Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-024-03003-7 OPEN

AI technologies affording the orchestration of ecosystem-based business models: the moderating role of AI knowledge spillover

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Due to the extraordinary capacity of artificial intelligence (AI) to process rich information from various sources, an increasing number of enterprises are using AI for the development of ecosystem-based business models (EBMs) that require better orchestration of multiple stakeholders for a dynamic, sustainable balance among people, plant, and profit. However, given the nascency of relevant issues, there exists scarce empirical evidence. To fill this gap, this research follows the affordance perspective, considering AI technology as an object and the EBM as a use context, thereby exploring how and whether AI technologies afford the orchestration of EBMs. Based on data from Chinese A-share listed companies between the period from 2014 to 2021, our findings show an inverted U-shape quadratic relationship between AI and EBM, moderated by knowledge spillover. Our results enhance the understanding of the role of AI in configuring EBMs, thus providing novel insights into the mechanisms between AI and a specific business practice with societal concerns (i.e., EBM).

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Introduction

Artificial Intelligence as the core of the fourth industrial revolution (Anshari and Almunawar 2022; Glikson and Woolley 2020) characterizes a competent and probably the most influential technology in the modern era, which leverages cutting-edge analytical and logic-based approaches like machine learning and deep learning to simulate human intelligence (HI) for comprehending events, making decisions, and performing actions (Guo and Polak 2023; Gartner 2023). As an anthropomorphized system with human-like reasoning, AI has profoundly transformed orthodox business into far more complex, digital-enabled forms involving an amalgamation of big data and advanced digital infrastructures (Ioana and Venturini 2023; Patrick and Gupta 2021). Firms increasingly rely on AI and try to identify new business models around it (Wellers et al. 2017), showing prospects appear promising. According to Pricewaterhouse Coopers (PWC 2017), approximately forty-five percent of work processes can be automated, potentially resulting in annual workforce cost savings of up to two trillion dollars. However, despite the increasing adoption of AI by enterprises across various business practices, scholars have called for more empirical investigations on the role of AI in the realms of business models (BMs) because AI algorithms posit the decision-making of all agents as perfectly rather than boundedly rational- which differs from the traditional value-creating assumptions of doing business based on bounded rationality (Drucker 1954). To fill this gap, this article aims to address the mechanisms of AI technology in orchestrating modern types of BMs.

To achieve the United Nations (UN) sustainable development goals (SGDs), it has become a key priority for global enterprises to orchestrate an ecosystem-based business model (EBM) which refers to a more innovative, eco-friendly open system where a large number of stakeholders from the main EBM and other nested BMs act like species of a biological circle with a shared future/destiny to perform different roles under the triple bottom line – Profit, People, Planet (Konietzko et al. 2020; Tsujimoto et al. 2018). Therefore, the value logic of EBMs differs from that of traditional BMs focusing mainly on economic returns. Although evidence has indicated that disruptive technologies like mobile and blockchains can facilitate the formulation of EBMs (Chin et al. 2022; Nambisan et al. 2019), hitherto limited research has addressed the link between AI technology and EBMs, which appear mostly in the practical operation of enterprises, such as the collaboration between Google and the Android ecosystem (Ghose and Han, 2014; Hatcher et al. 2016). As a globally renowned technology company, Google has established an extensive ecosystem centered around the Android operating system and collaborated with numerous partners to offer applications, hardware devices, and services. Leveraging artificial intelligence algorithms, Google analyzes user behavior data to deliver personalized search results, advertisements, and recommendations (Kietzmann et al. 2018). Additionally, Google actively encourages developers to utilize artificial intelligence technology through an open application programming interface (API) to create captivating and practical applications that further enhance the ecosystem's content diversity (Perrotta et al. 2021). This collaborative model facilitates data and resource sharing between Google and its partners, thereby fostering sustainable development across the entire ecosystem. Therefore, as a technology foundation, AI technology can support and promote the construction of EBM, which inspires us to focus here on AI research in the context of EBM.

While the most prominent feature of EBMs lies in their higher levels of platformization and stakeholder diversity than traditional business models (Chin et al. 2022), the orchestrating processes of EBMs often involve various complex sets of actors, which need to be afforded by proper technological tools and infrastructures. The affordance perspective coined by Norman (1999) explains the mechanisms of an object to underpin the possible opportunities/actions of specific actors for a desired set of goals. Simply stated, the notion of affordance implies "an action potential linked with an object that entails a specific user context" (Majchrzak and Markus 2013). Following this logic, AI technology can be positioned as the object, participating stakeholders of an EBM as the specific user context, and effective orchestration of an EBM as the desired objective.

Combining the arguments above, it seems appropriate to adopt the affordance view as the theoretical rationale for this current research. Further, the affordance offered by advanced technologies requires the building of a sufficient knowledge base, while the literature has also indicated the vital importance of AI knowledge spillovers to the effectiveness of EBMs (Nonnis et al. 2022; Cetindamar et al. 2020; Autio et al. 2018). Echoing this line of thought, we thus frame our research questions as follows:

1. How and whether AI technologies afford the orchestration of EBMs?
2. How do knowledge spillovers affect the relationships between AI and EBM?

The main contribution of this study is to provide empirical findings addressing the critical impact of AI on the orchestration of EBMs, which enriches the literature on the intersection between AI and business practice. Practically, we offer valuable implications for organizations and entrepreneurs to reevaluate the affordances offered by AI technology in establishing digital infrastructures for operating EBMs.

Theoretical foundation

AI and BMs. AI is commonly defined as "the activity of developing machines with the ability to perform tasks that would normally require human intelligence, and intelligence refers to the quality that enables an entity to function appropriately and with foresight in its environment" (Nilsson, 2009). Researchers have also noted that AI is connected to changes in business models (Madanaguli et al. 2024; Burstrom et al. 2021). The business model, according to Teece (2010), refers to the design or architecture of mechanisms for creating, delivering, and capturing value within a firm (Clauss, 2017). Within the context of business, AI is a technology that can be integrated into various products and systems, offering valuable services to customers at different stages in the value chain (Teece 2018).

With extraordinary abilities to process vast amounts of data, AI inarguably has been a point to ponder in designing and operating BMs. Numerous researchers have diverted their attention towards exploring relevant issues from different perspectives, such as organizational AI adoption (Johnk et al. 2021), AI startup BMs (Weber et al. 2022; Kulkov 2023), AI business model innovation (Sjodin et al. 2021; Burstrom et al. 2021) and role of AI business model in sustainable development (Vaio et al. 2020).

One of the most popular topics is to address how AI drives BM innovation. For instance, a study identified technological, social, and economic reasons as the vital antecedents behind adopting AI to innovate (Mariani et al. 2023). BM innovation was detected as one of the critical reasons behind AI integration. AI can outperform orthodox BMs in diverse aspects such as controllability, Internet of Things (IoT), predictive maintenance control, and computational efficiency (Ahmad et al. 2023). Plentiful sectors such as agriculture (Cavazza et al. 2023a, 2023b), health care (Garbuio and Lin 2018; Kulkov, 2023), manufacturing (Garrel and Jahn, 2022), and sustainable energy (Ahmad et al. 2023) have adapted AI to develop sustainable BMs or conduct strategic BM innovation.

Within the realm of technological transformation, BMs need significant alteration through value creation and value capture to fully capitalize on and commercialize disruptive technologies (Astrom et al. 2022; Kulkov 2023). Shreds of evidence indicate the proliferation of AI as a crucial antecedent behind radical changes in corporate BMs, which is being studied in four sub-streams i.e., 1) AI impact BMs, 2) AI-based BMs, 3) AI, BMs, and innovation ecosystems, and 4) IoT and BMs (Bahoo et al. 2023). Scholars suggested that BM innovation and ecosystem innovation may work parallelly, thereby proving their strong association (Burstrom et al. 2021). Moreover, the emergence of generative AI services like ChatGPT, Jasper, or Dall-E is considered a breakthrough that provides businesses with a deeper understanding of an efficient business model innovation (Kanbach et al. 2023).

A large number of studies indicates that BMs can deliberately transform with the integration of AI and enhance their characteristics; nevertheless, several studies have also highlighted the limitations of AI pertinent to trustworthiness, reliability, fairness, and accessibility as critical adoption barriers in BM innovation (Gerlach et al. 2022). In addition, too often people and organizations have over expectations towards AI readiness and AI adaptability. At the same time, algorithm aversion and other prejudices about high energy, cost, and time prevent AI-enabled BM innovation from reaching maturity (Patrick and Gupta 2021). A 2019 global executive study in MIT Sloan Management Review depicts that 7 out of 10 companies have had minimal or no benefits from AI adoption (Ransbotham et al. 2019).

In short, despite superior advantages, a strong productivity paradox exists in adopting AI for organizational decision-making (Brynjolfsson et al. 2017). Moreover, previous studies encountered a lower pervasiveness of AI induction as claimed, and found that only a few firms successfully exploit AI tools (Jacobides et al. 2021; Vannuccini and Prytkova 2021; Righi et al. 2020). In this vein, although a burgeoning number of studies have investigated the various mechanisms of AI on BMs, a more comprehensive explanation is still required to reveal more profound insights into the role of AI in different types of BMs (Gerlach et al. 2022).

EBs, EBMs, and AI. The use of digital technologies such as AI has transformed traditional business models into a more innovative, digitalized, yet sophisticated platform architecture (Kohtamäki et al. 2022), where more transparency and openness are required by joint innovation across multiple parties synchronously by complex transactions across organizational boundaries (Sternberg et al. 2021). It thus pushes business model studies closer to the new territory of the ecosystem-based business model (EBM). The business ecosystem is an organic, dynamic, and eco-friendly open system where a multitude of stakeholders from various BMs act as species in a biological ecosystem, performing distinct roles and sharing their fates under the triple-bottom-line framework of profit, people, and planet. (Chin et al. 2023; Konietzko et al. 2020; Laczko et al. 2019). Compared to conventional business models, EBMs exhibit a higher degree of platformization and stakeholder diversity (Nambisan et al. 2019a).

The concept of EBM is derived from the term "ecosystem" (Moore 1993), which denotes a biological system encompassing all organisms present in a specific environment and their interactions with both the environment and each other (Tsujimoto et al. 2018). The EBM, an offshoot of BM research, is characterized by a digital-driven (e.g. AI, blockchain) system with blurred organizational boundaries and intricate network structures, where a large number of stakeholders coordinate under the leadership of the focal firm to deliver value to customers and achieve economic profits collectively while taking collective responsibility for environmental stewardship and social concerns (Chin et al. 2023). During AI development, such collaboration requires data flow between stakeholders in the ecosystem. Hence, it is important to study the linkages between AI, business models, and ecosystems. Previous research has primarily focused on the overall impact of AI on work processes (Duan et al. 2019; Mikalef and Gupta 2021), providing limited insights into the intricate mechanisms underlying business-model collaboration and the profound transformations within ecosystems. To fill this gap, this article addresses the mechanisms of AI technology in EBMs, which orchestrates modern types of BMs.

The affordance perspective. Norman (1999) narrated affordances with the relationship of actors and objects underpinned by the desired set of objectives. The notion of affordance critically examines, "To what extent can a person or an organization use a technology to accomplish a specific goal?" (Majchrzak and Markus 2013, p83). Simply stated, affordance is defined as action potential (possibilities or opportunities for taking this action) offered by an object (Nambisan et al. 2019) embodies the relationships or interactions between this object (e.g., advanced technology with specific features) and an actor (e.g., individual, firm or other use context with particular goals). For instance, high-speed railway technology can afford the coordination of geographically dispersed suppliers and distributors.

Subsequent studies revamped the affordance concept in the context of innovations and entrepreneurship (Nambisan et al. 2019a; Autio et al. 2018), constituting more varieties of affordances pertinent to different scenarios such as digital affordance and spatial affordance (Autio et al. 2018). Following the above logic, this article thus positions AI technology as a distinctive form of digital affordance that may trigger significant relationships between firms and the development of EBMs for achieving UN goals.

Hypotheses development

Impact of AI on EBM. Studies have addressed the importance of AI in different types of unconventional business ecosystems, such as industrial ecosystems (Burstrom et al. 2021), and entrepreneurial ecosystems (Autio et al. 2018; Cetindamar et al. 2020). However, the findings from past literature were insufficient to solve the paradox between AI and EBMs. EBM is a term used to describe an organic, dynamic, and eco-friendly open system in which a large number of stakeholders from the primary EBM and other related nested BMs behave like various species in a biological circle, playing diverse roles and participating in the outcomes (Konietzko et al. 2020; Laczko et al. 2019). Integrating AI tools such as mobiles and the internet has facilitated businesses to indulge stakeholders in decision-making by connecting them through technology-embedded communication platforms, thus forming eco-friendly and sustainable systems. EBMs comparatively consist of higher platformization and stakeholder diversity than orthodox BMs (Nambisan et al. 2019; Chin et al. 2022), creating high transparency and bearing an ability to maximize knowledge diffusion among all members. Some cutting-edge AI technologies, such as blockchain, are vital in forming safe and efficient ecosystems, confirming strong value creation and stakeholder diversity (Chin et al. 2022).

Despite the massive adoption of AI in the real world, its disruptive role in forming efficient EBMs is still in its infancy; the prejudices pertinent to high energy, cost, and time are obstructing such innovations from reaching a maturity level (Patrick and Gupta 2021). From the affordance perspective, the aforementioned limitations of AI to form an EBM can be overcome by exploiting the digital affordances connected with EBMs (Autio et al. 2018). Ecosystems bear a distinctive type of cluster that effectively harnesses technological affordances formed through digital technologies and infrastructures known as digital affordances (Autio et al. 2018; Nambisan et al. 2019a). Moreover, strong value creation among stakeholders is required to orchestrate AI-integrated EBMs effectively (Chin et al. 2022), which motivates all its incumbent actors to be involved in technical knowledge exploitation and resource utilization pertinent to digital technologies and infrastructure, thereby amid a more mature and upgraded ecosystem (Autio et al. 2018).

Drawing on the affordance perspective, the study posits that AI-integrated EBMs are linked with several digital affordances pertinent to technology and its infrastructure, with substantial knowledge diffusion and resource utilization, companies start embracing digital affordances effectively, thus conducting an advanced AI-integrated EBM. However, these are somehow complex, resource-intensive, and time-consuming, thus creating hurdles for businesses in beginning to orchestrate the process of value creation, delivery, and capture among EBM stakeholders. Following this logic, we assume a quadratic relation between AI and EBMs.

H1: The relationship between AI and EBMs is quadratic (inverted U-shaped).

Paradox of AI and knowledge spillover (Direct & indirect) in orchestrating EBMs. A plethora of studies have shed light on solving the paradoxical nature of knowledge spillovers and AI (Colombelli et al. 2023: Saviano et al. 2023; Ioana and Venturini 2023), in orchestrating effective ecosystems (Autio et al. 2018; Cetindamar et al. 2020, Burstrom et al. 2021), in which a group of interdependent actors within a specific region shares knowledge to perform various entrepreneurial activities (Cetindamar et al. 2020). A range of scholars has investigated the knowledge bases for successfully adopting AI technology, which has an extraordinary capacity to transform diverse aspects of daily life (Cetindamar et al. 2020; Nonnis 2022). Knowledge is considerably studied as a vital antecedent to economic growth and productivity in the past (Arrow 1962; Machlup 1962) and afterward included in endogenous growth models, which redefine growth in terms of endogenous factors, including knowledge, innovation, and human capital (Nonnis, 2022). Moreover, knowledge spillovers through endogenous sources facilitate entrepreneurs to identify and exploit new opportunities effectively (Acs et al. 2009), thus enhancing business productivity (Nonnis 2022; Serrano-Domingo and Cabrer-Borrás 2017). Hitherto, studies have enacted the beneficial aspects of knowledge spillovers (Nonnis 2022; Audretsch and Keilbach 2007; Feldman and Audretsch 1999). However, scarce evidence is available on the exploratory role of technological knowledge and its spillovers pertinent to digital technology and its infrastructure among stakeholders within EBMs (Cetindamar et al. 2020). Most firms generate or obtain knowledge internally or externally through spillovers, which is termed knowledge diffusion (Chen and Hicks 2004). A study categorized knowledge spillover into direct and indirect based on the source from where they are generated, thereby impacting the firm's productivity (Serrano-Domingo and Cabrer-Borrás 2017). Thus, we identify the knowledge spillovers created internally by organizations as direct spillovers, such as the exploitation of knowledge among stakeholders through R&D; contrarily, the knowledge spillover made through external sources is termed indirect spillovers, such as knowledge diffusion among stakeholders through external patents or publications.

Drawing on the affordance perspective, we assume that digital affordances pertinent to AI-integrated EBMs can be effectively exploited through direct and indirect knowledge spillovers generated among all incumbent actors of EBM. Thus, by encapsulating the above convictions, we argue that the key to an effective EBM is the utilization of AI technologies with the fierce intervention of direct and indirect knowledge spillovers that facilitate stakeholders to understand and utilize the digital technology and its infrastructure i.e., digital affordances, to effectively orchestrate AI integrated EBMs. Hence, we further hypothesize the following.

H2a: The relationship between AI and EBMs is moderated by direct knowledge spillover

H2b: The relation between AI and EBMs is moderated by indirect knowledge spillover

Figure 1 depicts the relationships hypothesized in the study.

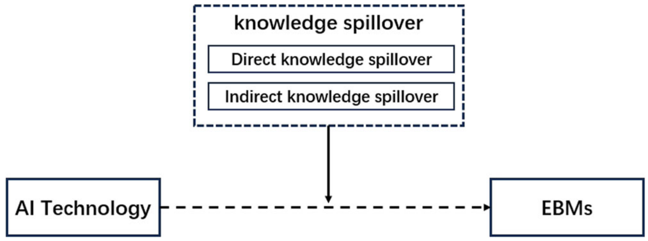

Fig. 1 The relationships among the variables. Artificial intelligence is the independent variable, ecosystem-based business model is the dependent variable, and knowledge spillover (Direct & Indirect) are moderating variables.

Methodology

Data collection and sample. To test the proposed hypotheses, we collected an initial sample of A-share listed firms in the Shanghai and Shenzhen Stock Exchange from 2014 to 2021. Artificial intelligence probably began to be gradually disclosed in China's corporate annual reports in 2014, signifying AI's rapid emergence. Therefore, we initialized 2014 as the starting year of our study. After obtaining the initial database, we applied specific criteria to filter out irrelevant firms as follows. Firstly, we excluded firms with special treatment, labeled as ST or *ST[1] in our obtained data. Secondly, we removed firms that were marked as suspended or terminated. Thirdly, we deleted firms whose annual reports did not contain the data required for our research framework. Finally, a total of 3632 pieces of yearly data with complete information were obtained from 454 companies in the years from 2014 to 2021.

We utilized the China Stock Market and Accounting Research (CSMAR) database to obtain crucial information such as financial performance and supply chain data. We used the dataset of corporation social responsibility (CSR) from Hexun Score (HXS) to measure part of the ecosystem-based business model. The Hexun Score is a commonly used dataset in China that provides an intuitive understanding of the performance of each company with its various stakeholders, in line with our measurement of an ecosystem-based business model.

Measurement

Dependent variable: EBM. EBM is generated by the entropy method of calculating four indicators in the CSR data of the Hexun Score and nine financial indicators of the company. The innovation of BM is mainly measured from three dimensions value creation, value delivery, and value acquisition (Clauss, 2017; Teece 2010). Value creation refers to a series of business activities and the cost structure of the enterprise to produce and supply products or services to meet the needs of target customers, including the core competencies of daily operations, capital situation, and other internal elements, which mainly include the ability to utilize funds and the ability to pay off debts. Hence, the current ratio (X_1), the debt coverage ratio (X_2), and the capitalization ratio (X_3) are selected to measure value creation. Value delivery dimension refers to the way and means by which consumers receive products or services, and how to establish sustainable long-term consumption relationships with consumers, where operational capability is the key element, so inventory turnover ratio (X_4), receivables turnover ratio (X_5), and total asset turnover ratio (X_6) are selected to measure value delivery. Value capture refers to the way a company controls and reduces costs to create more profit points and profitability. Profitability and growth ability are key factors thus the increasing rate of main business revenue (X_7), net profit growth rate (X_8), and main business profit margin (x_9) are selected to measure value acquisition.

The above measurements are extended by combining the definitions of EBM, which refers to an organic, dynamic, and environmentally friendly open system in which a large number of stakeholders from the main focal firm and other related nested business models play different roles and share their outcomes such as species in a system (Chin et al. 2022; Konietzko et al. 2020). According to this logic and based on the measurement of basic BM, this study extended measures EBM in three other dimensions – profit, people, and the planet. The CSR scored by the Hexun Score is assessed in terms of four indicators: shareholders' responsibility, employees' responsibility, suppliers', customers' and consumers' rights and interests' responsibility, and environmental responsibility with the first three ($X_{10}X_{11}X_{12}$) reflecting the people dimension, and the fourth one (X_{13}) reflecting the planet dimension. Another dimension of EBM is profit, and the measurement of value capture mentioned above is actually from the perspective of economic efficiency. Summarily, our study utilizes these 13 indicators and applies the entropy method to calculate a new value to comprehensively measure EBM from the perspectives of basic BM, economic benefits, stakeholders, and earth responsibilities.

The entropy method is a scientific and objective way of determining weight judgments based on the amount of information contained in the data. The greater the dispersion of the data, the greater the impact of the indicator on the overall evaluation. The following are the main steps of this method:

(1) Standardize the collected data. Since different indicators have different scales and units, they need to be standardized, and we choose the min-max method to standardize the raw data. In Eqs. (1) and (2), $\min X_{tij}$ and $\max X_{tij}$ are the minimum and maximum observed values, X_{tij} is the value of the indicator j in the t year of the company i and Z_{tij} is the standardized result with the range of values 0 to 1.
Positive indicator standardization:

$$Z_{tij} = \frac{X_{tij} - \min X_{tij}}{\max X_{tij} - \min X_{tij}} \tag{1}$$

Negative indicator standardization

$$Z_{tij} = \frac{\max X_{tij} - X_{tij}}{\max X_{tij} - \min X_{tij}} \tag{2}$$

(2) Calculate the entropy value of the collected data. The entropy value of the data can be calculated by equations. In Eqs. (3), (4), and (5), P_{tij} is the percentage of standardized data Z_{tij}, and E_j is the entropy value of indicator j.

$$P_{tij} = \frac{Z_{tij}}{\sum_{t=1}^{m}\sum_{i=1}^{k} Z_{tij}} (\mathrm{t} = 1, 2, \cdots \mathrm{m}; \mathrm{i} = 1, 2, \cdots \mathrm{k}) \tag{3}$$

$$k_1 = \frac{1}{Ln(m \times k)} \tag{4}$$

$$E_j = -k_1 \sum_{t=1}^{m}\sum_{i=1}^{k} P_{tij}\, LnP_{tij} \tag{5}$$

(3) Calculate the entropy weights of the collected data. After deriving the entropy value E_j of indicator j, the entropy weight of indicator j can be obtained. From Eq. (6), the indicator D_j is the utility value and the entropy weight W_j can be solved by Eq. (7).

$$D_j = 1 - E_j \tag{6}$$

$$W_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{7}$$

(4) Calculate the EBM score. Using the weighting method, the EBM score of company i in year t, i.e., EBM_{ti}, is calculated from Eq. (8).

$$EBM_{ti} = P_{tij} \times W_j \tag{8}$$

Independent variable: the degree of AI. AI, as one of the leading technologies of the enterprise, will be disclosed in the annual report with a summary and guidance, reflecting the strategic characteristics and prospects of the enterprise. Some scholars (Verhoef et al. 2021; Zhai et al. 2022) used the word frequency of "ABCD" technologies such as AI, blockchain, cloud computing, and big data to measure the degree of digital transformation. Therefore, we believe that it is feasible and scientific to measure the degree of AI from the perspective of word frequency statistics related to AI technologies in the annual report of listed enterprises. The AI data utilized comes from CSMAR, where previous researchers extracted AI-related datasets such as *Artificial Intelligence, Business Intelligence, Image Understanding, Intelligent Data Analytics, Intelligent Robotics, Machine Learning, Deep Learning, Semantic Search, Biometrics, Face Recognition, Speech Recognition, Identity Authentication, Autonomous Driving, and Natural Language Processing* from the annual reports by using the Pathon Crawler function (Wu et al. 2021). A review by experts and scholars in this relevant domain was also initiated, which approved the reliability of the measurement.

Moderating variables: direct knowledge spillover and indirect knowledge spillover

Direct knowledge spillover: We utilized R&D stock_t to examine direct knowledge spillover, as previously done by scholars Serrano-Domingo and Cabrer-Borrás (2017). Direct knowledge spillover is primarily caused by communication on specific R&D projects. The investment in cooperative innovation determines the number of projects or topics that cooperate on, the frequency of the resulting exchanges, and the direct knowledge spillover. According to Xu et al. (2023), we use the perpetual inventory method to measure the R&D stock. The specific formula is as follows:

$$R\&D\, stock_t = (1 - \delta) R\&D\, stock_{t-1} + RI_t \tag{9}$$

where R&D stock_t is the value of phase t, R&D stock_{t-1} is the R & D stock value of phase $t - 1$, RI_t is the R & D expense of phase t, δ represents R&D depreciation rate. Xu et al. (2023) estimated the profitability brought by corporate R&D and also verified the reasonableness of the estimated R&D depreciation rate of Chinese firms from 1990 to 2021 through domestic and international comparisons with the same industry as well as a robustness analysis, and the final measurements show that the R&D depreciation rate of corporates in the Chinese market is 26.37%.

Table 1 Variables and measurements.

Variable	Variable name	Variable measurement
Dependent variable	Ecosystem-based business model (EBM)	The weighted score was calculated by the entropy method using thirteen indexes.
Independent variable	The degree of AI (AI)	The word frequency of AI in the annual report.
Moderating variable	Direct knowledge spillover (DKS)	R&D stock.
	Indirect knowledge spillover (IDKS)	The proportion of management cost in total revenue, IDKS = Management cost/ revenue.
Control variables	Firm size (SIZE)	Log (total assets)
	Intangible asset ratio (IAR)	The proportion of intangible assets in total assets, iar = intangible asset/ total asset
	Supply chain concentration (SCC)	The average sum of the purchase and sales ratio of the top 5 suppliers and customers, namely: scc = (purchase ratio of the top 5 suppliers + sales ratio of the top 5 customers) /2.
	CEO age (AGE)	Age of chief executive officer.
	Overseas work experience/ education background (OBS)	Whether the CEO has overseas work experience or education background (Yes = 1; No = 0).

Therefore, we take 26.37% as the R&D depreciation rate of our research enterprises.

Indirect knowledge spillover: We use the management cost ratio in revenue to test the indirect knowledge spillover by following the footsteps provided by Singh (2005) and Serrano-Domingo and Cabrer-Borrás (2017). The company's operations play a crucial role in facilitating knowledge transfer. While communication among managers, employees, and other external organizations may not result in direct knowledge spillover, it can still have indirect effects. In other words, an invisible form of knowledge floats inside the organization and is acquired by people through better communication, thus increasing the organization's overall knowledge base.

Control variables. To ensure that an organization's EBM is not affected by other variables, we control several firm-level variables (i.e., firm size, intangible asset ratio, and supply chain concentration) and individual-level variables (i.e., CEO's age and overseas background) as shown in Table 1.

Firm size: The size of an enterprise reflects the scale of its operations and resource inputs. Larger firms usually have more human, financial, and technological capabilities, which can influence their ability to innovate their business models.

Intangible asset ratio: Intangible assets are non-material assets owned by the enterprise, such as intellectual property rights, brand value, innovation capability, goodwill, etc., which will influence the innovation capability of firms. Thus, the intangible asset ratio is used as one of the control variables.

Supply chain concentration: According to Osterwalder and Pigneur's business model canvas (2010), the formation of EBM is influenced by both customers and suppliers. Following this idea, we chose supply chain concentration as a control variable by calculating the average of the total purchase ratio for the top five suppliers and the total sales ratio for the top five sellers, as shown in formula (5).

$$Supply\ Chain\ Concentration = \frac{1}{2}\left(\frac{top\ five\ suppliers'\ purchase}{total\ purchases} + \frac{top\ five\ sellers'\ sales}{total\ sales}\right) \tag{10}$$

CEO age: CEO age was used as a control variable to assess the influence of top managers' personalities and attitudes on a company's strategic decisions. Young CEOs are likelier to adopt BM innovation than CEOs with a conventional mindset (Eugenio and Sicilia 2020).

CEO's overseas background: As mentioned, firm CEOs with overseas backgrounds may be more inclined toward adopting EBMs. Therefore, the CEO's overseas background was used as a control variable. We set it as a dummy variable stating that if the CEO has overseas work experience or educational background, the value is 1; otherwise, it is 0.

The model. Our study tests the theoretical model and hypotheses using panel data regression. Panel data contains data in both the time dimension and the firm dimension, so the heterogeneity between firms and the variation in the time dimension need to be taken into account in the analysis. The dependent variable AI in this study varies significantly in terms of firm heterogeneity and time dimension, and the use of fixed-effect regression can improve the accuracy and reliability of the analysis. We also performed Hausman's test ($\chi^2 = 147.63$, Prob > $\chi^2 = 0.0000$), and which results showed that fixed-effect regression is fit for our research.

To test hypothesis H1, the regression equation has been established as the following formula (11):

$$EBM_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 AI2_{i,t} + \alpha_3 \sum_t^i \delta \cdot Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{11}$$

In formula (11), AI is squared to generate the quadratic term AI2, which is used to test whether there is a U-shaped relationship between AI and EBM. $Controls_{i,t}$ represents the control variables. μ_i, λ_t represent firm-fixed and time-fixed effects, respectively. $\varepsilon_{i,t}$ represents the random disturbance term. *i* represents the firm, and *t* represents the year.

To test hypothesis H2a, which explores the moderating effect of direct knowledge spillover (DKS) on the relationship between the main variables, we added DKS, the interaction items AI*DKS and AI2*DKS to the regression equation. The regression equation has been established as the following formula (12):

$$EBM_{i,t} = \gamma_0 + \gamma_1 AI_{i,t} + \gamma_2 AI2_{i,t} + \gamma_3 AI_{i,t}DKS_{i,t} + \gamma_4 AI2_{i,t}DKS_{i,t} + \gamma_5 DKS_{i,t} + \gamma_6 \sum_t^i \delta \cdot Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{12}$$

To test hypothesis H2b, which examines the moderating effect of indirect knowledge spillover (IDKS) on the relationship between the main variables, we added IDKS, the interaction items AI*IDKS and AI2*IDKS to the regression equation. The regression equation has been established as the following formula (13):

$$EBM_{i,t} = \gamma_0 + \gamma_1 AI_{i,t} + \gamma_2 AI2_{i,t} + \gamma_3 AI_{i,t} IDKS_{i,t} + \gamma_4 AI2_{i,t} IDKS_{i,t} + \gamma_5 IDKS_{i,t} + \gamma_6 \sum_t^i \delta \cdot Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (13)$$

Empirical analysis and results

Descriptive statistics and correlation analysis. Table 2 displays the descriptive statistics of variables obtained from analyzing panel data in Stata 17, including mean, standard deviation, maximum, and minimum values. In the sample dataset, EBM's mean, minimum, and maximum values are 0.015, 0.003, and 0.308, respectively. Similarly, AI's mean, minimum, and maximum values are 8.93, 1, and 259, respectively. This highlights the significant gap between different companies. Moreover, the standard deviation of DKS and IDKS are 1.462 and 0.102, respectively. The minimum and maximum values of DKS are 8.344 and 24.177, while the minimum and maximum values of IDKS are −0.043 and 2.045. These results indicate that DKS and IDKS vary significantly among the sample firms.

Table 2 also displays the control variables. The data exhibits a wide range of values, as demonstrated by the mean values, standard deviations, maximum values, and minimum values of the CEO's age, CEO's overseas background, firm size, supply chain concentration, and intangible asset ratio.

Table 3 portrays the correlation coefficient matrix of variables. The results show that AI, DKS, and IDKS are related significantly to EBM with the pairwise correlation coefficients −0.029, 0.083, and 0.030. The preliminary correlation between them is supported but these correlations need further exploration through regression analysis.

Table 2 Descriptive statistics of variables.

Variables	Mean	S.D.	Min	Max
EBM	0.015	0.030	0.003	0.308
AI	8.93	18.336	1	259
DKS	18.949	1.462	8.344	24.177
IDKS	0.120	0.102	−0.043	2.045
Age	49.578	6.569	28	75
OBS	0.124	0.329	0	1
SCC	31.043	15.104	0	100
IAR	0.038	0.033	−0.058	0.278
SIZE	22.101	1.250	18.867	27.547

DKS Direct knowledge spillover, *IDKS* Indirect knowledge spillover, *Age* CEO's age, *OSB* CEO's overseas background, *IAR* Intangible assets ratio, *SCC* Supply chain concentration, *SIZE* Firm size.

In addition, we also performed a variance inflation factor (VIF) test to analyze the possibility of collinearity among variables. The largest VIF value 2.42, and the average VIF value 1.38 were found lower than 5, implying no multicollinearity among variables.

Analysis of the regression results. Our test's regression results are displayed in Table 4. Haans et al. (2015) identified three conditions necessary for an inverted U-shaped relationship. First, to ensure the validity of the model, the coefficient of the independent variable must be significantly positive, the coefficient of the quadratic term of the independent variable must be significantly negative, and the joint test for non-zero values should pass. Secondly, ensure that the curve's inflection point falls within the range of the sample data. Also, ensure that the slopes at both ends of the inverted U-curve are sufficiently steep.

Model 2 shows the regression result of AI and the ecosystem-based business model, with the coefficient −0.056 and the *P*-value < 0.1, which means that AI is significantly related to the ecosystem-based business model. Model 3 presents the results of a regression analysis that includes AI, its quadratic term, and an EBM. The coefficient of the AI term is 0.085, and for the quadratic term, it is −0.150. Both have *P*-values of less than 0.1 and 0.01, respectively. The curve's slope is positive when AI is at its lowest point, and negative when it is at its highest point. Therefore, the signs of the slope at both ends are opposite. Additionally, we did the u-test and the curve's turning point (AI = 40.53) falls within the range of the sample from 1 to 259. With the rise of AI, the ecosystem business model exhibits a pattern of initial growth followed by decline. Therefore, hypothesis H1 has been confirmed.

The following is to test the moderating effect of direct knowledge spillover and indirect knowledge spillover on the relationship between AI and EBM. To evaluate the moderating effect of the U-shaped relationship, we will use the movement of the curve's inflection point, as explained by Haans et al. (2015). We will also use the quadratic equation to determine the moderating effect as per formula (14), where Z represents the moderating variable:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 XZ + \beta_4 X^2 Z + \beta_5 Z \quad (14)$$

We derived formula (15) from (14), which shows that the moderating variable determines the inflection point.

$$X^* = \frac{-\beta_1 - \beta_3 Z}{2\beta_2 + 2\beta_4 Z} \quad (15)$$

To track the movement of the turning point for Z, we obtain the equation of X in terms of Z as formula (16). The denominator of this equation is always greater than 0. The direction in which the inflection point moves depends on the sign of the numerator. Specifically, if $\beta_1\beta_4-\beta_2\beta_3 > 0$, then the turning point moves to the

Table 3 Correlation coefficient matrix of variables.

Variables	EBM	AI	DKS	IDKS	Age	OBS	SCC	IAR	SIZE
EBM	1								
AI	−0.029*	1							
DKS	0.083***	0.193***	1						
IDKS	0.030*	0.0180	−0.175***	1					
Age	−0.031*	0.037**	0.067***	−0.081***	1				
OSB	−0.0170	0.064***	0.062***	0.047***	0.031*	1			
SCC	−0.079***	−0.043**	−0.216***	0.044***	−0.064***	0.00700	1		
IAR	0.0270	0.094***	0.120***	0.092***	0.046***	0.029*	−0.099***	1	
SIZE	0.113***	0.076***	0.729***	−0.320***	0.048***	0.042**	−0.259***	0.121***	1

t-statistics in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
DKS direct knowledge spillover, *IDKS* Indirect knowledge spillover, *Age* CEO's age, *OSB* CEO's overseas background, *IAR* Intangible assets ratio, *SCC* Supply chain concentration, *SIZE* firm size.

Table 4 Results of regression analysis.

Variables	Model 1 EBM	Model 2 EBM	Model 3 EBM	Model 4 EBM	Model 5 EBM	Model 6 EBM	Model 7 EBM
AI		−0.056* (−1.23)	0.085* (1.88)	0.087** (2.12)	0.059 (1.23)	0.083* (1.84)	0.094* (1.93)
AI2			−0.150*** (−3.26)	−0.145*** (−3.51)	−0.093 (−1.61)	−0.150*** (−3.21)	−0.154*** (−2.80)
DKS				−0.275** (−2.47)	−0.094 (−1.53)		
IDKS						−0.024 (−1.07)	−0.020 (−0.88)
DKS*AI					−0.311*** (−3.20)		
DKS*AI2					0.138** (2.38)		
IDKS*AI							0.139*** (2.67)
IDKS*AI2							−0.137** (−2.55)
age	−0.020 (−0.89)	−0.020 (−0.91)	−0.024 (−1.05)	−0.025 (−1.13)	−0.019 (−0.84)	−0.025 (−1.12)	−0.024 (−1.03)
OSB	−0.132 (−1.15)	−0.134 (−1.16)	−0.136 (−1.18)	−0.139 (−1.21)	−0.136 (−1.18)	−0.136 (−1.18)	−0.137 (−1.18)
SCC	−0.055* (−1.73)	−0.058* (−1.84)	−0.057* (−1.81)	−0.056* (−1.78)	−0.056* (−1.79)	−0.057* (−1.79)	−0.060* (−1.92)
IAR	0.025 (0.78)	0.029 (0.94)	0.024 (0.75)	0.034 (1.07)	0.028 (0.92)	0.025 (0.79)	0.028 (0.91)
SIZE	−0.185 (−1.47)	−0.186 (−1.48)	−0.184 (−1.47)	0.151 (0.94)	0.065 (0.57)	−0.183 (−1.46)	−0.171 (−1.39)
_cons	−0.028* (−1.83)	−0.021 (−1.35)	−0.030* (−1.94)	−0.009 (−0.51)	0.001 (0.08)	−0.028* (−1.87)	−0.028* (−1.85)
N	3632	3632	3632	3632	3632	3632	3632
R^2	0.319	0.320	0.324	0.330	0.342	0.324	0.328

t-statistics in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
DKS Direct knowledge spillover, *IDKS* indirect knowledge spillover, *Age* CEO's age, *OSB* CEO's overseas background, *IAR* intangible assets ratio, *SCC* Supply chain concentration, *SIZE* firm size.

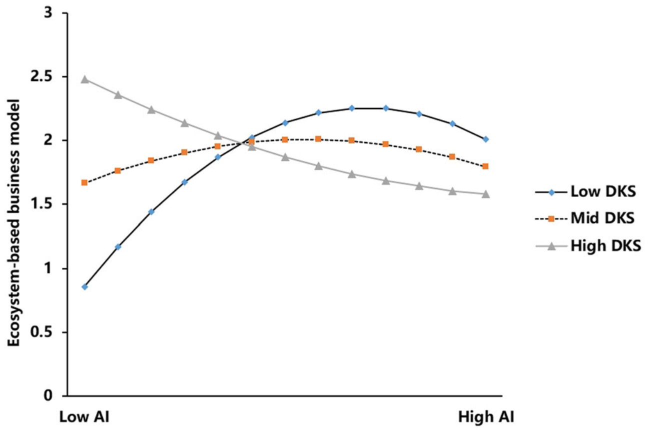

Fig. 2 Moderating effect plot. Moderating effect plot reflects the moderating effect of direct knowledge spillover on the relationship between AI and EBM.

right as Z increases. Conversely, if $\beta_1\beta_4$-$\beta_2\beta_3 < 0$, then the turning point moves to the left as Z increases.

$$\frac{dX^*}{dZ} = \frac{\beta_1\beta_4 - \beta_2\beta_3}{2(\beta_2 + \beta_4 Z)^2} \tag{16}$$

According to Model 5, direct knowledge spillover has a moderating effect. The interaction between direct knowledge spillover and AI has a coefficient of −0.311 with a *P*-value of less than 0.01. The quadratic term has a coefficient of 0.138 with a *P*-value of less than 0.05. Using the calculation of $\beta_1\beta_4$ - $\beta_2\beta_3 = -0.021$, which is less than 0, the curve's turning point shifts to the left as DKS increases, which can also be seen in Fig. 2. Additionally, as illustrated in Fig. 2, the inverted U-shaped curve is more pronounced at the Low DKS level, becomes less steep as DKS increases, and ultimately transforms into a U-shaped curve at the High DKS level. These findings suggest that DKS plays a crucial role in moderating the correlation between AI and EBM, thus providing support for H2a.

Model 7 is the moderating result of indirect knowledge spillover. The coefficient of the interaction term is 0.139 with a P value of less than 0.01, and the coefficient of the quadratic term is −0.137 with a *P*-value of less than 0.05. As per the above-mentioned, the multiplication result of $\beta_1\beta_4$ - $\beta_2\beta_3 = 0.0085$, which is more than 0. This means that the turning point of the curve will shift to the right as IDKS increases. According to the curve presented in Fig. 3, the inverted U-shaped curve remains relatively flat when IDKS is low but becomes increasingly steep as IDKS increases and reaches steepest at high IDKS levels. This demonstrates that IDKS plays a significant role in moderating the relationship between AI and EBM, confirming hypothesis H2b.

Robustness test. Concerning the possibility of a time lag in the influence of AI on EBM, we lag the EBM data by one year for robustness testing. The new results presented in Table 5 show the same coefficient sign and significance as the previous findings. Model 8 shows that the one-year lagged ecosystem-based business model increases initially with an increase in AI but then decreases as AI continues to increase, with the AI coefficient and quadratic AI coefficient 0.031 and −0.110, and quadratic AI's P-value < 0.01. The Model 9 indicates that direct knowledge spillover has a moderating effect. The interaction coefficient between direct knowledge spillover and AI is −0.422, with a P-value of less than 0.01. Additionally, the quadratic term coefficient is 0.198, with a P-value of less than 0.01. The Model 10 indicates the moderating effect of indirect knowledge spillover. According to this model, the interaction coefficient between indirect knowledge spillover and AI is 0.062, and its P-value is less than 0.1. Additionally, the quadratic term coefficient is −0.090, and its P value is also less than 0.01, thereby confirming the robustness of all the above results.

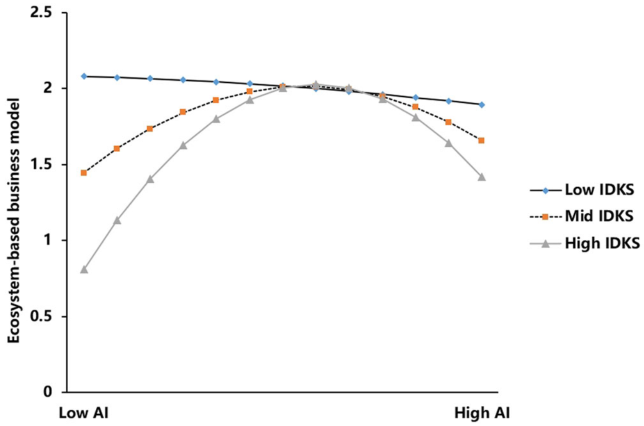

Fig. 3 Moderating effect plot. Moderating effect plot reflects the moderating effect of indirect knowledge spillover on the relationship between AI and EBM.

We also did the robustness test by reducing the sample size. Given the impact of the COVID-19 pandemic on international business, it was possible that the performance of firms could have affected the data quality and therefore the accuracy of our results. For this reason, we excluded the 2021 data and re-estimated the regression model. The new results presented in Table 5 show the same coefficient sign and significance as the previous findings. Model 11 shows that the ecosystem-based business model increases initially with an increase in AI but then decreases as AI continues to increase, with the AI coefficient and quadratic AI coefficient 0.096 and −0.169, and quadratic AI's P-value < 0.01. The Model 12 indicates that direct knowledge spillover has a moderating effect. The interaction coefficient between direct knowledge spillover and AI is −0.429, with a P-value of less than 0.01. Additionally, the quadratic term coefficient is 0.195, with a P-value of less than 0.01. The Model 13 indicates the moderating effect of indirect knowledge spillover. According to this model, the interaction coefficient between indirect knowledge spillover and AI is 0.145, and its P value is less than 0.01. Additionally, the quadratic term coefficient is −0.156, and its P-value is also less than 0.01, thereby confirming the robustness of all the above results.

Table 5 Robustness test results.

Variables	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
	EBM′	EBM′	EBM′	EBM	EBM	EBM
AI	0.031	−0.002	0.041	0.096**	0.056	0.102**
	(0.61)	(−0.04)	(0.76)	(2.09)	(1.07)	(1.99)
AI2	−0.110***	−0.053	−0.114**	−0.169***	−0.097	−0.165***
	(−2.80)	(−0.92)	(−2.29)	(−3.63)	(−1.61)	(−2.99)
DKS		0.038			−0.136**	
		(0.43)			(−2.00)	
IDKS			−0.036*			−0.026
			(−1.68)			(−1.00)
DKS*AI		−0.422***			−0.429***	
		(−3.43)			(−4.01)	
DKS*AI2		0.198***			0.195***	
		(2.89)			(3.10)	
IDKS*AI			0.062*			0.145***
			(1.72)			(2.68)
IDKS*AI2			−0.090***			−0.156***
			(−3.11)			(−2.83)
age	−0.001	0.005	−0.003	−0.025	−0.020	−0.026
	(−0.02)	(0.16)	(−0.10)	(−0.86)	(−0.70)	(−0.88)
OSB	−0.225**	−0.221**	−0.224**	−0.153	−0.148	−0.153
	(−2.11)	(−2.08)	(−2.11)	(−1.03)	(−0.99)	(−1.02)
SCC	−0.053*	−0.053*	−0.055*	−0.063*	−0.063*	−0.066*
	(−1.75)	(−1.80)	(−1.81)	(−1.73)	(−1.71)	(−1.81)
IAR	0.020	0.025	0.022	0.010	0.022	0.015
	(0.48)	(0.60)	(0.54)	(0.29)	(0.63)	(0.42)
SIZE	−0.301	−0.191	−0.293	−0.164	0.150	−0.149
	(−1.52)	(−0.94)	(−1.49)	(−1.21)	(1.31)	(−1.12)
_cons	−0.033*	−0.008	−0.030	0.020	0.057***	0.023
	(−1.72)	(−0.39)	(−1.54)	(1.02)	(3.07)	(1.21)
N	3178	3178	3178	3178	3178	3178
R^2	0.327	0.343	0.329	0.342	0.361	0.346

t-statistics in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
DKS direct knowledge spillover, *IDKS* indirect knowledge spillover, *Age* CEO's age, *OSB* CEO's overseas background, *IAR* Intangible assets ratio, *SCC* Supply chain concentration, *SIZE* Firm size.

Discussion

The study aims to investigate the notions behind the paradoxical relationship between AI and EBMs through the lens of digital affordances, leading us to postulate H1. Moreover, the study extended the arguments in H2 (a and b) within the realm of knowledge spillovers (i,e., direct and indirect) by exploring its imperative role as a moderator, facilitating to afford the orchestration of AI-integrated EBMs. The empirical results showed the sturdiest support for all developed hypotheses (i,e., H1, H2a, and H2b). A quadratic (inverted U-shaped) relationship occurs between AI and EBMs, which is moderated by direct and indirect knowledge spillovers, depicting that the effective formation of EBMs relies on accepting the digital affordances, and knowledge spillover facilitates undertaking the affordances associated with AI-integrated EBMs. Thus, the study findings are sufficient to answer both formulated research questions, i.e., How and whether AI technologies afford the orchestration of EBMs? How do AI knowledge spillovers affect the relationships between AI and EBM? Overall, the current study enriches our understanding of a new form of sustainable business model, efficiently integrated with disruptive technology through knowledge and its spillovers generated within the environment. The theoretical and practical implications are discussed below.

Theoretical contribution. First, based on the affordance paradigm, the study contributes to the BM literature, specifically pertinent to unorthodox BM setups, by examining the quadratic role of disruptive technology, such as AI, in effectively orchestrating more sustainable and advanced BMs such as EBMs. The findings narrate that, with the realization and acceptance of digital affordances associated with technologies, the incumbent actors in ecosystems can adopt cutting-edge technologies and reconstruct an established trajectory for sustainable and productive EBMs (Nambisan et al. 2019; Burstrom et al. 2023). At the early stage of EBM transformation, the cost, energy, knowledge, and time associated with technology adoption hinder its effect (Patrick and Gupta 2021); however, as soon as the digital affordances get recognized and exploited by incumbent actors, effective orchestration of EBMs occurs. Concludingly, the study provides some novel insights into forming a comprehensive understanding of technology-oriented EBM through an unorthodox paradoxical lens (Burstrom et al. 2023), thereby fostering the adoption of EBM in this contemporary era (Nambisan et al. 2019; Konietzko et al. 2020; Chin et al. 2022)

Second, we surpassed the conventional studies on EBMs, which mostly used qualitative approaches with scarce empirical evidence. By reconceptualizing the EBMs from multiple dimensions such as people, profit, and planet (Chin et al. 2022), and incorporating quantitative techniques to conduct this research, we thereby provided an enhanced understanding of AI integrated EBM concept.

Third, our study extensively contributes to knowledge management literature by providing a more sophisticated insight into the link between the use of disruptive technologies and the transformation of orthodox BMs towards EBMs by exploiting the knowledge within an ecosystem (Autio et al. 2018) through direct and indirect spillovers. The knowledge obtained facilitates all actors in EBMs to identify, understand, and accept the digital affordances associated with technology and utilize it effectively to form EBMs. Although plausible studies incorporated knowledge spillover in a similar study context, limited empirical research has configured this term separately as direct and indirect knowledge spillover, specifically in the EBM context.

Our study elaborated digital affordances through a knowledge management paradigm for the first time, suggesting direct and indirect knowledge spillovers within a platform-based nested model can enhance the understanding and capabilities of incumbent actors to tackle digital technologies and their infrastructure effectively. Thus, knowledge diffusion through spillovers should be a core aspect to consider while formulating organizational strategies (Ioana and Venturini 2023; Serrano-Domingo and Cabrer-Borrás 2017), which enables the actors of EBMs to transform it into a more profitable and sustainable BM.

Furthermore, pertinent to the UN SDGs agenda, several economies emphasized transforming and aligning business setups accordingly. EBMs contend to be more innovative and eco-friendlier and are more oriented toward people, planet, and profit, which makes them different from traditional BMs. Thus, effective orchestrations of EBMs through AI technology can significantly contribute to SDGs (Chin et al. 2022). Moreover, our findings respond to a previous call (Mariani et al. 2023) by unveiling the potential ways through which organizations with AI-integrated BMs can follow SDGs. Our study also adds to the entrepreneurship literature from the EBM context by solving the paradoxes pertinent to AI and EBM and the robust role of knowledge spillovers, thus helping entrepreneurs to identify the affordances and effectively orchestrating EBMs among all incumbent actors.

Practical Implication. First, considering the scarce empirical evidence pertinent to EBMs, our study findings bear substantial implications for practitioners, entrepreneurs, and businesses to effectively exploit AI technology in transforming EBMs.

Second, the study addressed the unique characteristics of EBMs and their effective orchestration through integrating contemporary disruptive technologies. The incumbent actors inside EBMs must understand and accept the affordances pertinent to digital technologies and their infrastructure to fully exploit their advantages. The awareness of digital affordances can help businesses and entrepreneurs effectively deal with the cost, time, and energy associated with AI adoption into EBMs.

Third, with high platformization and stakeholder diversity in EBMs, the connectivity among all actors is a challenge, especially when embracing cutting-edge technology; heterogeneous knowledge flows among everyone, making it difficult to exploit the advantages of technology within an EBM collectively. Thus, the infusion and absorption of new knowledge through direct and indirect knowledge spillovers among stakeholders to understand and accept the associated digital affordances for effective orchestration of EBMs through AI should be a core strategic tool.

Fourth, transforming EBMs effectively through modern-era technologies such as AI can facilitate businesses in aligning their strategies with SDGs to gain a competitive advantage in the market.

Conclusion

AI, as the core of the fourth industrial revolution, leverage with cutting-edge analytical and logic-based approaches such as deep learning and machine learning has stimulated orthodox businesses to transform but with some grand challenges pertinent to high cost and energy as well as the required new knowledge and its diffusion among the stakeholders. Moreover, while striving to achieve SDGs, businesses must strike a constant balance between people, profit, and the planet. Thus, the need to orchestrate innovative and eco-friendly BMs such as EBMs is in high demand in this contemporary era. Moreover, the role of disruptive technologies in transforming these EBMs calls for meaningful inquiries through an unorthodox paradoxical lens. The arguments in this study are aligned as per the affordance perspective and posit that the effective orchestration of AI-integrated EBMs depends on the acceptance of associated digital affordances, and knowledge diffusion through direct and indirect knowledge spillovers facilitates stakeholders in collectively accepting the digital affordances. Our findings enrich the studies on AI and BMs and provide substantial implications for scholars, entrepreneurs, and businesses.

Limitations and future scope. As a revolutionary technology in this contemporary era, AI bears countless opportunities for businesses to transform more innovatively and sustainably. However, due to its multifaceted and dynamic nature, several aspects of AI are still in their infancy, and literature on EBMs is also insufficient, opening bountiful opportunities for future researchers in the relevant domain. Albeit our study findings provide fruitful implications but some limitations may exist due to data deficiency, short time horizon, and limited options for measurement selection. Thus, future scholars are encouraged to invest more efforts in increasing the dataset and developing different suitable measures further to verify the reliability and validity of study findings. Furthermore, the dataset consists of national-level companies, which may create geographical boundaries for our research findings. Therefore, we suggest conducting the relevant studies globally, which may contain different companies across borders.

Data availability

Replication data for the study is available at https://doi.org/10.7910/DVN/ITV06Z.

Received: 11 November 2023; Accepted: 27 March 2024;
Published online: 08 April 2024

Note

1 ST is the abbreviation of "Special Treatment". Special treatment is carried out for the stock trading of listed companies with abnormal financial or other conditions, which is also known as ST stock. ST stock is not a punishment for listed companies, but a kind of objective revelation of the status of the listed companies, which is aimed at alerting investors of market risks and guiding investors to make rational investments. If the abnormal situation of the company is eliminated, normal trading may resume. If the company has suffered losses for three consecutive years, there may be a risk of delisting, at which time "*ST" will be added to the stock.

References

Acs ZJ, Braunerhjelm P, Audretsch DB, Carlsson B (2009) The knowledge spillover theory of entrepreneurship. Small Bus Econ 32(1):15–30. https://doi.org/10.1007/s11187-008-9157-3

Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, Chen H (2023) Artificial Intelligence in Sustainable Energy Industry: Status Quo, Challenges and Opportunities. J Clean Prod 289:125834. https://doi.org/10.1016/j.jclepro.2021.125834

Anshari M, Almunawar MN (2022) Adopting open innovation for SMEs and industrial revolution 4.0. J Sci Technol Policy 13(2):405–427. https://doi.org/10.1108/JSTPM-03-2020-0061

Arrow KJ (1962) Economic welfare and the allocation of resources for invention. In: The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton University Press

Arrow KJ (1962) Economic Welfare and the Allocation of Resources for Invention. The Rate and Direction of Inventive Activity: Economic and Social Factors, Princeton: Princeton University Press, 609–626. https://doi.org/10.1515/9781400879762-024

Astrom J, Reim W, Parida V (2022) Value creation and value capture for AI business model innovation: a three-phase process framework. Rev Manag Sci 16:2111–2133. https://doi.org/10.1007/s11846-022-00521-z

Audretsch DB, Keilbach M (2007) The Theory of Knowledge Spillover Entrepreneurship. J Manage Stud 44(7):1242–1254. https://doi.org/10.1111/j.1467-6486.2007.00722.x

Autio E, Nambisan S, Thomas LDW, Wright M (2018) Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. Strateg Entrep J 12:72–95. https://doi.org/10.1002/sej.1266

Bahoo S, Cucculelli M, Qamar D (2023) Artificial Intelligence and Corporate Innovation: A Review and Research Agenda. Technol Forecast Soc 188:122264. https://doi.org/10.1016/j.techfore.2022.122264

Brynjolfsson E, Rock D Syverson C (2017) Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. The Economics of Artificial Intelligence: an Agenda, NBER Working Paper No. 24001. http://www.nber.org/papers/w24001

Burstrom T, Parida V, Lahti T, Wincent J (2021) AI-enabled Business-model Innovation and Transformation in Industrial Ecosystems: A Framework, Model and Outline for Further Research. J Bus Res 127:85–95. https://doi.org/10.1016/j.jbusres.2021.01.016

Burstrom T, Lahti T, Parida V, Wartiovaara M, Wincent J (2023) A definition, review, and extension of global ecosystems theory: Trends, architecture and orchestration of global VCs and mechanisms behind unicorns. J Bus Res 157:113605

Cavazza A, Dal Mas F, Paoloni P, Manzo M (2023a) Artificial intelligence and new business models in agriculture: a structured literature review and future research agenda. Brit Food J 125(13):436–461. https://doi.org/10.1108/BFJ-02-2023-0132

Cavazza A, Dal Mas F, Campra M, Brescia V (2023b) Artificial intelligence and new business models in agriculture: the "ZERO" case study. Manage Decis Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/MD-06-2023-0980

Cetindamar D, Lammers T, Zhang Y (2020) Exploring the Knowledge Spillovers of a Technology in an Entrepreneurial Ecosystem—The Case of Artificial Intelligence in Sydney. Thunderbird Int Bus 62(5):457–474. https://doi.org/10.1002/tie.22158

Chen C, Hicks D (2004) Tracing knowledge diffusion. Scientometrics 59(2):199–211. https://doi.org/10.1023/B:SCIE.0000018528.59913.48

Chin T, Jin J, Wang S, Caputo F, Rowley C (2023) Cross-cultural legitimacy for orchestrating ecosystem-based business models in China: a Yin-Yang dialectical systems view. Asia Pac Bus Rev 1–24. https://doi.org/10.1080/13602381.2023.2290263

Chin T, Shi Y, Singh SK, Agbanyo GK, Ferraris A (2022) Leveraging Blockchain Technology for Green Innovation in Ecosystem-based Business Models: A Dynamic Capability of Values Appropriation. Technol Forecast Soc 183:121908. https://doi.org/10.1016/j.techfore.2022.121908

Clauss T (2017) Measuring business model innovation: conceptualization, scale development, and proof of performance. R&D Manage 47(3):385–403. https://doi.org/10.1111/radm.12186

Colombelli A, D'Amico E, Paolucci E (2023) When computer science is not enough: universities knowledge specializations behind artificial intelligence startups in Italy. J Technol Transfer. https://doi.org/10.1007/s10961-023-10029-7

Drucker PF (1954) The Practice of Management. Harper Brothers, New York

Duan Y, Edwards JS, Dwivedi YK (2019) Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. Int J Inform Manage 48:63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Eugenio AP, Sicilia M (2020) Do Top Managers' Individual Characteristics Affect Accounting Manipulation in the Public Sector? J Publ Adm Res Theor 465-484 https://doi.org/10.1093/jopart/muz038

Feldman MP, Audretsch DB (1999) Innovation in cities: science-based diversity, specialization and localized competition. Eur Econ Rev 43:409–429. https://doi.org/10.1016/S0014-2921(98)00047-6

Garbuio M, Lin N (2018) Artificial Intelligence as a Growth Engine for Health Care Startups: Emerging Business Models. Calif Manage Rev https://doi.org/10.1177/0008125618811931

Garrel VJ, Jahn C (2022) Design Framework for the Implementation of AI-based (Service) Business Models for Small and Medium-sized Manufacturing Enterprises. J Knowl Econ https://doi.org/10.1007/s13132-022-01003-z

Gartner (2023) Why does your organization need to define artificial intelligence? https://www.gartner.com/en/topics/artificial-intelligence. Accessed October 8, 2023

Gerlach J, Hoppe P, Jagels S (2022) Decision support for efficient XAI services - A morphological analysis, business model archetypes, and a decision tree. Electron Markets 32:2139–2158. https://doi.org/10.1007/s12525-022-00603-6

Ghose A, Han SP (2014) Estimating demand for mobile applications in the new economy. Manage Sci 60(6):1470–1488. http://www.jstor.org/stable/42919615

Glikson E, Woolley AW (2020) Human Trust in Artificial Intelligence: Review of Empirical Research. Acad Manag Ann. https://doi.org/10.5465/annals.2018.0057

Guo H, Polak P (2023) Intelligent finance and change management implications. Hum Soc Sci Commun 10 (1), https://doi.org/10.1057/s41599-023-01923-4

Haans RFJ, Pieters C, He Z-L (2015) Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. Strategic Manage J 37(7):1177–1195. https://doi.org/10.1002/smj.2399

Hatcher WG, Maloney D, Yu W (2016) Machine learning-based mobile threat monitoring and detection. In: 2016 IEEE 14th International Conference on

Software Engineering Research, Management and Applications (SERA), IEEE. 8-10 June 2016
Ioana I, Venturini F(2023) The Determinants of AI Innovation across European Firms Res Policy 52(2):104661 https://doi.org/10.1016/j.respol.2022.104661
Jacobides MG, Brusoni S, Candelon F (2021) The evolutionary dynamics of the artificial intelligence ecosystem. Strategy Sci. https://doi.org/10.1287/stsc.2021.0148
Johnk J, Weißert M, Wyrtki K (2021) Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. Bus Inf Syst Eng 63:5–20. https://doi.org/10.1007/s12599-020-00676-7
Kanbach DK, Heiduk L, Blueher G (2023) The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. Rev Manag Sci. https://doi.org/10.1007/s11846-023-00696-z
Kietzmann J, Paschen J, Treen E (2018) Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the consumer journey. J Advertising Res 58(3):263–267. https://doi.org/10.2501/JAR-2018-035
Kohtamäki M, Rabetino R, Parida V, Sjödin D, Henneberg S (2022) Managing digital servitization toward smart solutions: Framing the connections between technologies, business models, and ecosystems. Ind Market Manag 105:253–267. https://doi.org/10.1016/j.indmarman.2022.06.010
Konietzko J, Bocken N, Hultink EJ (2020) Circular ecosystem innovation: an initial set of principles. J Clean Prod 253(119942):1–15. https://doi.org/10.1016/j.jclepro.2019.119942
Kulkov I (2023) Next-generation business models for artificial intelligence startups in the healthcare industry. Int J Entrep Behav R 29(4):860–885. https://doi.org/10.1108/IJEBR-04-2021-0304
Laczko P, Hullova D, Needham A, Rossiter AM, Battisti M (2019) The role of a central actor in increasing platform stickiness and stakeholder profitability: Bridging the gap between value creation and value capture in the sharing economy. Ind Market Manag 76:214–230. https://doi.org/10.1016/j.indmarman.2018.08.010
Machlup F (1962) The Production and Distribution of Knowledge in the United States. Princeton University Press, Colophon
Madanaguli A, Sjödin D, Parida V, Mikalef P (2024) Artificial intelligence capabilities for circular business models: Research synthesis and future agenda. Technol Forecast Soc 200:123189. https://doi.org/10.1016/j.techfore.2023.123189
Majchrzak A, Markus ML (2013) Technology affordances and constraints in management information systems (MIS). Social Science Electronic Publishing
Mariani MM, Machado I, Nambisan S (2022) Types of Innovation and Artificial Intelligence: A Systematic Quantitative Literature Review and Research Agenda. J Bus Res 155: 113364. Accessed October 28, 2023. https://doi.org/10.1016/j.jbusres.2022.113364
Mikalef P, Gupta M (2021) Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inform Manage-Amster 58(3):103434. https://doi.org/10.1016/j.im.2021.103434
Moore JF (1993) Predators and prey: A new ecology of competition. Harvard Bus Rev 71(3):75–86
Nambisan S, Wright M, Feldman M (2019) The Digital Transformation of Innovation and Entrepreneurship: Progress, Challenges and Key Themes. Res Policy 48(8):103773. Accessed October 8, 2023. https://doi.org/10.1016/j.respol.2019.03.018
Nambisan S, Zahra A, Luo Y (2019a) Global platforms and ecosystems: implications for international business theories. Journal of International Business Studies. Encyclopedia of Management Theory. Sage Publications. https://doi.org/10.1057/s41267-019-00262-4
Nilsson NJ (2009) The quest for artificial intelligence. Cambridge University Press
Nonnis A, Bounfour A, Kim K (2022) Knowledge spillovers and intangible complementarities: Empirical case of European countries. Res Policy 52(1). https://doi.org/10.1016/j.respol.2022.104611
Norman DA (1999) Affordance, conventions, and design. Interactions 6(3):38–43. https://doi.org/10.1145/301153.301168
Osterwalder A, Pigneur Y (2010) Business Model Generation: A Handbook for Visionaries, Game Changers and Challenges. John Wiley and Sons, Hoboken: NJ
Patrick M, Gupta M (2021) Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance. Inform Manage-Amster 58(3):103434. https://doi.org/10.1016/j.im.2021.103434
Perrotta C, Gulson KN, Williamson B, Witzenberger K (2021) Automation, APIs and the distributed labour of platform pedagogies in Google Classroom. Crit Stud Educ 62(1):97–113. https://doi.org/10.1080/17508487.2020.1855597
PWC. (2017). Robotic process automation: a primer for internal audit professionals. Retrieved from: https://www.pwc.com/us/en/risk-assurance/publications/assets/pwc-robotics-process-automation-a-primer-for-internal-audit-professionals-october-2017.pdf
Ransbotham S, Khodabandeh R, Fehling B, LaFountain D, Kiron (2019) Winning with AI. Mit Sloan Manage Rev 61180. https://sloanreview.mit.edu/ai2019 Accessed 4 Mar 2024
Righi R, Samoili S, Cobo ML, Baillet MV, Cardona M, De Prato G (2020) The AI techno-economic complex System: Worldwide landscape, thematic subdomains and technological collaborations. Telecommun Policy 44:101943. https://doi.org/10.1016/j.telpol.2020.101943
Saviano M, del Prete M, Mueller J, Caputo F (2023) The challenging meet between human and artificial knowledge: A systems-based view of its influences on firms-customers interaction. J Knowl Manag 27(11):101–111. https://doi.org/10.1108/JKM-12-2022-0940
Serrano-Domingo G, Cabrer-Borrás B (2017) Direct and indirect knowledge spillovers and industrial productivity. Ind Innov 24(2):165–189. https://doi.org/10.1080/13662716.2016.1224706
Singh J (2005) Collaborative Networks as Determinants of Knowledge Diffusion Patterns. Manage Sci 51(5):756–770. https://doi.org/10.1287/mnsc.1040.0349
Sjodin D, Parida V, Palmié M, Wincent J (2021) How AI Capabilities Enable Business Model Innovation: Scaling AI through Co-evolutionary Processes and Feedback Loops. J Bus Res 134:574–587. https://doi.org/10.1016/j.jbusres.2021.05.009
Sternberg HS, Hofmann E, Roeck D (2021) The struggle is real: insights from a supply chain blockchain case. J Bus Logist 42(1):71–87. https://doi.org/10.1111/jbl.12240
Teece DJ (2010) Business models, business strategy and innovation. Long Range Plann 43:172–194. https://doi.org/10.1016/j.lrp.2009.07.003
Teece DJ (2018) Profiting from innovation in the digital economy: Standards, complementary assets, and business models in the wireless world. Res Policy 47:1367–1387
Tsujimoto M, Kajikawa Y, Tomita J, Matsumoto Y (2018) A Review of the Ecosystem Concept — Towards Coherent Ecosystem Design. Technol Forecast Soc 136:49–58. https://doi.org/10.1016/j.techfore.2017.06.032
Vaio DA, Palladino R, Hassan R, Escobar OR (2020) Artificial Intelligence and Business Models in the Sustainable Development Goals Perspective: A Systematic Literature Review. J Bus Res 121:283–314. https://doi.org/10.1016/j.jbusres.2020.08.019
Vannuccini S, Prytkova E (2021) Artificial Intelligence? New Clothes? From General Purpose Technology to Large Technical System, SPRU Working Paper Series 2021-02, SPRU - Science Policy Research Unit, University of Sussex Business School. https://EconPapers.repec.org/RePEc:sru:ssewps:2021-02
Verhoef PC, Broekhuizen T, Bart Y, Bhattacharya A, Qi DJ, Fabian N, Haenlein M (2021) Digital transformation: a multidisciplinary reflection and research agenda. J Bus Res 122:889–901. https://doi.org/10.1016/j.jbusres.2019.09.022
Weber M, Beutter M, Weking J (2022) AI Startup Business Models. Bus Inf Syst Eng 64:91–109. https://doi.org/10.1007/s12599-021-00732-w
Wellers D, Elliott T, Noga M (2017) 8 Ways machine learning is improving companies' work processes. Harvard Bus Rev 1(1):2–6
Wu F, Hu H, Lin H, Ren X (2021) Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity. Management World 37(07):130–144+10. https://doi.org/10.19744/j.cnki.11-1235/f.2021.0097
Xu Y, Du Y, Wang L (2023) R&d capital depreciation rate and stock estimates in China. J Stat Res 40(8):3–17. https://doi.org/10.19343/j.carolcarrollnki.11-1302/c.2023.08.001
Zhai H, Yang M, Chan KC (2022) Does digital transformation enhance a firm's performance? Evidence from China. Technol Soc 68:101841. https://doi.org/10.1016/j.techsoc.2021.101841

Acknowledgements

This paper is supported by the National Natural Science Foundation of China (No.72272136).

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Tachia Chin: Conceptualization and Supervision. Writing original draft - Introduction. Muhammad Waleed Ayub Ghouri: Writing original draft - Theoretical foundation, Discussion and Conclusion. Editing. Jiyang Jin: Data collection. Writing original draft - Methodology, Empirical analysis and results. Reviewing and Editing. Muhammet Deveci: Writing original draft - Discussion and Conclusion.

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants.

Informed consent
This article does not contain any studies with human participants performed by any of the authors.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-024-03003-7.

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