Townshend and Turner, 2000), and the acute bed blockage problem (Rashwan et al., 2015).

The works dealing with the **risk management** topic (#**7**) are broader in scope, and they addressed several risk dimensions and application areas using different approaches. Feng et al. (2019) developed a system dynamics model to evaluate security investment strategies and their effects on business value. Nazareth and Choi (2015) proposed an SD model to support decision-making related to systems' security management strategies based on investment and security cost perspectives. On the other hand, some AI-related works were also found, which combined deep learning technology and data mining methods in an artificial intelligence environment and were applied to an analysis of financial risk prevention based on listed companies (Gao, 2022), while others employed Bayesian Network modeling to explore the causal interactions between monetary fundamentals and exchange rate fluctuations (Charfi et al., 2020).

Concerning the **innovation** topic (#**8**), several studies used SD models to explore different aspects of the innovation diffusion dynamics, e.g., competition diffusion and technology transition (Xue et al., 2013; Tigabu et al., 2015).

Regarding energy (#**9**), SD-based studies have primarily addressed macro-policy levels concerning behavioral changes. Caponio et al. (2015) proposed a simulation model for a medium-sized city and assessed "what-if" scenarios of implementing energy efficiency policies. Dyner et al. (1995) developed an SD model to simulate the substitution of installed household appliances for more efficient appliances to assist in decision-making regarding gas penetration policies. Kunsch et al. (2004) used an SD model to discuss pollution taxes, emission-trading permits, and green certificates for reducing CO2 emissions in the electricity sector. A few AI-based studies have been identified within this topic, in which machine learning classifiers were used to develop predictive models for forecasting power generation (Rezaee et al., 2019) and electrical grid loads (Alkaldy et al., 2019).

Regarding the **price control** topic (#**11**), some studies used SD simulation models to address macro-and national policies for price regulation of commodities, such as government interventions in rice production and imports (Dordkeshan et al., 2017; Chung, 2018) and housing mortgage loans and real estate markets (Hwang et al., 2010). Zhang et al. (2018) argued that SD models could more easily accommodate the non-market features and unique institutional components of emerging real estate markets where long-range historical data are not readily available. Some AI-based studies have been conducted on predictive price models for stock markets, cryptocurrencies, and portfolio management (Er and Hushmat, 2017; Manahov and Zhang, 2019).

Some works were grouped into topics (#**10**) with **soft modeling**. A soft system dynamics methodology (SSDM) was proposed, in which the authors combined the soft systems methodology and system dynamics approach to address complex social problems (Rodriguez-Ulloa and Paucar-Caceres, 2005; Paucar-Caceres and Rodriguez-Ulloa, 2007). Kopainsky and Luna-Reyes (2008) explored better methods for conceptualizing system dynamics models by reviewing theory-building approaches from other social sciences fields, such as grounded theory and case study research. Powell and Mustafee (2017) presented Qualitative System Dynamics, a soft systems method, in the healthcare context.

5.4. Topics mostly connected to AI

These topics are closely related to artificial intelligence, which focuses on developing algorithms and computer systems for solving complex problems.

All the studies collected under topic #**20** used **Artificial Intelligence** (**AI**) **and Machine Learning** (**ML**). All the articles discuss the use of these technologies to analyze data, make predictions, and develop solutions for various applications, and discuss the bias associated with these types of analyses, such as data mining (Smith, 2020), categorization and clustering (Chekima and Anthony, 2010), segmentation (Pitt et al., 2020), monitoring (Kaiser et al., 2020), and fake news detection (Paschen, 2020).

Topic #**21** includes articles focusing on the use of **AI in customer service** (Prentic and Nguyen, 2020) and its impact on customer satisfaction and loyalty (Prentice et al., 2023), customer willingness to use AI service agents (Yang et al., 2022), customer attributions of responsibility after service failure or success (Pitardi et al., 2022), and customer perceptions of service quality (Chiang et al., 2022). These studies explored how customers interact with or feel about artificial intelligence (AI) and service robots, how AI affects service quality and customer satisfaction, and how service robots interact with other robots and customers. In addition, the topic includes studies discussing the impact of augmented reality on overall service satisfaction and the impact of knowledge sharing on employees' service quality.

Works on topic #**22** are all connected to **AI pathways** as they all discuss topics related to artificial intelligence (AI), including its application (Bai, 2017), influence (Stancu and Dutescu, 2021; Ferreira et al., 2020), usage and ethics (Kozikowski et al., 2020; Huelsen et al., 2021), and its implications for the future of management (Gruia et al., 2020; Khmiadashvili, 2019) and cyber security. Additionally, many papers discuss the practical implications and research opportunities AI provides and the potential risks associated with its use.

The works belonging to topic #**23** are all related to **algorithms or optimization algorithms** in various ways. Many discuss specific algorithms that can be used to solve various problems, such as genetic algorithms for function optimization (Tam, 1992), differential evolution (Salman et al., 2007), and mixed integer programming (Xia et al., 2005). Other studies have discussed using algorithms in specific applications such as facility layout design, parallel processor scheduling, and assembly line balancing. Finally, some articles discuss new heuristics and extensions to existing algorithms to improve performance and efficiency.

Articles collected under topic #**24** involved using artificial intelligence, statistical, or hybrid techniques to **forecast outcomes or predict results**. This includes predicting exchange rates (Nag and Mitra, 2002), electricity demand (Khashei and Chahkoutahi, 2022), wind power generation (Jafarian-Namin et al., 2019; Konchou et al., 2021), healthcare expenditure (Ceylan and Atalan, 2021), bankruptcy (Krusinskas et al., 2014), and the success of a new tourism service (Atsalakis et al., 2018).

Topic #**25** discussed the **role of AI in consumer-aiding tasks** in some way. They examined how AI can be used to make recommendations, provide financial services, interact with customers, and influence consumer behavior, brand engagement, and the customer journey (Zhang et al., 2021; Wien and Peluso, 2021; McLean et al., 2021). They also discuss the effects of AI on consumer decision-making; the influence of human versus AI recommenders, and the roles of political ideology, human likeness, and psychological distance in AI-enabled services (Ahn et al., 2022; Kim et al., 2022).

Works on topic #**19** mostly explored the **use of AI in different areas of management**, such as customer relationship management, supply chain management, human resource management, and performance measurement, while also showing some incursions from the SD front. Articles on AI explore the use of AI and other technologies to enhance customer service and operations management, discuss the current state of the art, provide research propositions for future directions in the field, and provide insights into the potential challenges and benefits of using AI in service management (Kobbacy et al., 2007; Loureiro et al., 2021; Lv et al., 2022; Toorajipour et al., 2021). Oladimeji et al. (2020, 2021) presented a systematic literature review of system dynamics in performance measurement research and practice, revealing that applications of SDs are most commonly used in performance system design. The bibliometric analysis revealed that research in this area is in a relatively early stage of development and that most studies use exploratory methods, further suggesting an important methodological gap in the area as over 50 % of the causal models have not been validated.

Topic #**18** discusses various aspects of **decision-making** from negotiation support systems and artificial intelligence to case-based decision support systems and automated leadership decision-making in organizations, exploring the implications of machine-making decisions and the various decision-making frameworks and tools available (Espinasse et al., 1997; Hess et al., 2000; Parry et al., 2016). From the SD front, Gelman (2005) used a single, structural, and dynamic model as a starting point and then examined abstraction techniques, such as exogenization and equilibration, which were originally proposed in qualitative reasoning research, to propose a new time-scale-based abstraction, called quasi-exogenization, which is used to extend the set of time-scale-based abstractions.

The articles on topic #**17** discuss using artificial intelligence (AI) in **human resources**. They explore the effects of AI on recruitment, employee performance, and work engagement, change leadership, and the Fourth Industrial Revolution (Braganza et al., 2021; Huang et al., 2019; Kambur and Akar, 2022; Kong et al., 2021; Pillai and Sivathanu, 2020). Zhou et al. (2019) sought to develop and test a process-oriented theory of leader goal striving, drawing on self-regulation theory to explain the core process mechanisms involved in a leader-subordinate dyadic goal pursuit system.

5.5. Topics connected to both SD and AI

A few topics (i.e., knowledge, business and enterprise, workforce/labour force, market knowledge, and education) contained a mixed sample of articles concerning their approach to tackling each topic.

Topic #**12** labeled **knowledge** was formed using AI- and SD-based works. Rahmandad and Repenning (2016) used an SD model to evaluate a company's capability erosion, and they found that managers' well-intentioned efforts to search for optimal workload balance can sometimes lead them to overload their organization and cause capabilities to erode. Zaim et al. (2013) used an SD model to assess how knowledge management process activities affect organizational performance and concluded that they have a positive relationship. Grum (2020) designed a knowledge management (KM) approach that integrates technical knowledge and represents it as a Neuronal KM, so that humans and artificial kinds of knowledge bearers can be managed symbiotically. Sundaresan and Zhang (2022) developed a framework for analyzing AI-enabled knowledge management systems and compared them to traditional systems.

A topic dealing with **business** & **enterprise** #**13** was also identified, containing AI- and SD-based works. Segura et al. (2019) used an SD model to analyze the impact of lean manufacturing strategies on business performance from a business model canvas perspective. Some authors have combined conventional business model schemas with system dynamics to propose a strategy design tool to overcome the limitations of a static view of business model representation (Cosenz and Noto, 2018; Cosenz and Bivona, 2021). AI-related studies are qualitative studies that seek to assess the impact of AI-related technologies on business performance, such as marketing capabilities (Rahman et al., 2021; Westermann and Forthmann, 2021) and organizational creativity and firm performance (Mikalef and Gupta, 2021).

Discussions about the **impact of digital and technological advances on labor practices**, **income**, **and employment** are the central topic of topic #**14**. Contributions related to the topic explore the implications of artificial intelligence, robots, and online labor markets, as well as the effects of minimum wages and other factors (Akaev et al., 2021; Bordot, 2022; Duch-Brown et al., 2022). On the other hand, contributions also discuss, through a shared SD perspective, the potential for sustainable development (Huang et al., 2007), the need for organizational resilience (Jnitova et al., 2021), and the importance of knowledge work design for the future (Ghaffarzadegan et al., 2017).

Articles belonging to topic #**15** discuss different aspects of the intersection of **technology**, **marketing**, **and business** with mixed approaches linked to AI and SD. They offer perspectives on how technology is changing the way businesses operate and interact with customers (Wiart et al., 2022; Lusch and Watts, 2018), as well as how marketing and advertising can be used to influence customer behavior (Middleton and Turnbull, 2021). From the same perspective, some studies have explored the implications of AI, deep fakes, and avatars in the marketing and business environment (Campbell et al., 2022; Eugeni, 2019).

Articles collected under the **Education** topic (**#16**) are linked to education in various ways. Some studies have discussed technology and analytics in education, focusing on image processing for potential hospital data-storage applications (Perolla and Dey, 2021; Srinivasan and Dey, 2021). Other contributions look at quality education classrooms in schools using an SD approach (Sajjad and Yusuf, 2007), software tools for information sharing (Redmond and Baveja, 2002), the use of genetic algorithms in business e-negotiation (Simkova and Smutny, 2021), the use of artificial intelligence in the business curriculum (Xu and Babaian, 2021), and a new technological platform as an innovative teaching model in high schools (Noniashvili et al., 2020), thus showing common ground for both AI and SD scholars.

6. Discussion and implications

In the previous paragraphs, we described the main findings of the two methodologies applied in this study: bibliometric analysis and topic modeling. In the following section, we discuss the results of our research question: "to what extent and in which direction is the literature on AI and SD converging within the business and management landscape?"

As for the *bibliometric analysis*, SD and AI appear to have distinct relevance in their respective fields, with areas of tangency regarding topics related to decision-making, project management, knowledge management, forecasting, supply chain, and risk management. For topic modeling, we first discuss the findings in terms of the retrieved topics that show a certain spectrum of use between SD and AI for the same topics. Fig. 7 shows the related number of articles dealing with AI or SD over each of the 25 topics retrieved from the topic modeling activity. We then discussed three macro clusters: topics characterized by the prevalence of SD work, topics characterized by the prevalence of AI work, and topics - only a few–characterized by the blended presence of both approaches.

In particular, based on the findings of the bibliometric analysis, there is a lack of communication and collaboration between these two fields, resulting in a lack of progress in both. In addition, recent studies on artificial intelligence are very recent (ref. Fig. 2); therefore, the application of these tools in other scientific fields is still in the embryonic stage, and the primary reason for this lack of communication is the different goals of the two fields. Artificial intelligence is focused on creating intelligent and automated processing of data. In contrast, system dynamics is focused on understanding the behavior of complex systems over time to manage them by evaluating the outcomes of applied policies/strategies. Additionally, AI-based applications and techniques aid the modeling process through resource savings, increases in insights, and limitations in subjectivity (Shrestha et al., 2021; Garbero et al., 2021; Jana et al., 2022; Gruetzemacher et al., 2021).

Another reason is that artificial intelligence research has traditionally been more concerned with theoretical issues than practical applications. On the other hand, system dynamics is a methodology (theoretically sound) that is more concerned with practical applications than with theory. Consequently, a mismatch exists between the interests of researchers in the two fields. Another reason for the poor integration between artificial intelligence and system dynamics is that they use different methods and techniques and rely on different concepts. Artificial Intelligence research heavily relies on quantitative mathematical methods aimed at the extraction of data "correlation" among variables in the system, while system dynamics mostly relies on "causation" (and can be used both for qualitative and quantitative modeling methods). These substantial differences make it difficult for researchers in these two fields to understand each other's works.

Some relevant considerations emerged from analyzing the findings of the two applied methodologies.

First, knowledge and knowledge management are the two topics that emerge as the current and future lines of research concerning the joint use of SD methodology and AI. Furthermore, the bibliometric results identify strategic planning as a common area with conceptual content similar to that labeled in the topic modeling of business and enterprise. Another key result is the "decision-making" label in bibliometrics, consistent with the DSS label emerging from topic modeling. From the bibliometric analysis, the research stream dedicated to learning emerges as a point of contact, whereas from topic modeling, the point of contact is education.

From the *topic modeling analysis*, we can retrieve more interesting insights.

The first striking (but somehow obvious) aspect is the presence, in the "mostly-SD" macro cluster of typical topics dealt with the System Dynamics approach, that are (apart from methodological papers dealing with the SD approach itself) topics where the **social variable** (mainly, people's behavior) is a very important one (Project Management, Risk Management, Ecological & Socio-Economic Systems, Innovation) or where the very same behavior of users can characterize the system's behavior - especially in the utility sector (i.e.: energy, price-control, transportation, healthcare, supply chain). Such predominance of the social aspect is pretty evident in the "blended-SD-AI" macro cluster (especially in the topics dealing with Knowledge Management) and indeed spans also over some of the "mostly-AI" macro clusters (like in Human Resource Management, Service Management, Education, Decision Making, Role of AI in consumers aids, Sentiment/Emotions). The latter cluster also shows topics typical of the AI methodological approach (AI pathways, algorithms/optimisation, data bias, Forecasting/Prediction).

By coupling the cluster information emerging from Table 1 and Fig. 7 (number of papers related to SD and AI in each topic composed of 20 papers) with the distribution (in terms of percentage) of topics over the full collection of papers shown in Fig. 5, we can observe how the two topics AI and System Dynamics are the most recurring. Other relevant topics are Business and Enterprise, Soft Modeling, Ecological and Socio-Economic Systems, Decision-Making, Market Knowledge, and Innovation, which clearly show the interest of the authors in exploring the use of modeling approaches (e.g., causal loop diagramming or other mental mapping approaches) aimed at making decisions on complex issues and in complex contexts (at the junction of business and socio-ecological environments).

At the same time, by coupling the information emerging from Table 1 and Fig. S.2 with the trends of topics shown in Fig. 7, we note that the soft modeling topic seems to start losing momentum (not as much as other topics, though), whereas business and enterprises seem to continue growing in interest. Accordingly, decision-making also seems to be losing some momentum. However, the interesting aspect is that other topics that would hint at analyzing some of the resulting dynamics happening inside and outside organizations (which we can position into the business and enterprise cluster) start to be growing in interest: market knowledge, service management, sentiment emotions, consumer aid (as external factors to organizations), as well as HRM and Education (as internal factors to organizations), with the workforce/labor also being quite stable. Topics like AI pathways and data bias are gaining momentum since data biases effectively affect AI applications.

Table 2 summarizes the main outcomes from the literature reviews performed in this paper.

The above discussion leads to methodological, managerial, and policy implications, mainly related to the distinction between the "soft" and "hard" connections. About *methodological implications*, this study contributes to the two analyzed research streams, SD and AI, with particular reference to the possible areas of integration, past and future, that emerge from research in the Business and Management field. System dynamics is a powerful tool for analyzing complex systems; however, its use is often limited by a lack of data and the difficulty of obtaining accurate models. On the other hand, AI can help overcome these limitations by providing big data-based methods for modeling and forecasting. However, AI methods are often not well integrated into existing system dynamics models and tools, and the bias in the data and stochastic models used in AI does not allow for highly reliable

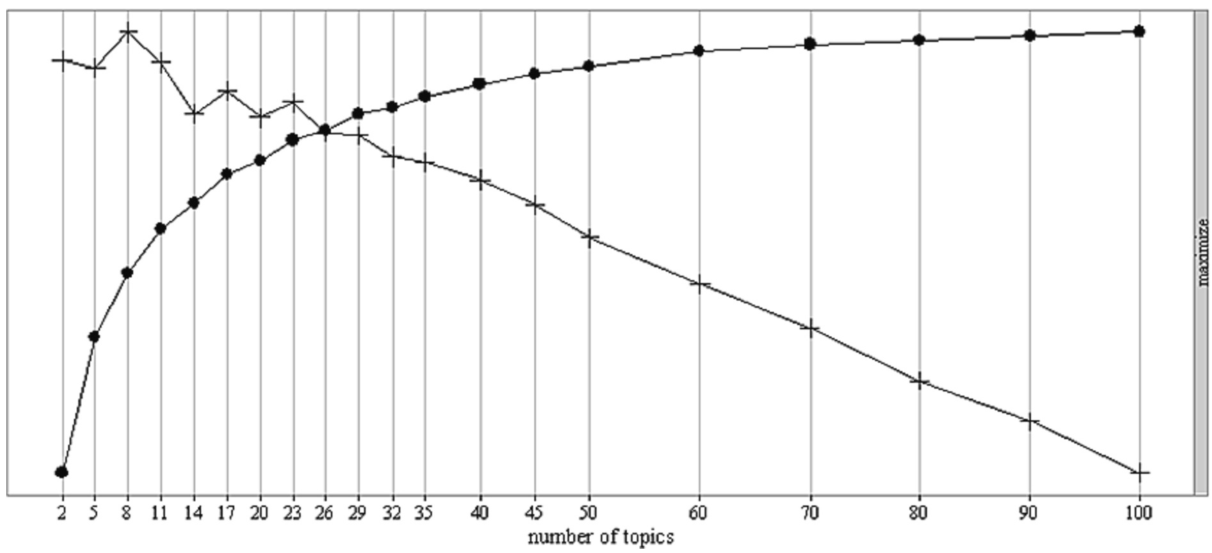

Fig. 5. Optimal number of topics.
Source: Authors elaboration.

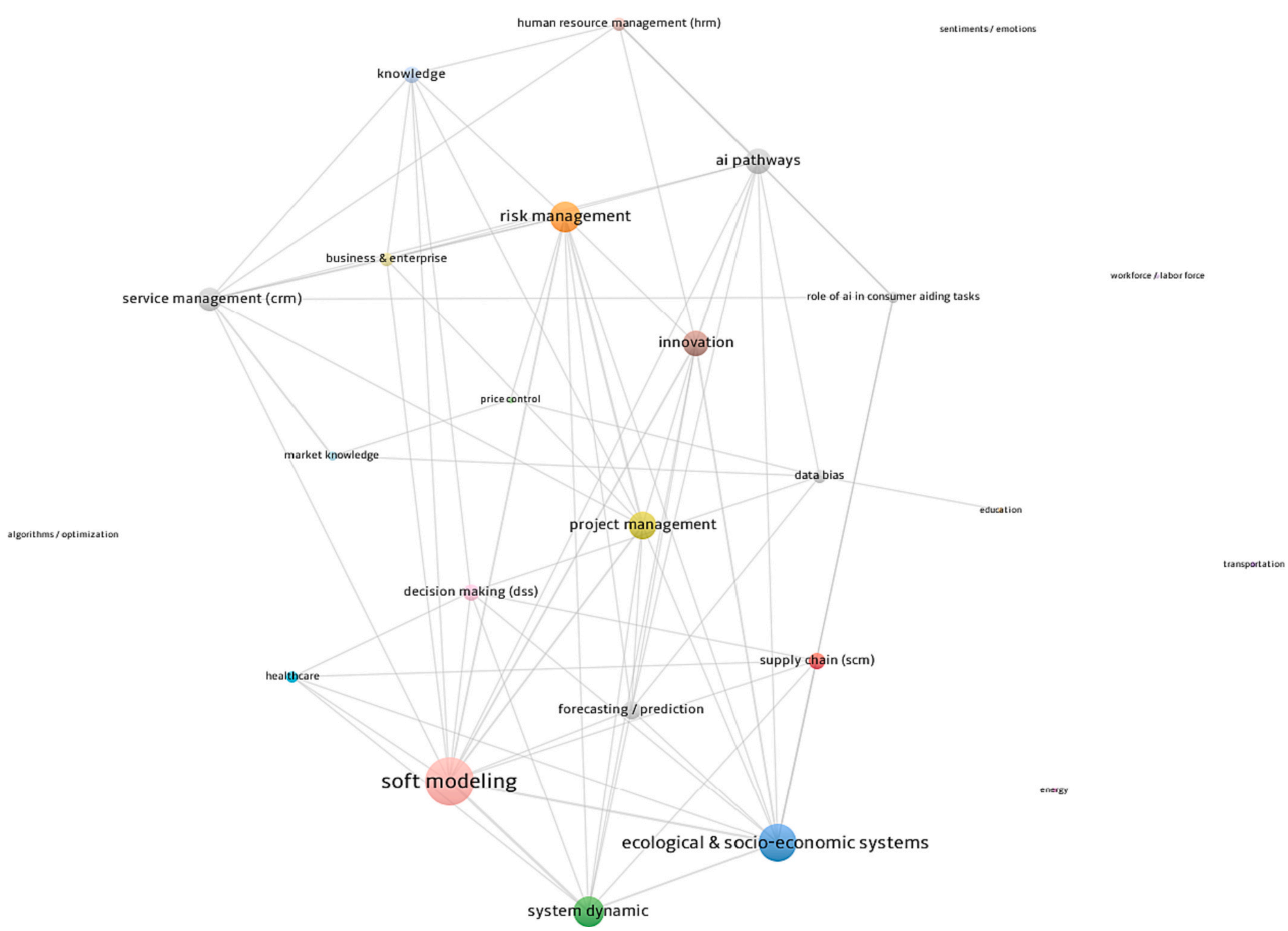

Fig. 6. Strategic topic map.
Source: Authors' elaboration.

predictions. As a result, the potential of AI to improve System Dynamics modeling and prediction and SD to improve AI has not been fully realized (Armenia et al., 2017, 2018; Armenia, 2019; Armenia et al., 2023; Badinelli et al., 2012). The results of the bibliometric analysis show that the convergence between the two research streams is not yet structured except for some areas of tangency, which do not identify the presence of

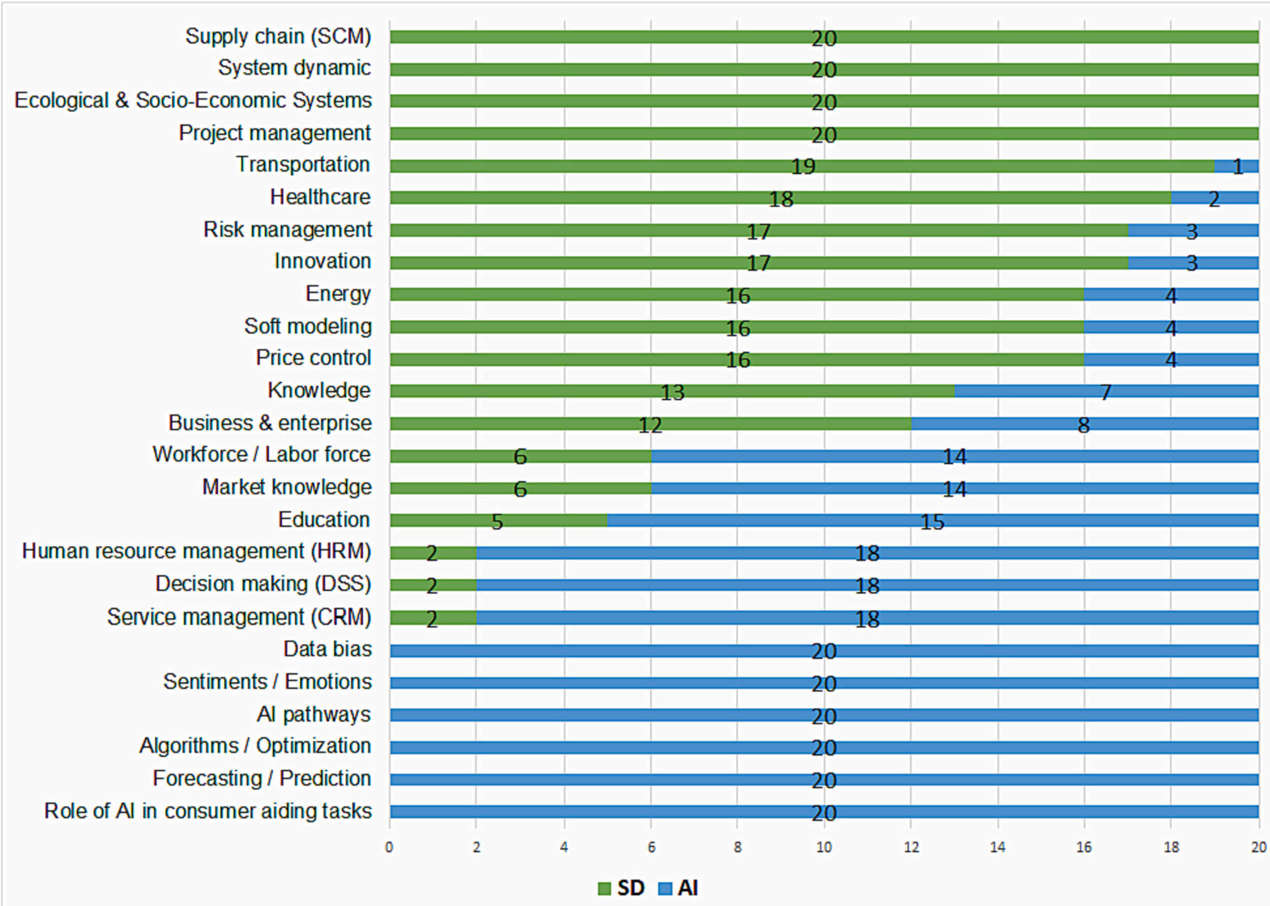

Fig. 7. First 20 contributions by probability in each of the 25 topics between SD and AI.
Source: Authors elaboration.

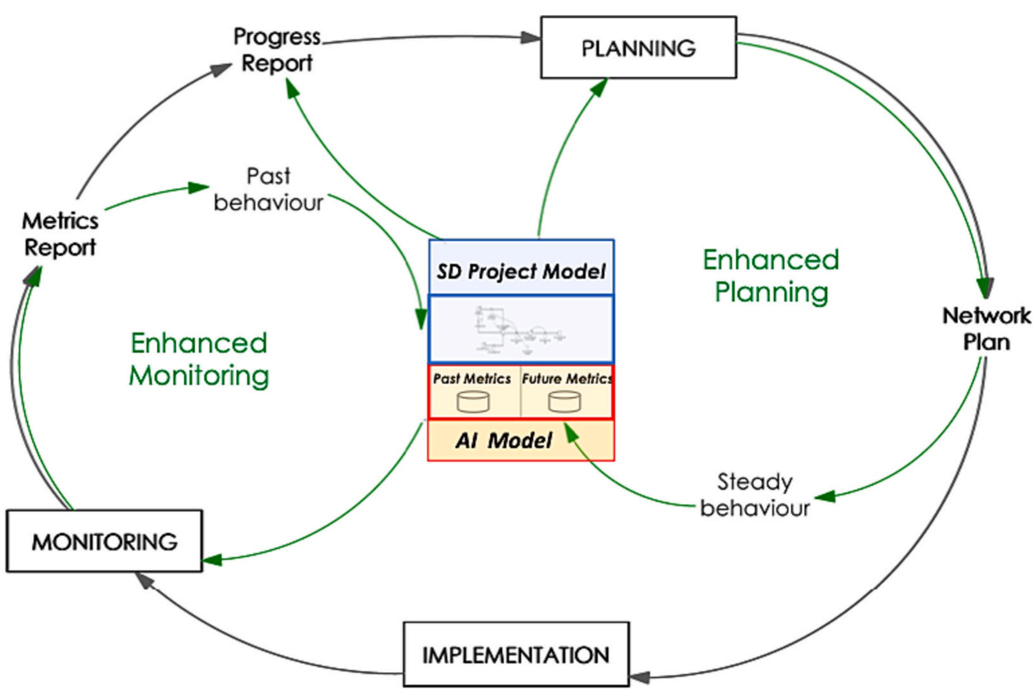

Fig. 8. Example of joint/hybrid application (in Project Management) of SD and AI to Decision Support Systems.
Source: Authors elaboration and adaptation of an image from Rodrigues (2001).

Table 2
Main outcomes summary from the analyses.

	Forecasting	Knowledge	Decision
SD	System Dynamics as a forecasting approach suitable for several contexts and scenarios and different levels of analysis (i.e. business, urban management, worldwide challenges, new product development, market forecasting, environment and waste management). Main topics retrieved: supply chain, transportation, healthcare, energy. ***Main contributions***: Sharif and Kabir, 1976; Martino, 1980; Forrester, 1961, 1971; Maier, 1998; Lyneis, 2000; Forrester, 2007; Barlas and Gunduz, 2011; Hwarng and Xie, 2008; Kim and Springer, 2008; Wang and Ding, 2009; Clay et al., 2018.	System Dynamics models usually leverage multiple information streams, including quantitative data, written records, knowledge-intensive processes, and information in the mental models of individuals and groups. Main topics retrieved: ecological and socio-economic systems, innovation, healthcare, risk management. ***Main contributions***: Vennix et al., 1992; Vennix et al., 1990; Vennix and Gubbels, 1992; Ford & Sterman, 1998; Vennix, 1999.	System dynamics is as approach able to create ‘microworlds,’ which enables scenarios evaluation and “what-if” analysis by capturing decision-makers’ mental models and could trigger richer debates and discussions that produce a consensus for action; it allows for the understanding of the ‘endogenous point of view,’ i.e., the endogenous sources of complex system behaviors. Main topics retrieved: price control, project management. ***Main contributions***: Forrester, 1992; Morecroft, 1988; Rouwette et al., 2004; Richardson, 2011; Ghaffarzadegan et al., 2011.
AI	AI-based tools (mainly machine learning) have been used to analyze large amounts of data and generate predictive models for a variety of domains (i.e. finance, healthcare, manufacturing). AI-driven forecasting models have also proven effective in technology adoption and innovation management. Main topics retrieved: AI and ML, AI pathways, Optimization algorithms, forecast outcomes. ***Main contributions***: Dwivedi et al., 2021; Goodell et al., 2021; Jiang et al., 2017; Zhang et al., 2019; Hengstler et al., 2016; Haefner et al., 2021; Smith, 2020; Chekima & Anthony, 2010; Pitt et al., 2020; Kaiser et al., 2020; Paschen, 2020; Bai, 2017; Stancu & Dutescu, 2021; Ferreira et al., 2020; Kozikowski et al., 2020; Huelsen et al., 2021; Gruia et al., 2020; Khmiadashvili, 2019; Tam, 1992; Salman et al., 2007; Xia et al., 2005.	NLP and expert systems have been used to extract, represent, and store knowledge from various sources (human experts, documents, databases); wide use in DSSs, and knowledge management and warehousing; less value with human leadership skills (i.e. team development, stakeholder management). Main topics retrieved: use of AI in different areas of management, human resources. ***Main contributions***: Duan et al., 2019; Aamodt and Nygård, 1995; O’Leary, 1998; Liebowitz, 2001; Nemati et al., 2002; Malik et al., 2021; Fridgeirsson et al., 2021.	AI techniques, such as multi-agent systems, game theory, and optimization algorithms, have been used to model complex decision-making processes, support collaboration among multiple decision-makers, and find optimal solutions to challenging problems. Main topics retrieved: AI in customer service, AI role in consumer-aiding tasks, decision-making. ***Main contributions***: Kahneman, 2011; Bennet & Hauser, 2013; Jarrahi, 2018; Shrestha et al., 2019; Prentic & Nguyen, 2020; Prentice et al., 2020; Yang et al., 2022; Pitardi et al., 2022; Chiang et al., 2022.
AI & SD *convergence*	Impact of digital and technological advances on labor practices, income, and employment. ***Main contributions***: Akaev et al., 2021; Bordot, 2022; Duch-Brown et al., 2022; Huang, 2007; Jnitova et al., 2021; Ghaffarzadegan et al., 2017.	Knowledge Management processes, SD and AI-enabled systems and their impact on companies’ performance; ***Main contributions***: Rahmandad and Repenning, 2016; Zaim et al., 2013; Grum, 2020; Sundaresan and Zhang, 2022. Education processes supported/enabled by technology. **Main contributions**: Perolla and Dey, 2021; Srinivasan and Dey, 2021; Redmond and Baveja, 2002; Noniashvili et al., 2020, Xu and Babaian, 2021; Simkova and Smutny, 2021	Business & enterprise models redesign and impact of technology on performances. ***Main contributions***: Segura et al. (2019); Cosenz and Noto, 2018; Cosenz and Bivona, 2021; Rahman et al., 2021; Westermann and Forthmann, 2021; Mikalef and Gupta, 2021. Technology, marketing and business and the link between technology and market perceptions and performance. ***Main contributions***: Wiart et al., 2022; Lusch and Watts, 2018; Middleton and Turnbull, 2021; Campbell et al., 2022; Eugeni, 2019.

a real research network focused on these two areas.

However, topic modeling provided us with additional forecasting analysis, indicating that topics in which convergence was insignificant were minimal. Despite, as shown, the future convergence that is being created in five topics, the presence of SD and AI is homogeneous, and these appear to be all linked to elements of “soft” convergence at the moment. However, the lack of “hard” convergence is quite a surprising result. For example, on issues related to Industry 4.0, machine learning is used exclusively structurally. For example, there is a lack of convergence in matters where the structural part of systems analysis, which characterizes both SD and AI, is a prerequisite for analysis or research.

This seems to suggest, in our opinion, that notwithstanding the still good presence of topics aimed at describing systems structures, hence allowing explaining the “why” of certain behaviors in relevant managerial aspects, research is steering towards a more focused approach in trying to explain the behavior of specific systems areas (HRM, Education, Consumer behavior, market knowledge, etc.)

This brings out important implications from a methodological point of view linked to the need to investigate such structural or hard convergences, as SD and AI start from the structural analysis of systems. Regarding *practical implications*, the main implication, derived from the potential of topic modeling analysis, concerns understanding future applications. This is more valid if we consider convergence topics, especially in knowledge, business, and enterprises, and the impact of digital and technological advances on labor practices, income, employment, technology, marketing, and business. Expanding the level of analysis, the implications in this sense concern the possible impacts of datafication, especially in socioeconomic contexts driven by digitization (Iandolo et al., 2021; Caputo et al., 2019, 2020, 2021). Recent research has shown that superior data analytics capabilities enable the generation of data-driven insights, especially in highly regulated industries, as they offer a path to break down the high barriers to entry in these industries and address the data access bottleneck (Ozalp et al., 2022). In this sense, combining SD with AI in the issues that emerge from topic modeling will support the definition of technological systems, forecasting capabilities, and planning, providing more accuracy and consistency. Finally, the convergence topics identified have significant implications in terms of *policy*. There is much debate regarding AI, its applications, limitations, and blind spots. In this paper, the main areas of convergence concern, as mentioned, soft connections. In our opinion, this element has greater policy implications than hard convergence. Considering emerging topics, a large part of the effort and policy implications will be required in terms of regulation, especially regarding the identified topics related to education and the impact of digital and technological advances on labor practices, income, and employment. In this sense, the convergence of SD and AI will have implications, especially in the case of applications in industries sensitive to data and linked to essential services such as education. In this sense, future policy actions are required, such as granting access, handling large amounts of data, violating user privacy, mishandling user data, and any important consequences for human rights and civil liberties.

Ultimately, it appears clear, from the above analysis, how research shows that decision-makers and current applications keep on leaning towards either a completely organizational approach or, on the "opposite" side, on a profoundly IT-based (data-based) approach. We argue that there is still a critical lack of a theory, or at least a framework, combining these two approaches convincingly and effectively; for example, considering the presence of structural feedback loops in AI applications, thus avoiding on one side the logical errors stemming from linearization and/or stochastic econometric approaches typical of most current AI-based decision support systems and leading to more realistic behavioral projections (updated using technological power and robust data automation coming from AI) over time for SD-based decision support systems. An example of such a hybrid approach is shown in Fig. 8, in which SD and AI are combined to provide a decision-support system in the project management context.

The feedback loop between enhanced monitoring and planning, enabled by the convergence of AI and SD (Fig. 8), has theoretical implications for technological forecasting and the nature of technological change. These implications relate to the deeper impact that unprecedented data gathering/analytics capabilities may have upon questioning the socio-technological assumptions underpinning existing systems and their behaviors. However, our analysis highlights the scarcity of theoretical and empirical contributions to AI's role in fundamentally changing system dynamics from conceptualization to design and implementation.

7. Conclusions, limitations & future directions

This study combines bibliometric analysis and topic modeling methodologies to investigate how and to what extent research on SD and AI converges within the business and management landscape. Logically, these two streams of literature offer ample opportunities for convergence, as they share the same focus on complex systems analysis and management, with artificial intelligence and data analytics potentially opening the space to cutting-edge technologies for complex analysis and problem-solving. However, empirical evidence that such converging trends exist in any structured manner remains elusive, prompting our investigation. We analyze convergence concerning three overarching themes in business and management: technological forecasting, knowledge elicitation, and decision-making.

First, we analyze the business and management literature landscape through a bibliometric analysis. This initial step of our investigation confirmed the weak convergence between system dynamics and artificial intelligence. Networks seem mostly separated, with a few exceptions concerning scholars in system dynamics discussing artificial intelligence technologies to support various activities such as decision-making, negotiations, and forecasting. Artificial intelligence is used to improve processes but not to redefine their logic.

We then zoomed out on the business and management landscape through topic modeling. The second part of the analysis revealed a slightly different picture, providing a more nuanced understanding of the relationship between SD and AI. This shows the emergence of topics in which the convergence between SD and AI starts to shape more organically. To be more precise, we identify three types of topic clusters: the first includes a limited number of topics in business and management with no connection at all between SD and AI, that is, papers falling in these specific clusters address *either* system dynamics *or* artificial intelligence with no cross-reference between the two. The second type of topic cluster includes most topics featuring published works in SD *and* AI, with varying degrees of convergence. The bibliographic references were disproportionately distributed in one of the two fields for most of these topics. Finally, there were five topics for which the distribution of papers across SD and AI began to appear a bit more even. These topics include knowledge, business and enterprises, workforce/labour, market knowledge, and education. We interpret these five topics as evidence of the emergence of a "soft convergence." Thus, these five topics feature research papers focusing on socio-technological systems more deeply characterized by social aspects (e.g., knowledge management, education, human relations, market analysis and intelligence, behavioral forecasting, and business governance). Interestingly, topics showing a "hard convergence" are less represented than those featuring the soft convergence between SD and AI. Hard convergence refers to more quantitative papers that analyze topics such as Industry 4.0, smart manufacturing, robotics, digital platforms, and cross-reference SD and AI. The underrepresentation of these topics is surprising considering how artificial intelligence, data analytics, and deep learning systems may shape the dynamics of smart production systems.

This underrepresentation may reflect the limitations of our sample, which was restricted to the Web of Science. Another limitation of our methodology is that it is more intrinsic to bibliometric analysis. First, these types of analyses are usually restricted to paper abstracts that contain a sheer amount of data at a computationally manageable level. One consequence of this approach is that bibliometric methods depend highly on the search strategies in bibliographic databases. Further research should be extended to include the conclusion sections of papers, along with abstracts. The results could be probed by analyzing limited subsamples in which the full text was included.

Despite these limitations, our findings provide important directions for future research. First, identifying topics highlighting the soft convergence between SD and AI is significant for policymakers and practitioners. The fields and practices in which this soft convergence is unfolding mostly relate to the service industry and require rethinking policies, regulations, and administrative practices to customer protection. For example, in the case of health services worldwide, the ability to share and analyze data locally, nationally, and internationally can provide real progress in the ability to improve and deliver health care but poses relevant issues in terms of governance, privacy, and protection of the most sensitive data. This, in turn, might steer future research and prompt the emergence of new topics featuring the convergence of systems dynamics, artificial intelligence, and public management and policy.

Future research could leverage novel methodological approaches that combine both SD and AI tools to question and improve existing theories, as well as to develop new theoretical foundations underlying some technological forecasts and the current challenges our society is facing, such as rapidly changing business conditions, pressures imposed by climate change, and international crises. Although mainly connected to methodological implications, the portrait depicted in the present work also identifies research fields that use hybrid approaches (AI and SD) to question and refine existing knowledge.

The lower visibility of our results for topics addressing the hard convergence between system dynamics and artificial intelligence is theoretically interesting and highly unexpected. However, there is a tentative explanation for this under-representation. The literature on hard convergence in our sample addresses data analytics and artificial intelligence as technologies that can increase the efficiency of production systems through functionality monitoring, analytics, and problem forecasting. This approach pursues more efficient system debottlenecking without questioning the underlying assumptions of the system design or investigating the relationship between assumptions and the emergence of bottlenecks. What is missing in our sample, which drives the underrepresentation of the whole hard convergence, is the specific literature that looks at artificial intelligence as a technological philosophy for developing smart systems capable of redefining the assumptions underpinning their system dynamics. This literature stream is relevant to business strategists and managers but also raises questions about system governance and human-technology interactions in the workplace. Hence, its underrepresentation is surprising, but it also points towards what we can expect to be the next frontier of research in SD and AI.

Both the identification of topics featuring an emerging soft convergence and the underrepresentation of the topics of hard convergence are relevant starting points in the challenge of envisaging the next frontier in both systems dynamics and artificial intelligence, and indeed, to predict how and to what extent these two fields are likely to converge in the future.

CRediT authorship contribution statement

Stefano Armenia: Conceptualization, Writing – original draft, Writing – review & editing. **Eduardo Franco:** Methodology, Writing – original draft, Writing – review & editing, Conceptualization. **Francesca Iandolo:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing, Project administration. **Giuliano Maielli:** Conceptualization, Writing – original draft, Writing – review & editing. **Pietro Vito:** Data curation, Methodology, Resources, Software, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix A

Based on our work on an indirect method of identifying topics covered in both the SD and AI domains (in the WoS categories Business, Management), assuming that they constitute the topics potentially likely to share contributions belonging to joint SD and AI in the future, we wanted to verify its reliability by repeating the analysis using topic modeling on the results obtained from Web of Science with the query "artificial intelligence" AND "system* dynamic*" in all fields, thus using a direct method.

Looking again at WoS and performing the research, we obtained 677 documents, of which only 9 were in common with our database.

https://www.webofscience.com/wos/woscc/summary/b4b9850e-d73d-4a24-8305-274a8e3afe9b-6493c70f/relevance/1 677

"system* dynamic*" AND "artificial intelligence" (All Fields)

In this case, the optimal number of topics is 14.

Topics containing jointly "artificial intelligence" and "system dynamics" among their top 10 terms are not detected.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2023.123131.

References

Aamodt, A., Nygård, M., 1995. Different roles and mutual dependencies of data, information, and knowledge—an AI perspective on their integration. Data Knowl. Eng. 16 (3), 191–222.

Adya, M., Collopy, F., 1998. How effective are neural networks at forecasting and prediction? A review and evaluation. J. Forecast. 17 (5-6), 481–495. https://doi.org/10.1002/(SICI)1099-131X(1998090)17:5/6<481::AIDFOR709>3.3.CO;2-H.

Ahn, J., Kim, J., Sung, Y., 2022. The effect of gender stereotypes on artificial intelligence recommendations. J. Bus. Res. 141, 50–59. https://doi.org/10.1016/j.jbusres.2021.12.007.

Akaev, A., Devezas, T., Ichkitidze, Y., Sarygulov, A., 2021. Forecasting the labor intensity and labor income share for G7 countries in the digital age. Technol. Forecast. Soc. Chang. 167, Article 120675 https://doi.org/10.1016/j.techfore.2021.120675.

Akkermans, H., van Oorschot, K.E., 2016. Pilot error? Managerial decision biases as explanation for disruptions in aircraft development. Proj. Manag. J. 47 (2), 79–102.

Alinasab, J., Mirahmadi, S.M.R., Ghorbani, H., Caputo, F., 2022. Discovering knowledge and cognitive based drivers for SMEs internationalization. J. Knowl. Econ. 13 (3), 2490–2518.

Alkaldy, E.A.H., Albaqir, M.A., Hejazi, M.S.A., 2019. A new load forecasting model considering planned load shedding effect. Int. J. Energy Sect. Manag. 13 (1), 149–165.

Antons, D., Kleer, R., Salge, T.O., 2016. Mapping the topic landscape of jpim, 1984–2013: in search of hidden structures and development trajectories. J. Prod. Innov. Manag. 33 (6), 726–749.

Armenia, S., 2019. Smart model-based governance: taking decision making to the next level by integrating data analytics with systems thinking and system dynamics. In: New Challenges in Corporate Governance: Theory and Practice, pp. 41–42. https://doi.org/10.22495/ncpr_10.

Armenia, S., Ferreira, Franco E., Mecella, M., Onori, R., 2017. Smart model-based governance: from big-data to future policy making. In: Proceedings of the BSLab-SYDIC Workshop 2017, Rome (Italy). ISBN 9788890824258.

Armenia, S., Franco, E.F., Medaglia, C.M., Pompei, A., 2018. Smart model-based governance: systems thinking and data analytics to the rescue of policy making. In: Proceedings of the 60th Conference of the UK OR Society (OR60), 178. Lancaster, UK.

Armenia, S., Barile, S., Iandolo, F., Pompei, A., Sicca, L.M., 2023. Organisational ambidexterity and knowledge management: a systems perspective towards smart model-based governance. Syst. Res. Behav. Sci. 1–14.

Arroyabe, M.F., Schumann, M., Arranz, C.F.A., 2022. Mapping the entrepreneurial university literature: a text mining approach. Stud. High. Educ. 0 (0), 1–9.

Atsalakis, G.S., Atsalaki, I.G., Zopounidis, C., 2018. Forecasting the success of a new tourism service by a neuro-fuzzy technique. Eur. J. Oper. Res. 268 (2), 716–727. https://doi.org/10.1016/j.ejor.2018.01.044.

Azadeh, A., Darivandi Shoushtari, K., Saberi, M., & Teimoury, E. (2014). An integrated artificial neural network and system dynamics approach in support of the viable system model to enhance industrial intelligence: the case of a large broiler industry. Syst. Res. Behav. Sci., 31(2), 236–257.

Badakhshan, E., Humphreys, P., Maguire, L., & McIvor, R. (2020). Using simulation-based system dynamics and genetic algorithms to reduce the cash flow bullwhip in the supply chain. Int. J. Prod. Res., 58(17), 5253–5279.

Badinelli, R., Barile, S., Ng, I., Polese, F., Saviano, M., Di Nauta, P., 2012. Viable service systems and decision making in service management. J. Serv. Manag. 23 (4), 498–526.

Bai, G.H., 2017. Research on the application and influence of auditing artificial intelligence. In: DEStech Transactions on Social Science, Education and Human Science,(eiem).

Baldwin, C. Y. and Clark, K. B. (2000). Design Rules. Volume 1, The Power of Modularity. The MIT Press, Cambridge, MA.

Baldwin, R., Lopez-Gonzalez, J., 2015. Supply-chain trade: a portrait of global patterns and several testable hypotheses. World Econ. 38 (11), 1682–1721.

Ballester, O., Penner, O., 2022. Robustness, replicability and scalability in topic modelling. J. Informet. 16 (1), 101224 https://doi.org/10.1016/j.joi.2021.101224.

Barile, S., Lusch, R., Reynoso, J., Saviano, M., Spohrer, J., 2016. Systems, networks, and ecosystems in service research. J. Serv. Manag. 27 (4), 652–674.

Barlas, Y., Gunduz, B., 2011. Demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply chains. J. Oper. Res. Soc. 62 (3), 458–473.

Bayer, S., Eom, K., Sivapragasam, N., Silva, D.A.D., Choon, G., Koh, H., Matchar, D.B., 2021. Estimating costs and benefits of stroke management: a population-based simulation model. J. Oper. Res. Soc. 72 (9), 2122–2134.

Bennet, C.C., Hauser, K., 2013. Artificial intelligence framework for simulating clinical decision-making. Artif. Intell. Med. 57, 9–19.

Blei, D.M., 2012. Probabilistic topic models. Commun. ACM 55 (4), 77–84.

Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. J. Mach. Learn. Res. 3 (Jan), 993–1022.

Bordot, F., 2022. Artificial intelligence, robots and unemployment: evidence from OECD countries. J. Innov. Econ. Manag. 1, 117–138.

Braganza, A., Chen, W., Canhoto, A., Sap, S., 2021. Productive employment and decent work: the impact of AI adoption on psychological contracts, job engagement and employee trust. J. Bus. Res. 131, 485–494.

Brailsford, S.C., Lattimer, V.A., Tarnaras, P., Turnbull, J.C., 2004. Emergency and on-demand health care: modelling a large complex system. J. Oper. Res. Soc. 55, 34–42.

Campbell, C., Plangger, K., Sands, S., Kietzmann, J., 2022. Preparing for an era of deepfakes and AI-generated ads: a framework for understanding responses to manipulated advertising. J. Advert. 51 (1), 22–38.

Caponio, G., Massaro, V., Mossa, G., Mummolo, G., 2015. Strategic energy planning of residential buildings in a smart city: a system dynamics approach. Int. J. Eng. Bus. Manag. 7, 20.

Caputo, F., Cillo, V., Candelo, E., Liu, Y., 2019. Innovating through digital revolution: the role of soft skills and Big Data in increasing firm performance. Manag. Decis. 57 (8), 2032–2051.

Caputo, F., Mazzoleni, A., Pellicelli, A.C., Muller, J., 2020. Over the mask of innovation management in the world of Big Data. J. Bus. Res. 119, 330–338.

Caputo, F., Magni, D., Papa, A., Corsi, C., 2021. Knowledge hiding in socioeconomic settings: matching organizational and environmental antecedents. J. Bus. Res. 135, 19–27.

Ceylan, Z., Atalan, A., 2021. Estimation of healthcare expenditure per capita of Turkey using artificial intelligence techniques with genetic algorithm-based feature selection. J. Forecast. 40 (2), 279–290.

Charfi, S., BenHamad, S., Masmoudi, A., 2020. Assessing the impact of monetary fundamentals on exchange rate fluctuations a Bayesian network approach. J. Model. Manag. 15 (1), 166–181.

Chekima, K., Anthony, P., 2010. Document Categorizer Agent for Computer Science Academic Papers.

Chiang, A.H., Trimi, S., Lo, Y.J., 2022. Emotion and service quality of anthropomorphic robots. Technol. Forecast. Soc. Chang. 177, 121550.
Chung, B., 2018. System dynamics modelling and simulation of the Malaysian rice value chain: effects of the removal of price controls and an import monopoly on rice prices and self-sufficiency levels in Malaysia. Syst. Res. Behav. Sci. 35 (3), 248–264.
Clay, N.M., Abbasi, B., Eberhard, A., Hearne, J., 2018. On the volatility of blood inventories. Int. Trans. Oper. Res. 25 (1), 215–242.
Collins, C., Dennehy, D., Conboy, K., Mikalef, P., 2021. Artificial intelligence in information systems research: a systematic literature review and research agenda. Int. J. Inf. Manag. 60, 102383.
Core, M.G., Lane, H.C., Van Lent, M., Gomboc, D., Solomon, S., Rosenberg, M., 2006. Building explainable artificial intelligence systems. In: AAAI, pp. 1766–1773. July.
Cosenz, F., Bivona, E., 2021. Fostering growth patterns of SMEs through business model innovation. A tailored dynamic business modelling approach. J. Bus. Res. 130, 658–669.
Cosenz, F., Noto, G., 2018. A dynamic business modelling approach to design and experiment new business venture strategies. Long Range Plan. 51 (1), 127–140.
Cramton, C.D., 2001. The mutual knowledge problem and its consequences for dispersed collaboration. Organ. Sci. 12 (3), 346–371. https://doi.org/10.1287/orsc.12.3.346.10098.
Cronin, M.A., Gonzalez, C., Sterman, J.D., 2009. Why don't well-educated adults understand accumulation? A challenge to researchers, educators, and citizens. Organ. Behav. Hum. Decis. Process. 108 (1), 116–130. https://doi.org/10.1016/j.obhdp.2008.03.003.
Cusumano, M.A., Gawer, A., Yoffie, D.B., 2019. The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power, 320. Harper Business, New York.
Das, S.R., Chen, M.Y., 2007. Yahoo! for Amazon: sentiment extraction from small talk on the web. Manag. Sci. 53 (9), 1375–1388.
Davenport, J.H., England, M., Griggio, A., Sturm, T., Tinelli, C., 2020. Symbolic computation and satisfiability checking. J. Symb. Comput. 100, 1–10.
De Solla Price, D.J., 1965. Networks of scientific papers. Science 149 (3683), 510–515.
de Vasconcelos Gomes, L.A., Facin, A.L.F., Salerno, M.S., Ikenami, R.K., 2018. Unpacking the innovation ecosystem construct: evolution, gaps and trends. Technol. Forecast. Soc. Chang. 136, 30–48.
Dejonckheere, J., Disney, S.M., Lambrecht, M.R., Towill, D.R., 2003. Measuring and avoiding the bullwhip effect: a control theoretic approach. Eur. J. Oper. Res. 147 (3), 567–590. https://doi.org/10.1016/S0377-2217(02)00369-7.
Deveaud, R., SanJuan, E., Bellot, P., 2014. Accurate and effective latent concept modeling for ad hoc information retrieval. In: Document numérique, 17(1), pp. 61–84.
Dordkeshan, M.J., Shamsudin, M.N., Mohamed, Z., Radam, A., 2017. Assessing the impact of rice import quota policy on the Malaysian rice sector. J. Food Prod. Mark. 23 (8), 890–900.
Duan, Y., Edwards, J.S., Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. Int. J. Inf. Manag. 48, 63–71.
Duch-Brown, N., Gomez-Herrera, E., Mueller-Langer, F., Tolan, S., 2022. Market power and artificial intelligence work on online labour markets. Res. Policy 51 (3), 104446. https://doi.org/10.1016/j.respol.2021.104446.
Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Williams, M. D., 2021. Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int. J. Inf. Manag. 57, 101994.
Dyner, I., Smith, R.A., Peña, G.E., 1995. System dynamics modelling for residential energy efficiency analysis and management. J. Oper. Res. Soc. 46, 1163–1173.
Dyson, B., Chang, N.B., 2005. Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. Waste Manag. 25 (7), 669–679.
Er, H., Hushmat, A., 2017. The application of technical trading rules developed from spot market prices on futures market prices using CAPM. Eurasian Bus. Rev. 7, 313–353.
Espinasse, B., Picolet, G., Chouraqui, E., 1997. Negotiation support systems: a multi-criteria and multi-agent approach. Eur. J. Oper. Res. 103 (2), 389–409. https://doi.org/10.1016/s0377-2217(97)00127-6.
Eugeni, R., 2019. The post-advertising condition. A socio-semiotic and semio-pragmatic approach to algorithmic capitalism. In: Social Computing and Social Media. Communication and Social Communities: 11th International Conference, SCSM 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26-31, 2019, Proceedings, Part II, 21. Springer International Publishing, pp. 291–302. https://doi.org/10.1007/978-3-030-21905-5_23.
Fan, W., Chen, P., Shi, D., Guo, X., Kou, L., 2021. Multi-agent modeling and simulation in the AI age. Tsinghua Sci. Technol. 26 (5), 608–624.
Feng, N., Wang, M., Li, M., Li, D., 2019. Effect of security investment strategy on the business value of managed security service providers. Electron. Commer. Res. Appl. 35, 100843.
Ferreira, P., Teixeira, J.G., Teixeira, L.F., 2020. Understanding the impact of artificial intelligence on services. In: Exploring Service Science: 10th International Conference, IESS 2020, Porto, Portugal, February 5–7, 2020, Proceedings 10. Springer International Publishing, pp. 202–213.
Fethi, M.D., Pasiouras, F., 2010. Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey. Eur. J. Oper. Res. 204 (2), 189–198.
Fiala, P., 2005. Information sharing in supply chains. Omega-Int. J. Manag. Sci. 33 (5), 419–423. https://doi.org/10.1016/j.omega.2004.07.006.
Ford, A., 1997. System dynamics and the electric power industry. Syst. Dyn. Rev. 13 (1), 57–85.
Ford, D.N., Sterman, J.D., 1998. Expert knowledge elicitation to improve formal and mental models. Syst. Dyn. Rev.: J. Syst. Dyn. Soc. 14 (4), 309–340. ISO 690.
Forrester, J.W., 1961. Industrial Dynamics, 1st ed. The MIT Press.
Forrester, J.W., 1969. Urban Dynamics, 1st ed. The MIT Press.
Forrester, J.W., 1971. World Dynamics, 1st ed. The MIT Press.
Forrester, J.W., 1992. Policies, decisions and information sources for modeling. Eur. J. Oper. Res. 59 (1), 42–63. https://doi.org/10.1016/0377-2217(92)90006-U.
Forrester, J.W., 2007. System dynamics—the next fifty years. Syst. Dyn. Rev. 23 (2–3), 359–370.
Fridgeirsson, T.V., Ingason, H.T., Jonasson, H.I., Jonsdottir, H., 2021. An authoritative study on the near future effect of artificial intelligence on project management knowledge areas. Sustainability 13 (4), 2345.
Gao, B., 2022. The use of machine learning combined with data mining technology in financial risk prevention. Comput. Econ. 59 (4), 1385–1405.
Garbero, A., Carneiro, B., Resce, G., 2021. Harnessing the power of machine learning analytics to understand food systems dynamics across development projects. Technol. Forecast. Soc. Chang. 172, 121012.
Gawer, A., 2014. Bridging differing perspectives on technological platforms: toward an integrative framework. Res. Policy 43 (7), 1239–1249.
Gawer, A., 2020. Digital platforms's boundaries: the interplay of firm scope, platform sides, and digital interfaces. Long Range Plan. 25.
Gary, M.S., 2005. Implementation strategy and performance outcomes in related diversification. Strateg. Manag. J. 26 (7), 643–664. https://doi.org/10.1002/smj.468.
Gelman, I.A., 2005. Addressing time-scale differences among decision-makers through model abstractions. Eur. J. Oper. Res. 160 (2), 325–335. https://doi.org/10.1016/j.ejor.2003.09.004.
Ghaffarzadegan, N., Lyneis, J., Richardson, G.P., 2011. How small system dynamics models can help the public policy process. Syst. Dyn. Rev. 27 (1), 22–44.
Ghaffarzadegan, N., Xue, Y., Larson, R.C., 2017. Work-education mismatch: an endogenous theory of professionalization. Eur. J. Oper. Res. 261 (3), 1085–1097. https://doi.org/10.1016/j.ejor.2017.02.041.
Goodell, J.W., Kumar, S., Lim, W.M., Pattnaik, D., 2021. Artificial intelligence and machine learning in finance: identifying foundations, themes, and research clusters from bibliometric analysis. J. Behav. Exp. Financ. 32, 100577.
Griffiths, T.L., Steyvers, M., 2004. Finding scientific topics. Proc. Natl. Acad. Sci. 101 (suppl_1), 5228–5235.
Gruetzemacher, R., Dorner, F.E., Bernaola-Alvarez, N., Giattino, C., Manheim, D., 2021. Forecasting AI progress: a research agenda. Technol. Forecast. Soc. Chang. 170, 120909.
Gruia, L., Bibu, N., Roja, A., 2020. Digital transformation generates a new business paradigm. In: Human-made in the Age of Artificial Intelligence, pp. 443–452.
Grum, M., 2020. Managing human and artificial knowledge bearers: the creation of a symbiotic knowledge management approach. In: Business Modeling and Software Design: 10th International Symposium, BMSD 2020, Berlin, Germany, July 6-8, 2020, Proceedings, 10. Springer International Publishing, pp. 182–201.
Guerreiro, J., Rita, P., Trigueiros, D., 2016. A text mining-based review of cause-related marketing literature. J. Bus. Ethics 139, 111–128.
Haefner, N., Wincent, J., Parida, V., Gassmann, O., 2021. Artificial intelligence and innovation management: a review, framework, and research agenda. Technol. Forecast. Soc. Chang. 162, 120392.
Hannigan, T.R., Haans, R.F., Vakili, K., Tchalian, H., Glaser, V.L., Wang, M.S., Jennings, P.D., 2019. Topic modeling in management research: rendering new theory from textual data. Acad. Manag. Ann. 13 (2), 586–632. https://doi.org/10.5465/annals.2017.0099.
Harrison, G., Thiel, C., 2017. An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe. Technol. Forecast. Soc. Chang. 114, 165–178.
Hein, R., Kleindorfer, P.R., Spinler, S., 2012. Valuation of electric vehicle batteries in vehicle-to-grid and battery-to-grid systems. Technol. Forecast. Soc. Chang. 79 (9), 1654–1671.
Hekkert, M.P., Suurs, R.A.A., Negro, S.O., Kuhlmann, S., Smits, R., 2007. Functions of innovation systems: a new approach for analysing technological change. Technol. Forecast. Soc. Chang. 74 (4), 413–432. https://doi.org/10.1016/j.techfore.2006.03.002.
Henderson, R.M., Clark, K.B., 1990. Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. Adm. Sci. Q. 9–30.
Hengstler, M., Enkel, E., Duelli, S., 2016. Applied artificial intelligence and trust—the case of autonomous vehicles and medical assistance devices. Technol. Forecast. Soc. Chang. 105, 105–120.
Hess, T.J., Rees, L.P., Rakes, T.R., 2000. Using autonomous software agents to create the next generation of decision support systems. Decis. Sci. 31 (1), 1–31. https://doi.org/10.1111/j.1540-5915.2000.tb00922.x.
Hovmand, P.S., Andersen, D.F., Rouwette, E., Richardson, G.P., Rux, K., Calhoun, A., 2012. Group model-building 'scripts' as a collaborative planning tool. Syst. Res. Behav. Sci. 29 (2), 179–193.
Huang, M.H., Rust, R.T., 2018. Artificial intelligence in service. J. Serv. Res. 21 (2), 155–172.
Huang, L., Zimmerm, B., Hasan, J., 2007. System dynamics model for renewable enerpry: case from a country. In: Proceedings of the 2007 Conference on Systems Science, Management Science and System Dynamics: Sustainable Development and Complex Systems, vols 1-10, pp. 793–799.
Huang, M.H., Rust, R., Maksimovic, V., 2019. The feeling economy: managing in the next generation of artificial intelligence (AI). Calif. Manag. Rev. 61 (4), 43–65. https://doi.org/10.1177/0008125619863436.

Huang, D., Jin, X., Coghlan, A., 2021. Advances in consumer innovation resistance research: a review and research agenda. Technol. Forecast. Soc. Chang. 166, 120594.
Huelsen, P., Graglia, M.A.V., Lazzareschi, N., 2021. The growing moral challenge in the face of technologies: internet, social networks, IoT, blockchain and artificial intelligence. Risus-J. Innov. Sustain. 12 (2), 17–29. https://doi.org/10.23925/2179-3565.2021v12i2p17-29.
Hwang, S., Park, M., Lee, H.S., Yoon, Y., Son, B.S., 2010. Korea n real estate market and boosting policies: focusing on mortgage loans. Int. J. Strateg. Prop. Manag. 14 (2), 157–172.
Hwarng, H.B., Xie, N., 2008. Understanding supply chain dynamics: a chaos perspective. Eur. J. Oper. Res. 184 (3), 1163–1178.
Iandolo, F., Loia, F., Fulco, I., Nespoli, C., Caputo, F., 2021. Combining big data and artificial intelligence for managing collective knowledge in unpredictable environment—insights from the Chinese case in facing COVID-19. J. Knowl. Econ. 12 (4), 1982–1996.
Jacobides, M.G., Cennamo, C., Gawer, A., 2018. Towards a theory of ecosystems. Strateg. Manag. J. 39 (8), 2255–2276.
Jafarian-Namin, S., Goli, A., Qolipour, M., Mostafaeipour, A., Golmohammadi, A.M., 2019. Forecasting the wind power generation using Box-Jenkins and hybrid artificial intelligence a case study. Int. J. Energy Sect. Manag. 13 (4), 1038–1062. https://doi.org/10.1108/ijesm-06-2018-0002.
Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L.K., Young, T., 2010. Simulation in manufacturing and business: A review. Eur. J. Oper. Res. 203 (1), 1–13. https://doi.org/10.1016/j.ejor.2009.06.004.
Jana, R.K., Ghosh, I., Wallin, M.W., 2022. Taming energy and electronic waste generation in bitcoin mining: insights from Facebook prophet and deep neural network. Technol. Forecast. Soc. Chang. 178, 121584 https://doi.org/10.1016/j.techfore.2022.121584.
Jarrahi, M.H., 2018. Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making. Bus. Horiz. 61 (4), 577–586.
Jelodar, H., Wang, Y., Yuan, C., et al., 2019. Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. Multimed. Tools Appl. 78, 15169–15211. https://doi.org/10.1007/s11042-018-6894-4.
Jiang, Y.Y., Wen, J., 2020. Effects of COVID-19 on hotel marketing and management: a perspective article. Int. J. Contemp. Hosp. Manag. 32 (8), 2563–2573. https://doi.org/10.1108/IJCHM-03-2020-0237.
Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., 2017. Artificial intelligence in healthcare: past, present and future. Stroke Vasc. Neurol. 2 (4).
Jnitova, V., Joiner, K., Efatmaneshnik, M., Chang, E., 2021. Modelling workforce employability pipelines for organisational resilience. Int. J. Eng. Bus. Manag. 13 https://doi.org/10.1177/18479790211004010.
Kabir, C., Sharif, M.N., Adulbhan, P., 1981. System dynamics modeling for forecasting technological substitution. Comput. Ind. Eng. 5 (1), 7–21.
Kahneman, D., 2011. Thinking, Fast and Slow. macmillan. ISO 690.
Kaiser, C., Ahuvia, A., Rauschnabel, P.A., Wimble, M., 2020. Social media monitoring: what can marketers learn from Facebook brand photos? J. Bus. Res. 117, 707–717.
Kambur, E., Akar, C., 2022. Human resource developments with the touch of artificial intelligence: a scale development study. Int. J. Manpow. 43 (1), 168–205. https://doi.org/10.1108/ijm-04-2021-0216.
Kampmann, C.E., Oliva, R., 2008. Structural dominance analysis and theory building in system dynamics. Syst. Res. Behav. Sci. 25 (4), 505–519.
Kaplan, A., Haenlein, M., 2019. Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. 62 (1), 15–25.
Kessler, M.M., 1963. Bibliographic coupling between scientific papers. Am. Doc. 14 (1), 10–25.
Khashei, M., Chahkoutahi, F., 2022. Electricity demand forecasting using fuzzy hybrid intelligence-based seasonal models. J. Model. Manag. 17 (1), 154–176. https://doi.org/10.1108/jm2-06-2020-0159.
Kim, I., Springer, M., 2008. Measuring endogenous supply chain volatility: beyond the bullwhip effect. Eur. J. Oper. Res. 189 (1), 172–193.
Kim, J., Kang, S., Bae, J., 2022. Human likeness and attachment effect on the perceived interactivity of AI speakers. J. Bus. Res. 144, 797–804. https://doi.org/10.1016/j.jbusres.2022.02.047.
Kitanaka, H., Kwiatek, P., Panagopoulos, N.G., 2021. Introducing a new, machine learning process, and online tools for conducting sales literature reviews: an application to the forty years of JPSSM. J. Pers. Sell. Sales Manag. 41 (4), 351–368.
Khmiadashvili, L., 2019. Building progressive future: human–ai collaboration. Calitatea 20 (S3), 85–88.
Kobbacy, K.A.H., Vadera, S., Rasmy, M.H., 2007. AI and OR in management of operations: history and trends. J. Oper. Res. Soc. 58 (1), 10–28. https://doi.org/10.1057/palgrave.jors.2602132.
Kogan, K., Lou, S., 2003. Multi-stage newsboy problem: a dynamic model. Eur. J. Oper. Res. 149 (2), 448–458.
Konchou, F.A.T., Kapen, P.T., Magnissob, S.B.K., Youssoufa, M., Tchinda, R., 2021. Prediction of wind speed profile using two artificial neural network models: an ab initio investigation in the Bapouh's city, Cameroon. Int. J. Energy Sect. Manag. 15 (3), 566–577. https://doi.org/10.1108/ijesm-04-2020-0008.
Kong, H.Y., Yuan, Y., Baruch, Y., Bu, N.P., Jiang, X.Y., Wang, K.P., 2021. Influences of artificial intelligence (AI) awareness on career competency and job burnout. Int. J. Contemp. Hosp. Manag. 33 (2), 717–734. https://doi.org/10.1108/ijchm-07-2020-0789.
Kopainsky, B., Luna-Reyes, L.F., 2008. Closing the loop: promoting synergies with other theory building approaches to improve system dynamics practice. Syst. Res. Behav. Sci. 25 (4), 471–486.
Kozikowski, D., Zema, T., Sulich, A., 2020. Artificial intelligence usage and ethics in the choice theory. In: Proceedings of the Education Excellence and Innovation Management: A, p. 2025.
Krenz, P., Basmer, S., Buxbaum-Conradi, S., Redlich, T., Wulfsberg, J.P., 2014. Knowledge management in value creation networks: establishing a new business model through the role of a knowledge-intermediary. Procedia CIRP 16, 38–43.
Krusinskas, R., Lakstutiene, A., Stankeviciene, J., 2014. The research of reliability of bankruptcy prediction models in Lithuanian companies. Transform. Bus. Econ. 13 (2), 102–123.
Kunc, M., Mortenson, M.J., Vidgen, R., 2018. A computational literature review of the field of System Dynamics from 1974 to 2017. J. Simul. 12 (2), 115–127.
Kunsch, P.L., Springael, J., Brans, J.P., 2004. The zero-emission certificates: a novel CO2-pollution reduction instrument applied to the electricity market. Eur. J. Oper. Res. 153 (2), 386–399.
Kunsch, P., Springael, J., 2008. Simulation with system dynamics and fuzzy reasoning of a tax policy to reduce CO2 emissions in the residential sector. Eur. J. Oper. Res. 185 (3), 1285–1299. https://doi.org/10.1016/j.ejor.2006.05.048.
Kwakkel, J.H., Pruyt, E., 2015. Using system dynamics for grand challenges: the ESDMA approach. Syst. Res. Behav. Sci. 32 (3), 358–375.
Lambrecht, A., Tucker, C., 2019. Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. Manag. Sci. 65 (7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093.
Lee, K., Yan, A.H., Joshi, K., 2011. Understanding the dynamics of users' belief in software application adoption. Int. J. Inf. Manag. 31 (2), 160–170.
Liebowitz, J., 2001. Knowledge management and its link to artificial intelligence. Expert Syst. Appl. 20 (1), 1–6.
Liu, Q., 2018. Research on city electric logistics vehicle upgrade based on system dynamics. Manag. Des. Eng. 32, 67–76.
Liu, C., Mak, V., Rapoport, A., 2015. Cost-sharing in directed networks: experimental study of equilibrium choice and system dynamics. J. Oper. Manag. 39, 31–47.
Loureiro, S.M.C., Guerreiro, J., Tussyadiah, I., 2021. Artificial intelligence in business: state of the art and future research agenda. J. Bus. Res. 129, 911–926. https://doi.org/10.1016/j.jbusres.2020.11.001.
Lusch, R.F., Watts, J.K.M., 2018. Redefining the market: a treatise on exchange and shared understanding. Mark. Theory 18 (4), 435–449. https://doi.org/10.1177/1470593118777904.
Lustig, I.J., Puget, J.F., 2001. Program does not equal program: constraint programming and its relationship to mathematical programming. Interfaces 31 (6), 29–53. https://doi.org/10.1287/inte.31.7.29.9647.
Lv, H., Shi, S., Gursoy, D., 2022. A look back and a leap forward: a review and synthesis of big data and artificial intelligence literature in hospitality and tourism. J. Hosp. Mark. Manag. 31 (2), 145–175. https://doi.org/10.1080/19368623.2021.1937434.
Lyneis, J.M., 2000. System dynamics for market forecasting and structural analysis. Syst. Dyn. Rev. 16 (1), 3–25.
Maier, F.H., 1998. New product diffusion models in innovation management—a system dynamics perspective. Syst. Dyn. Rev. 14 (4), 285–308.
Maliapen, M., Dangerfield, B.C., 2010. A system dynamics-based simulation study for managing clinical governance and pathways in a hospital. J. Oper. Res. Soc. 61 (2), 255–264.
Manahov, V., Zhang, H., 2019. Forecasting financial markets using high-frequency trading data: examination with strongly typed genetic programming. Int. J. Electron. Commer. 23 (1), 12–32.
Marshakova, I.V., 1973. System of document connections based on references. In: Nauchno-Tekhnicheskaya Informatsiya Seriya 2-Informatsionnye Protsessy I Sistemy, 6, pp. 3–8.
Martínez-López, F.J., Casillas, J., 2013. Artificial intelligence-based systems applied in industrial marketing: an historical overview, current and future insights. Ind. Mark. Manag. 42 (4), 489–495.
Martino, J.P., 1980. Technological forecasting—an overview. Manag. Sci. 26 (1), 28–33.
McLean, G., Osei-Frimpong, K., Barhorst, J., 2021. Alexa, do voice assistants influence consumer brand engagement? - examining the role of AI powered voice assistants in influencing consumer brand engagement. J. Bus. Res. 124, 312–328. https://doi.org/10.1016/j.jbusres.2020.11.045.
Mendoza, J.D., Mula, J., Campuzano-Bolarin, F., 2014. Using systems dynamics to evaluate the tradeoff among supply chain aggregate production planning policies. Int. J. Oper. Prod. Manag. 34 (8), 1055–1079.
Middleton, K., Turnbull, S., 2021. How advertising got 'woke': the institutional role of advertising in the emergence of gender progressive market logics and practices. Mark. Theory 21 (4), 561–578. Article 14705931211035163. https://doi.org/10.1177/14705931211035163.
Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manag. 58 (3), 103434.
Mingers, J., White, L., 2010. A review of the recent contribution of systems thinking to operational research and management science. Eur. J. Oper. Res. 207 (3), 1147–1161. https://doi.org/10.1016/j.ejor.2009.12.019.
Morecroft, J.D., 1988. System dynamics and microworlds for policymakers. Eur. J. Oper. Res. 35 (3), 301–320.
Moxnes, E., 1990. Interfuel substitution in OECD-European electricity production. Syst. Dyn. Rev. 6 (1), 44–65.
Nag, A.K., Mitra, A., 2002. Forecasting daily foreign exchange rates using genetically optimized neural networks. J. Forecast. 21 (7), 501–511. https://doi.org/10.1002/for.838.
Nasirzadeh, F., Nojedehi, P., 2013. Dynamic modeling of labor productivity in construction projects. Int. J. Proj. Manag. 31 (6), 903–911.

Nazareth, D.L., Choi, J., 2015. A system dynamics model for information security management. Inf. Manag. 52 (1), 123–134.
Nemati, H.R., Steiger, D.M., Iyer, L.S., Herschel, R.T., 2002. Knowledge warehouse: an architectural integration of knowledge management, decision support, artificial intelligence and data warehousing. Decis. Support. Syst. 33 (2), 143–161.
Nicholson, C.F., Kaiser, H.M., 2008. Dynamic market impacts of generic dairy advertising. J. Bus. Res. 61 (11), 1125–1135.
Nikita, M., Chaney, N., 2016. Ldatuning: Tuning of the latent dirichlet allocation models parameters. R package version 0.2-0. URL. https://CRAN.R-project.org/package=ldatuning.
Noniashvili, M., Dgebuadze, M., Griffin, G., Balas, A.N., 2020. A new tech platform as an innovative teaching model in high schools in the republic of Georgia. J. East. Eur Cent. Asian Res. 7 (1), 96–104. https://doi.org/10.15549/jeecar.v7i1.386.
North, K., Kumta, G., 2018. Knowledge Management: Value Creation Through Organizational Learning. Springer.
Nyam, Y.S., Kotir, J.H., Jordaan, A., Ogundeji, A.A., 2022. Identifying behavioural patterns of coupled water-agriculture systems using system archetypes. Syst. Res. Behav. Sci. 39 (2), 305–323.
Oladimeji, O.O., Keathley-Herring, H., Cross, J.A., 2020. System dynamics applications in performance measurement research: a systematic literature review. Int. J. Product. Perform. Manag. 69 (7), 1539–1576. https://doi.org/10.1108/IJPPM-12-2018-0453.
O'Leary, D.E., 1998. Enterprise knowledge management. Computer 31 (3), 54–61.
Oliva, R., 2003. Model calibration as a testing strategy for system dynamics models. Eur. J. Oper. Res. 151 (3), 552–568.
Oliva, R., Sterman, J.D., 2001. Cutting corners and working overtime: quality erosion in the service industry. Manag. Sci. 47 (7), 894–914. https://doi.org/10.1287/mnsc.47.7.894.9807.
Ozalp, H., Ozcan, P., Dinckol, D., Zachariadis, M., Gawer, A., 2022. "Digital colonization" of highly regulated industries: an analysis of big tech platforms' entry into health care and education. Calif. Manag. Rev. 64 (4), 78–107.
Parry, K., Cohen, M., Bhattacharya, S., 2016. Rise of the machines: a critical consideration of automated leadership decision making in organizations. Group Org. Manag. 41 (5), 571–594. https://doi.org/10.1177/1059601116643442.
Patterson, D. (1990). Introduction to Artificial Intelligence and Expert Systems. Prentice-Hall, Inc.
Paucar-Caceres, A., Rodriguez-Ulloa, R., 2007. An application of soft systems dynamics methodology (SSDM). J. Oper. Res. Soc. 58 (6), 701–713.
Park, E., Chae, B., Kwon, J., 2018. Toward understanding the topical structure of hospitality literature: applying machine learning and traditional statistics. Int. J. Contemp. Hosp. Manag. 30 (11), 3386–3411.
Paschen, J., 2020. Investigating the emotional appeal of fake news using artificial intelligence and human contributions. J. Prod. Brand Manag. 29 (2), 223–233.
Perolla, H., Dey, N., 2021. Comparative study on MATLAB based joint photographic experts group image size reduction using Shearlet and wavelet packet transform for X-ray images with potential hospital data storage applications. Rev. Geintec-Gestao Inov. Tecnol. 11 (2), 1312–1323.
Pillai, R., Sivathanu, B., 2020. Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking Int. J. 27 (9), 2599–2629. https://doi.org/10.1108/bij-04-2020-0186.
Pitardi, V., Wirtz, J., Paluch, S., Kunz, W.H., 2022. Service robots, agency and embarrassing service encounters. J. Serv. Manag. 33 (2), 389–414.
Pitt, C.S., Bal, A.S., Plangger, K., 2020. New approaches to psychographic consumer segmentation: exploring fine art collectors using artificial intelligence, automated text analysis and correspondence analysis. Eur. J. Mark. 54 (2), 305–326.
Powell, J.H., Mustafee, N., 2017. Widening requirements capture with soft methods: an investigation of hybrid M&S studies in health care. J. Oper. Res. Soc. 68 (10), 1211–1222.
Prentic, C., Nguyen, M., 2020. Engaging and retaining customers with AI and employee service. J. Retail. Consum. Serv. 56, 102186 https://doi.org/10.1016/j.jretconser.2020.102186.
Prentice, C., Dominique Lopes, S., Wang, X., 2020. The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. J. Hosp. Mark. Manag. 29 (7), 739–756.
Prentice, C., Wong, I.A., Lin, Z.W., 2023. Artificial intelligence as a boundary-crossing object for employee engagement and performance. J. Retail. Consum. Serv. 73, 103376 https://doi.org/10.1016/j.jretconser.2023.103376.
Rahman, M.S., Hossain, M.A., Fattah, F.A.M.A., 2021. Does marketing analytics capability boost firms' competitive marketing performance in data-rich business environment? J. Enterp. Inf. Manag. 35 (2), 455–480.
Rahmandad, H., Repenning, N., 2016. Capability erosion dynamics. Strateg. Manag. J. 37 (4), 649–672.
Rahmandad, H., Sterman, J., 2008. Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models. Manag. Sci. 54 (5), 998–1014. https://doi.org/10.1287/mnsc.1070.0787.
Rashwan, W., Abo-Hamad, W., Arisha, A., 2015. A system dynamics view of the acute bed blockage problem in the Irish healthcare system. Eur. J. Oper. Res. 247 (1), 276–293.
Reddi, K.R., Moon, Y.B., 2011. System dynamics modeling of engineering change management in a collaborative environment. J. Adv. Manuf. Technol. 55 (9–12), 1225–1239.
Redmond, M., Baveja, A., 2002. A data-driven software tool for enabling cooperative information sharing among police departments. Eur. J. Oper. Res. 141 (3), 660–678. https://doi.org/10.1016/s0377-2217(01)00264-8 (Article Pii s0377-2217(01)00264-8).
Rezaee, M.J., Dadkhah, M., Falahinia, M., 2019. Integrating neuro-fuzzy system and evolutionary optimization algorithms for short-term power generation forecasting. Int. J. Energy Sect. Manag. 13 (4), 828–845.
Richardson, G.P., 2011. Reflections on the foundations of system dynamics. Syst. Dyn. Rev. 27 (3), 219–243.
Rodrigues, A.G., 2001. Managing and modelling project risk dynamics a system dynamics-based framework. In: Fourth European Project Management Conference, pp. 1–7. June.
Rodriguez-Ulloa, R., Paucar-Caceres, A., 2005. Soft system dynamics methodology (SSDM): combining soft systems methodology (SSM) and system dynamics (SD). Syst. Pract. Action Res. 18 (3), 303–334.
Rouwette, E.A., Größler, A., Vennix, J.A., 2004. Exploring influencing factors on rationality: a literature review of dynamic decision-making studies in system dynamics. Syst. Res. Behav. Sci. 21 (4), 351–370.
Russel, M.G., Somorodinskaya, N.V., 2018. Leveraging complexity for ecosystemic innovation. Technol. Forecast. Soc. Chang. 136, 114–131.
Sajjad, R., Yusuf, I., 2007. A SD approach on quality education class room environment of management in schools. In: Proceedings of the 2007 Conference on Systems Science, Management Science and System Dynamics: Sustainable Development and Complex Systems, vols 1-10, pp. 1713–1721.
Salman, A., Engelbrecht, A.P., Omran, M.G.H., 2007. Computing, artificial intelligence and information management - empirical analysis of self-adaptive differential evolution. Eur. J. Oper. Res. 183 (2), 785–804. https://doi.org/10.1016/j.ejor.2006.10.020.
Scherer, M.U., 2015. Regulating artificial intelligence systems: risks, challenges, competencies, and strategies. Harv. JL & Tech. 29, 353.
Schwaninger, M., 2006. System dynamics and the evolution of the systems movement. Syst. Res. Behav. Sci. 23 (5), 583–594.
Segura, M.G., Oleghe, O., Salonitis, K., 2019. Analysis of lean manufacturing strategy using system dynamics modelling of a business model. Int. J. Lean Six Sigma 11 (5), 849–877.
Sharif, M.N., Kabir, C., 1976. System dynamics modeling for forecasting multilevel technological substitution. Technol. Forecast. Soc. Chang. 9 (1–2), 89–112.
Shrestha, Y.R., Ben-Menahem, S.M., Von Krogh, G., 2019. Organizational decision-making structures in the age of artificial intelligence. Calif. Manag. Rev. 61 (4), 66–83.
Shrestha, Y.R., Krishna, V., von Krogh, G., 2021. Augmenting organizational decision-making with deep learning algorithms: principles, promises, and challenges. J. Bus. Res. 123, 588–603.
Simkova, N., Smutny, Z., 2021. Business E-NeGotiAtion: a method using a genetic algorithm for online dispute resolution in B2B relationships. J. Theor. Appl. Electron. Commer. Res. 16 (5), 1186–1216. https://doi.org/10.3390/jtaer16050067.
Simon, H.A., 1955. A behavioral model of rational choice. Q. J. Econ. 69 (1), 99–118.
Smith, G., 2020. Data mining fool's gold. J. Inf. Technol. 35 (3), 182–194.
Srinivasan, N., Dey, N., 2021. Comparative study on MATLAB based JPEG image size reduction using discrete cosine transform and Shearlet transform for mammogram images with potential hospital data storage applications. Rev. Geintec-Gestao Inov. Tecnol. 11 (2), 1526–1536.
Stancu, M.S., Duțescu, A., 2021. The impact of the Artificial Intelligence on the accounting profession, a literature's assessment. In: Proceedings of the International Conference on Business Excellence, 15, No. 1, pp. 749–758.
Sterman, J., Oliva, R., Linderman, K.W., Bendoly, E., 2015. System dynamics perspectives and modeling opportunities for research in operations management. J. Oper. Manag. 39 (40), 1–5.
Sundaresan, S., Zhang, Z., 2022. AI-enabled knowledge sharing and learning: redesigning roles and processes. Int. J. Organ. Anal. 30 (4), 983–999.
Suryani, E., Hendrawan, R.A., Adipraja, P.F.E., Wibisono, A., Dewi, L.P., 2021. Urban mobility modeling to reduce traffic congestion in Surabaya: a system dynamics framework. J. Model. Manag. 16 (1), 37–69.
Swaminathan, J.M., Smith, S.F., Sadeh, N.M., 1998. Modeling supply chain dynamics: a multiagent approach. Decis. Sci. 29 (3), 607–632. https://doi.org/10.1111/j.1540-5915.1998.tb01356.x.
Talafidaryani, M., 2021. A text mining-based review of the literature on dynamic capabilities perspective in information systems research. Manag. Res. Rev. 44 (2), 236–267.
Tam, K.Y., 1992. Genetic algorithms, function optimization, and facility layout design. Eur. J. Oper. Res. 63 (2), 322–346.
Tigabu, A.D., Berkhout, F., van Beukering, P., 2015. The diffusion of a renewable energy technology and innovation system functioning: comparing bio-digestion in Kenya and Rwanda. Technol. Forecast. Soc. Chang. 90, 331–345.
Tiwana, A., Konsynski, B., Bush, A.A., 2010. Platform evolution: coevolution of platform architecture, governance, and environmental dynamics (research commentary). Inf. Syst. Res. 21 (4), 675–687.
Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., Fischl, M., 2021. Artificial intelligence in supply chain management: a systematic literature review. J. Bus. Res. 122, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009.
Townshend, J.R.P., Turner, H.S., 2000. Analysing the effectiveness of Chlamydia screening. J. Oper. Res. Soc. 51 (7), 812–824.
van de Poel, I., 2020. Embedding values in artificial intelligence (AI) systems. Mind. Mach. 30 (3), 385–409.
van Eck, N.J., Waltman, L., 2010. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics 84 (2), 523–538. https://doi.org/10.1007/s11192-009-0146-3.
Van Eck, N.J., Waltman, L., 2011. Text Mining and Visualization Using VOSviewer arXiv preprint arXiv:1109.2058.

Van Eck, N.J., Waltman, L., 2017. Citation-based clustering of publications using CitNetExplorer and VOSviewer. Scientometrics 111 (2), 1053–1070.
van Oorschot, K.E., Sengupta, K., Van Wassenhove, L.N., 2018. Under pressure: the effects of iteration lengths on agile software development performance. Proj. Manag. J. 49 (6), 78–102.
Vennix, J.A., 1999. Group model-building: tackling messy problems. Syst. Dyn. Rev. 15 (4), 379–401.
Vennix, J.A., Gubbels, J.W., 1992. Knowledge elicitation in conceptual model building: a case study in modeling a regional Dutch health care system. Eur. J. Oper. Res. 59 (1), 85–101.
Vennix, J.A., Gubbels, J.W., Post, D., Poppen, H.J., 1990. A structured approach to knowledge elicitation in conceptual model building. Syst. Dyn. Rev. 6 (2), 194–208.
Vennix, J.A., Andersen, D.F., Richardson, G.P., Rohrbaugh, J., 1992. Model-building for group decision support: issues and alternatives in knowledge elicitation. Eur. J. Oper. Res. 59 (1), 28–41.
Wang, C., Ding, X., 2009. Analysis on the impact of reverse logistics on the dynamic behaviors in a two-stage supply chain. In: 2009 International Conference on Management of e-Commerce and e-Government. IEEE, pp. 339–342. September.
Westermann, A., Forthmann, J., 2021. Social listening: a potential game changer in reputation management how big data analysis can contribute to understanding stakeholders' views on organisations. Corp. Commun. Int. J. 26 (1), 2–22.
Wiart, L., Ozcaglar-Toulouse, N., Shaw, D., 2022. Maintaining market legitimacy: a discursive-hegemonic perspective on meat. J. Bus. Res. 144, 391–402. https://doi.org/10.1016/j.jbusres.2022.02.024.
Wien, A.H., Peluso, A.M., 2021. Influence of human versus AI recommenders: the roles of product type and cognitive processes. J. Bus. Res. 137, 13–27. https://doi.org/10.1016/j.jbusres.2021.08.016.
Williams, T., Eden, C., Ackermann, F., Tait, A., 1995. The effects of design changes and delays on project costs. J. Oper. Res. Soc. 46 (7), 809–818.
Winz, I., Brierley, G., Trowsdale, S., 2009. The use of system dynamics simulation in water resources management. Water Resour. Manag. 23, 1301–1323.
Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S., Martins, A., 2018. Brave new world: service robots in the frontline. J. Serv. Manag. 29 (5), 907–931.
Wirth, N., 2018. Hello marketing, what can artificial intelligence help you with? Int. J. Mark. Res. 60 (5), 435–438. https://doi.org/10.1177/1470785318776841.
Xia, M., Stallaert, J., Whinston, A.B., 2005. Solving the combinatorial double auction problem. Eur. J. Oper. Res. 164 (1), 239–251. https://doi.org/10.1016/j.ejor.2003.11.018.
Xu, J.J., Babaian, T., 2021. Artificial intelligence in business curriculum: the pedagogy and learning outcomes. Int. J. Manag. Educ. 19 (3) https://doi.org/10.1016/j.ijme.2021.100550.
Xue, C.G., Liu, J.J., Cao, H.W., 2013. Research on competition diffusion of the multiple-advanced manufacturing mode in a cluster environment. J. Oper. Res. Soc. 64 (6), 864–872.
Yang, Y., Liu, Y., Lv, X., Ai, J., Li, Y., 2022. Anthropomorphism and customers' willingness to use artificial intelligence service agents. J. Hosp. Mark. Manag. 31 (1), 1–23.
Zaim, S., Bayyurt, N., Tarim, M., Zaim, H., Guc, Y., 2013. System dynamics modeling of a knowledge management process: a case study in Turkish Airlines. Procedia Soc. Behav. Sci. 99, 545–552.
Zhang, G.Q., Hu, M.Y., Patuwo, B.E., Indro, D.C., 1999. Artificial neural networks in bankruptcy prediction: general framework and cross-validation analysis. Eur. J. Oper. Res. 116 (1), 16–32. https://doi.org/10.1016/s0377-2217(98)00051-4.
Zhang, X., Geltner, D., de Neufville, R., 2018. System dynamics modeling of Chinese urban housing markets for pedagogical and policy analysis purposes. J. Real Estate Financ. Econ. 57 (3), 476–501.
Zhang, L.X., Pentina, I., Fan, Y.H., 2021. Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. J. Serv. Mark. 35 (5), 628–640. https://doi.org/10.1108/jsm-05-2020-0162.
Zhou, L., Wang, M., Vancouver, J.B., 2019. A formal model of leadership goal striving: development of core process mechanisms and extensions to action team context. J. Appl. Psychol. 104 (3), 388–410. https://doi.org/10.1037/apl0000370.
Zhao, W., Chen, J.J., Perkins, R., et al., 2015. A heuristic approach to determine an appropriate number of topics in topic modeling. BMC Bioinformatics 16 (Suppl. 13), S8. https://doi.org/10.1186/1471-2105-16-S13-S8.
Zhao, J., Wu, G., Xi, X., Na, Q., Liu, W., 2018. How collaborative innovation system in a knowledge-intensive competitive alliance evolves? An empirical study on China, Korea and Germany. Technol. Forecast. Soc. Chang. 137, 128–146.

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