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Artificial intelligence-driven scalability and its impact on the sustainability and valuation of traditional firms

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The objective of this study is to determine the impact of artificial intelligence (AI) on the earnings before interest, taxes, depreciation, and amortization (EBITDA) of firms as a proxy of their financial and economic margins by improving revenues and minimizing expenses. This impact is positive on the market value and scalability by improving the economic and financial sustainability of companies. The methodology is based on a business plan that considers the savings obtained by a traditional firm implementing AI. Specifically, a sensitivity analysis will demonstrate that AI savings impact key parameters, leading to economic and financial sustainability. Additionally, a mathematical interpretation, based on network theory, will be produced to provide and compare the added value of two ecosystems (without and with AI that adds up new nodes and strengthens the existing ones). The main contribution of this paper is the combination of two unrelated approaches, showing the potential of AI in scalable ecosystems. In future research, this innovative methodology could be extended to other technological applications.

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Introduction

The term "Artificial Intelligence" (hereinafter, AI) refers to the implementation of human intelligence in machines that are capable of thinking and learning like humans. Specifically, it uses computer systems and algorithms that can perform human tasks, such as visual perception, speech recognition, decision-making, problem-solving, and language translation. AI involves computer systems that, thanks to their self-learning behavior, can perform tasks that usually need natural human intelligence (Mikalef and Gupta, 2021).

According to Jaber (2022), AI systems are designed to analyze vast amounts of data, recognize patterns, and make predictions or decisions based on that information.

AI (Minh et al., 2022) is a future-oriented technology, as it extrapolates past trends, typically in the form of big data (Acciarini et al., 2023; Duan et al., 2019), to estimate trendy scenarios, enhanced by self-learning processes that add value to the business models that become more sustainable and resilient.

According to Enholm et al. (2022), there is still a lack of the main value-generating mechanisms and there is a missed understanding of the use and adoption of AI in organizations. This study aims to partially fill this gap by addressing the scalability features of AI, enhanced by network theory properties (power laws). The target of this value chain is represented by digital applications (social networks, the metaverse, eCommerce and other digital platforms, NFTs, telemedicine, etc.), even concerning Industry 4.0 (Popkova and Sergi, 2020). Institutions that use AI generate added business value gains, through increased sales, and cost reduction, with an impact on cost/benefit analysis. Business efficiency is also improved (AlSheibani et al., 2020). As shown in Fig. 1, networked scalability (passages 2 and 3) ignited by AI (1) improves the economic/financial differentials, proxied by the EBITDA (earnings before interest, taxes, depreciation, and amortization), either increasing the revenues and/or reducing the monetary OPerating EXpenses (OPEX). This virtuous process improves the overall valuation of the business and its sustainability (resilience), consistently with trendy ESG targets. Škapa et al. (2023) examine AI-driven ESG investments compared to non-ESG investing; this comparison is consistent with the "without-or-with" approach used in this study.

Consistently with this framework, *the research question of this study addresses the scalability impact of AI on the EBITDA of a traditional company that represents a proxy for economic and financial margins. This impact influences the market value of the company*. The rationale behind the present paper can be found in publications such as Berawi (2020) who states that AI creates profits for other industries by improving efficiency and extending markets towards the so-called digital economy. Specifically, this scholar argues that "the value of tomorrow's product or service will not much depend on production costs but rather on the intellectual properties involved in designing and creating a product or service". Lee et al. (2019) focus on the proactive use of AI technology to reach business model innovation. Moreover, this study provides a brief overview of AI and justifies how it transforms business models. On the other hand, Huang and Lee (2023) affirm that more and more companies "have begun developing AI to promote their own competitive advantage and increase their business value", by empirically demonstrating that the announcement of AI implementation, gives rise to added value (specifically, positive abnormal returns).

In order to understand how AI business models may differ from traditional companies, Widayanti and Meria (2023) create a taxonomy of business models for AI businesses by using a sample of 162 Worldwide Startups: "Deep technology researcher, data analytics suppliers, AI product and service provider, and facilitator of AI development", by suggesting interesting directions for further investigation. Winter (2021) provides some practical examples of the successful implementation of AI in offerings of products and services which are "hyperconnected, smart, personalized, and highly automated". Finally, Wodecki (2019) shows that AI may give rise to both value creation and competitive advantage (efficiency, creativity, and flexibility) by analyzing 400 case studies and assessing different models of technology-based value creation.

The structure of this paper is as follows:

- Section "From artificial intelligence to scalability drivers" illustrates the scalability impact of bundled (synergistic) intangibles;
- Section "The model" illustrates the model;
- Section "Results" shows the empirical evidence and sensitivity simulations conducted on a business plan template;
- Section "Evolving networks" complements the business model with network theory interpretations;
- Section "Discussion" contains the discussion;
- Section "Conclusion" is dedicated to the conclusions.

Because of the innovativation and heterogeneity of this topic, a review of the existing literature is spread throughout the whole paper.

The existing literature stream of AI for decision-making (see, for instance, Dear, 2019; Gupta et al., 2022; Tien, 2017) covers business

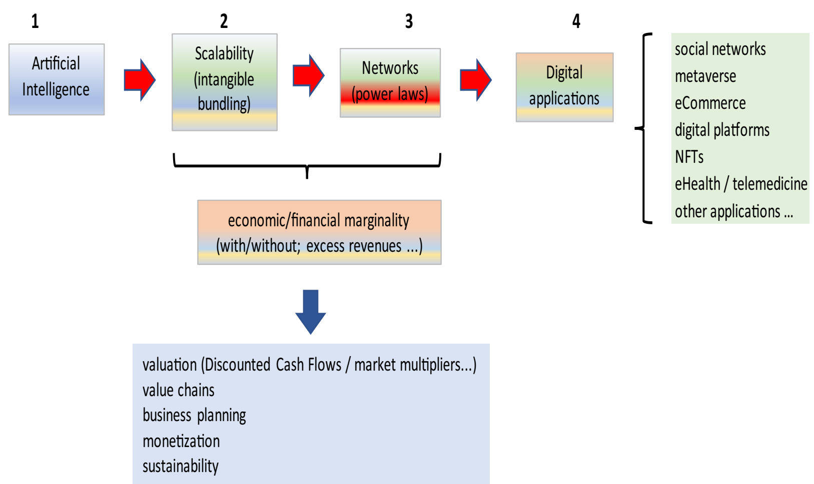

Fig. 1 Networked scalability impact of AI. AI generates network scalability which increases the economic/financial margins (EBITDA) and generates digital applications.

planning and value creation issues that are anchored to cost/benefit analysis and EBITDA generation. These issues are possibly the closest to the research question and perimeter of this paper.

From artificial intelligence to scalability drivers

Artificial intelligence (AI) can significantly impact a traditional company's scalability and value drivers in terms of cost-revenue analysis. Here are some key aspects to consider:

1. Cost reduction: AI can automate various accomplishments, reducing the need for manual labor and lowering operational costs. By automating repetitive and time-consuming processes, AI can streamline operations, increase efficiency, and reduce human error. This cost reduction can positively impact a company's bottom line and enhance its scalability.
2. Enhanced decision-making: AI can analyze vast amounts of data and generate insights that humans might miss. By leveraging machine learning algorithms, companies can make data-driven decisions more efficiently and accurately. AI can optimize processes, identify cost-saving opportunities, and improve revenue generation by enabling better strategic planning and resource allocation.
3. Customer experience and revenue growth: AI-powered technologies such as chatbots, virtual assistants, and recommendation systems can enhance the customer experience. These tools can provide personalized recommendations, offer real-time support, and automate customer interactions. By improving customer satisfaction and engagement, companies can drive revenue growth, increase customer loyalty, and tap into new market opportunities.
4. Predictive analytics and forecasting: AI can analyze historical data, detect patterns, and make accurate predictions. This capability enables companies to optimize inventory management, demand forecasting, and supply chain operations. By aligning resources and production with market demands, companies can minimize costs, reduce waste, and increase revenue through improved sales forecasting.
5. Productivity and innovation: AI can augment human capabilities and enable employees to focus on higher-value tasks. Automating repetitive and mundane activities allows employees to allocate more time to creativity, innovation, and problem-solving. This can lead to the development of new products and services, improving the company's competitive advantage and revenue potential.
6. Scalability and flexibility: AI-driven systems can be easily scaled to handle increasing workloads without significant infrastructure changes. Cloud-based AI platforms and services provide the flexibility to adapt to changing business needs and market dynamics. This scalability allows companies to expand their operations rapidly and efficiently, without incurring substantial costs.
7. Risk mitigation: AI can help identify and mitigate risks, both operational and financial. AI systems can proactively identify potential fraud, security breaches, and compliance issues by analyzing large datasets and detecting anomalies. This risk mitigation capability can save costs associated with legal penalties, reputational damage, and operational disruptions.

Synergistic intangibles (see Moro-Visconti, 2022b) enhance scalability patterns. Key technologies like big data, cloud storage, and blockchain validation represent future applications. The integration of artificial intelligence with these innovations, together with scalability upgrades, improves overall efficiency (Belgaum et al., 2021; Balgaum et al., 2019; Saadia, 2021; Soni and Kumar, 2022).

Scalability refers to the ability of a system, network, or organization to handle increasing amounts of work, data, or users without sacrificing performance or efficiency. A system can adapt and grow to meet the demands of a growing workload or an expanding user base. Scalability fosters economic marginality (proxied by the EBITDA), especially in intangible-driven businesses.

In the context of economic and financial parameters for valuation, scalability plays a significant role in enhancing the overall value and performance of a system (Gupta et al., 2017).

The model

As anticipated in the introduction, this manuscript analyzes the impact of artificial intelligence (AI) on the EBITDA (specifically on cash flows) of firms as a proxy of their financial and economic margins by improving revenues and minimizing operating expenses. This impact is both positive and scalable, and brings positive consequences on the market value of the company and its economic/financial sustainability.

Figure 2 exhibits the value-generating process which illustrates the consequential steps along the value chain and its recursive return to the value-originating platform (from 4 to 1). These steps follow network theory paradigms. It will be shown that:

1. AI-driven cost savings positively impact the EBITDA as a proxy for financial and economic firm margins. The interaction of the networking stakeholders consequently grows.
2. Improved economic/financial marginality, driven by AI adoption, boosts the sustainability of the company.
3. The AI-driven added value is partitioned among the company's stakeholders.
4. In the context of stakeholder interaction, the concept of network theory can help explain how AI embedded in digital platforms facilitates and enhances collaboration, value co-creation, and sharing among stakeholders.

Figure 2 contains a double-sided arrow, as it shows that value co-creation in the context of AI adoption can be seen as a circular process, driven by the incentive of stakeholders to monetize the benefits it brings.

The "with-or-without" sensitivity simulation is based on a "traditional" business plan (AI-free).

This case represents the basic template for a simulation of the impact of AI. The integration of AI technologies within a

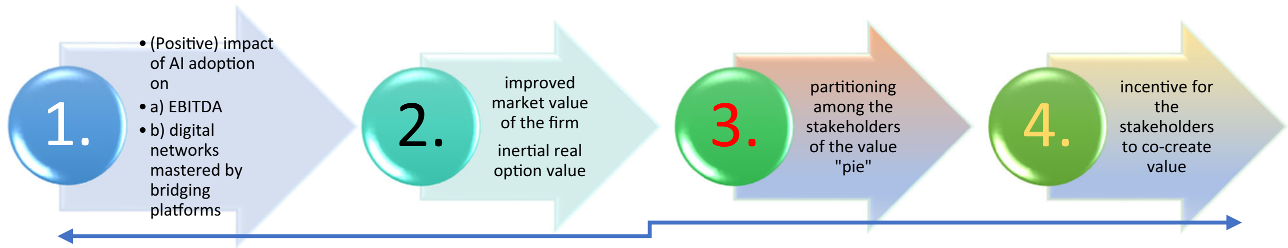

Fig. 2 Value-creating patterns ignited by AI. Circular process: AI creates incentive for stakeholders and then positive impact on EBITDA.

company's operations can have a positive impact on the forecast income statement, operating leverage, EBITDA, liquidity generation, debt service capacity, and overall sustainability.

AI improves net operating efficiency, net profitability, and overall return on marketing-related investment while reducing advertising costs, ultimately creating jobs (Mishra et al., 2022). Since AI incorporates feedback, it improves overall system performance, enhancing past information reflected in big data.

The described analysis, comparing a traditional network with a smart AI-driven network by examining the differences between the two, is consistent with a "with or without" differential approach commonly used in estimating intangible assets. This approach involves comparing the performance or value of a company or system with the presence or absence of a specific intangible asset, such as a patent, as illustrated in the International Valuation Standard 210 (par. 80.1).

The methodology of the study follows an empirical "with-or-without" case, introducing AI savings into a sensitivity analysis that can help evaluate and quantify the impact of cost reductions or efficiency improvements on economic margins. Two complementary methodologies will be used in the next sub-paragraphs:

(a) A sensitivity analysis, based on EBITDA differentials, where digitized savings impact economic/financial sustainability;
(b) A mathematical interpretation, where the stakeholders of two contiguous ecosystems—respectively, without and with AI—are compared, using network theory analysis.

This sequential and interdisciplinary methodology is consistent with the research question, as it shows a comprehensive impact of AI-driven savings. Network theory analysis follows with an innovative interpretation of the interactions of the firm's stakeholders.

The study will be carried on with a numerical simulation, complemented by network analysis.

EBITDA is the starting parameter for the appraisal of the company's market value, following two complementary approaches:

a. Discounted cash flows (DCF).
b. Market multipliers.

DCF is also influenced by risk (embedded in the cost of capital, used to discount expected cash flows); as anticipated, the empirical evidence shows that the impact of AI on risk mitigation is not meaningful (for the time being).

Section "Discounted cash flows and market multipliers" shortly recalls these two approaches, showing the impact of AI on value creation.

Both methodologies estimate either the enterprise value or the equity value of the company. The enterprise value incorporates the outstanding financial debt, whereas the equity value is residually attributable to the shareholders.

The purpose of the study is to show that incorporating AI into a sensitivity simulation can help demonstrate the benefits it brings to a company and the stakeholders involved. By comparing a traditional business plan without AI to an innovative business plan that incorporates AI, the potential impact on margins, sustainability, and value co-creation can be assessed.

A sensitivity simulation compares a "traditional" (AI-free) business plan versus an innovative business plan that incorporates AI.

Discounted cash flows and market multipliers. The cash flow statement used in the estimate of DCF and reproduced in Table 1 considers both the EBITDA (Table 2) and the operating cash flows (see Moro–Visconti, 2022a).

An analytical representation of the EBITDA, showing the impact of AI, is recalled in Table 3.

The impact of AI on the EBITDA is considered below.

Once the present value of the cash flows has been determined, the calculation of the market value (W) of the company may correspond to the:

(a) Unlevered cash flow approach, used to estimate a company's enterprise value. It involves calculating the present value of the expected future cash flows generated by the company before accounting for any debt or interest payments. This approach focuses on the cash flows available to all providers of capital (both debt and equity) and is often used to determine the

Table 1 Cash flow statement and link with the cost of capital.

Sales (monetary revenues)	
- OPEX	
= EBITDA (A)	
± Δ Operating Net Working Capital	
± Δ fixed assets (CAPEX)	
= Operating cash flow (unlevered cash flow to the firm - FCFF) (B)	
- Financial charges	debt service/bankability
± Δ net financial liabilities	
± Extraordinary income and charges	
- Taxes	
± Δ Equity	
= Net (free) cash flow to the shareholders (levered cash flow - FCFE) (C)	

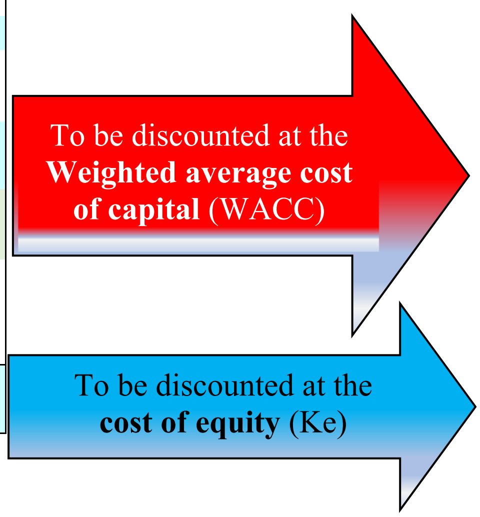

Table 2 EBITDA determination.

Income statement (input data)	Impact of AI
Monetary revenues (sales)	AI improves sales (new AI-based products and markets; new clients with customer segmentation and service analytics, etc.)
- Monetary OPEX	AI improves the supply chain efficiency, optimizing the service operations, and reducing the OPEX
= EBITDA	EBITDA improves

Table 3 Impact of AI on the company's key parameters.

Sensitivity analysis			
		AI intervention	
	Base Case	Sales + 5% Opex - 5%	Sales + 10% Opex - 10%
Average sales t1-3	€ 1,21,36,667	€ 1,33,11,250	€ 1,45,60,000
Average Opex t1-t3	€ 97,09,333	€ 88,27,000	€ 80,00,000
Average EBITDA t1-t3	€ 24,27,333	€ 44,84,250	€ 65,60,000
Average net result t1-t3	€ 13,18,203	€ 27,70,397	€ 42,35,000
Average net financial position t1-t3	€ 1,99,549	€ 22,04,533	€ 42,20,977
Average equity t1-t3	€ 54,48,563	€ 77,91,670	€ 1,01,49,333
Equity value (DCF)	€ 1,85,99,227	€ 3,64,11,256	€ 5,43,76,197
Equity value (multiples)	€ 1,78,06,273	€ 3,45,90,713	€ 5,15,28,833
Enterprise value (DCF)	€ 2,05,99,994	€ 3,84,12,023	€ 5,63,76,964
Enterprise value (multiples)	€ 1,98,07,040	€ 3,65,91,480	€ 5,35,29,600

intrinsic value of the business (to estimate the enterprise value):

$$W \approx \sum \frac{\mathrm{CF}_0}{\mathrm{WACC}} \tag{1}$$

(b) Levered cash flow approach (to estimate the equity value):

$$W \approx \sum \frac{\mathrm{CF}_n}{K_e} \tag{2}$$

where $\Sigma(\mathrm{CF}_0)/\mathrm{WACC}$ = present value of operating cash flows (FCFF); $\sum(\mathrm{CF}_n)/K_e$ = present value of net cash flows (FCFE); K_e = cost of equity; WACC = weighted average cost of capital.

The EBITDA multiple approach is a widely used empirical criterion for estimating the value of a company. It is often employed in business valuation to determine the enterprise value, which represents the total value of the company. The net financial position is then algebraically added to the enterprise value to derive the equity value, which reflects the value of the company's net assets attributable to equity holders. The formulation is as follows:

$$W = \text{average perspective EBITDA} * \text{enterprise value/sector EBITDA} = \text{enterprise value of the company} \tag{3}$$

And then:

$$\text{Equity value} = \text{enterprise value} \pm \text{net financial position} \tag{4}$$

A networked interpretation of AI-sensitive business planning. The main methodological purpose of this study is to integrate the standard business planning framework, described in the section "Results", sensitive to the AI impact on revenues and OPEX, with an evolving network theory analysis.

Whereas the impact of AI on business planning and predictive analytics has been investigated in literature streams (Zellner et al., 2021) considering Advanced Forecasting Methods (ARIMA), as shown in Fang et al., 2022, or Artificial Neural Networks (see Abiodun et al., 2018), there is no evidence, to the authors' best knowledge, of any link between the traditional business planning (AI-sensitive) and the dynamics of network theory forecasting, with its new nodes and edges created by AI. In other words, these literature streams explain how AI impacts the prediction of sales, etc., but not how it affects future revenues (and OPEX).

A decomposition of formula (1), useful to understand its main constituents, brings to the following enterprise value of the AI-adopting company:

$$W \approx \mathrm{DCFoperating} \sum \frac{\mathrm{CF}_0}{\mathrm{WACC}} = \sum_{i=1}^{n} \frac{(\text{AI driven Sales}) - (\text{AI driven OPEX}) = (\text{AI driven EBITDA}) \pm \Delta\text{OperatingNWC} \pm \Delta\text{CAPEX} = \text{CFo}}{\mathrm{WACC}} \tag{5}$$

The flow-chart of the formulation that represents the discounted cash flows can be re-expressed below.

What will be considered here is the main formulation of unlevered (operating) discounted cash flows, calculated before financial debt service and used to assess the enterprise value of the AI-adopting company. The equity value assessment naturally follows, being influenced only by financial debt service, taxation, and other minor parameters, hardly sensitive to AI.

Each passage (from 1 to 7) in Fig. 3 can be reinterpreted with evolving networks, establishing a bridge with traditional (accounting) business planning and dynamic network theory.

It should be preliminary noted that:

a. 1 − 2 = 3 (EBITDA is the difference between sales and OPEX);
b. The variation in the operating NWC is influenced by greater sales (that increase accounts receivable and stock) and lower OPEX (which decrease accounts payable);
c. The CAPEX variation could include (to a small extent) even AI investments (with a consequent positive expected payoff);
d. Operating cash flows correspond to EBITDA ± Δ operating net working capital ± Δ CAPEX;
e. In a DCF analysis, future cash flows are projected and then discounted back to their present value by using the WACC. The WACC is sensitive to the volatility of the numerator of the DCF formula, represented by free cash flows to the firm.

Evolving networks affect each of these passages.

Results

The results are consistent with the research question and the model illustrated in the section "The model".

Section "From standard to AI-driven business planning: a sensitivity simulation" contains a sensitivity simulation, incorporating the impact on a hypothetical business plan of AI adoption.

Section "A with-or-without simulation using network theory" is dedicated to a network theory without-or-with simulation that examines the same issues from a complementary side, showing how AI can increase the number of nodes and the intensity (internet traffic, monetary transactions, and, consequently, improved EBITDA) within the ecosystem.

From standard to AI-driven business planning: a sensitivity simulation. This empirical setting provides a theoretical background of the main accounting and financial indicators

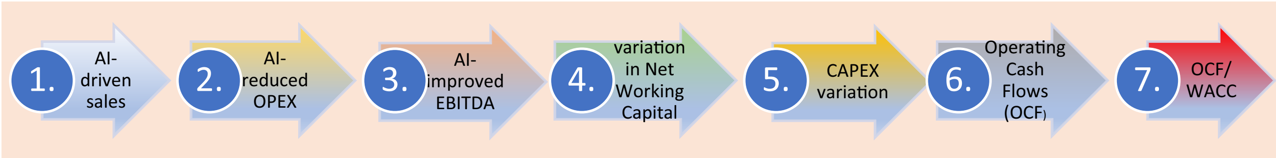

Fig. 3 Discounted cash flows ignited by AI. Effect of AI-driven sales and AI-reduced OPEX on Operating Cash Flows (OCF).

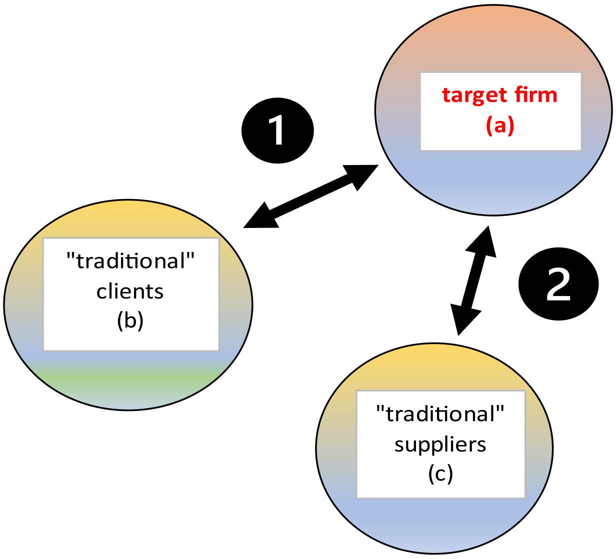

Fig. 4 Standard procurement/supply chain. Relationships in a supply chain with traditional firms.

underlying sustainability issues and the interrelations among stakeholders, along with the potential impact of AI-driven savings. The AI-driven sensitivity analysis shows the potential effect of savings on the life-long parameters of the investment, consistently with the "without or with (AI-driven) approach" illustrated in the comparison between Figs. 3 and 4, and indicated in the methods.

The income statement is a fundamental financial statement that serves as the "engine" behind profitability considerations and plays a crucial role in determining the overall financial health and sustainability of a company.

The hypothetical impact on operating revenues and costs is the following:

1. A scenario with +10% revenues/−10% costs;
2. A scenario with +5% revenues/−5% costs.

When conducting sensitivity analysis to estimate the impact of AI on financial performance, it is indeed reasonable to consider the potential repercussions on revenues and operating costs. The sensitivity analysis allows for the assessment of the potential variability in these factors, considering the potential benefits of AI integration.

1. Revenue increase: AI can enhance revenue generation through various means, such as improved customer targeting, personalized recommendations, or enhanced sales effectiveness. By leveraging AI technologies, companies can optimize their pricing strategies, identify new revenue streams, or develop innovative products or services. Sensitivity analysis considers the potential increase in revenues resulting from AI-driven improvements.
2. Operating cost decrease (OpEx): AI can bring cost-saving opportunities through automation, process optimization, and resource allocation efficiencies. By streamlining operations and reducing manual efforts, companies can potentially lower their operating costs. Sensitivity analysis considers the potential decrease in operating costs resulting from AI adoption, leading to improved profitability.

The combined effect of revenue increase and operating cost decrease has a positive impact on financial and economic margins. It enhances the company's financial performance, profitability, and value-creation potential. Sensitivity analysis helps estimate the magnitude of these improvements, allowing decision-makers to evaluate the potential benefits of AI integration and make informed choices.

Unfortunately, this variability in revenues and costs is not still backed by empirical evidence and this justifies the use of sensitivity analysis. This idea is reinforced by taking into account that the use of bundled intangibles may cause about 10% variations both in higher revenues and lower costs.

Empirical evidence shows that AI leads to EBIT or EBITDA improvements, because of both revenue increases and cost-cutting. According to McKinsey and Company (2022), "at least 5 percent of their organizations' EBIT was attributable to AI in 2021, in line with findings from the previous two years". The impact of AI on depreciation/amortization is presumably small, and so is EBIT ≈ EBITDA.

Other sources show similar results (Pifer, 2023; Pipeline, 2023; Appen, 2022; Oberlo, 2022; Statista, 2023; Zhang et al., 2021; Human-Centered Artificial Intelligence, 2022).

This impact somewhat underestimates the long-term effect of AI (capacity to self-ignite virtuous processes) that can be dealt with as a "real option" to expand the business, with already undertaken investments. Real options analysis is a framework that is consistent with the concept of Net Present Value of Growth Opportunities (NPVGO). NPVGO is a calculation used to estimate the net present value per share of all future cash flows associated with growth opportunities, including new projects or potential acquisitions. NPVGO is typically fueled by innovative intangibles with hidden and still underexploited potential, such as AI.

A sensitivity simulation applied to an ideal client—a company purchasing AI products—shows which is the impact on the economic and financial metrics and the corporate valuation of an increase in revenues (and decrease in OPEX).

This case represents a basic simulation of the impact of adopting AI. The comparison of a simple network without AI with a smart AI-driven network including new nodes aligns with the "with or without" differential approach commonly used to estimate the value of intangibles.

By applying the "with or without" differential approach and comparing the straightforward network without AI to the smart platform-driven network with AI integration, it is possible to quantitatively assess the impact on financial performance, value creation, and overall sustainability. This approach aligns with the traditional methodology used to estimate the value of intangibles and demonstrates the potential benefits of AI integration within the analyzed context, as illustrated in the International Valuation Standard 210 (par. 80.1).

Table 4 The adjacency matrix of a standard 3 × 3 network.

	a	b	c
a	0	1	1
b	1	0	0
c	1	0	0

This empirical setting is fully compliant with the research question, a theoretical story that illustrates the main accounting and financial indicators associated with AI adoption, as well as the interrelations among stakeholders. Additionally, it highlights the sensitivity analysis to evaluate the impact of AI adoption on investment parameters by using the "without or with AI adoption" approach.

The income statement of the AI-adopting company is the "engine" behind any profitability consideration.

When a company adopts AI technologies, the resulting increase in revenues or decrease in operating expenses (OPEX) can significantly improve its financial and economic margins, as represented by EBITDA. These improvements have a positive impact on value creation.

A brief comparison is illustrated in Table 4 where a sensitivity analysis applied to the base case, 5, and 10% growth in operating revenues (and a corresponding reduction in operating costs, mostly monetary OpEx) is reported in each column.

The first column shows the base case of a standardized company that consequently adopts AI solutions, with increasing economic marginality.

A with-or-without simulation using network theory. Network theory analyzes the relationships, whether symmetric or asymmetric, between discrete objects through the representation of graphs. In this context, a network is typically defined as a graph where the edges and/or nodes (vertices) possess attributes such as names or other characteristics.

A network is said to be interdependent if it consists of a system of coupled networks where the nodes in one network depend on the vertices in the other networks. This interdependence is a key characteristic of complex ecosystems and can provide an innovative perspective on the interactions among different stakeholders.

The impact of AI on the business model scalability can be explained in a complementary way, considering how AI can create additional nodes within a networked ecosystem, and how these nodes increase their connections, mainly in the form of digitized Internet traffic that hosts big data (AI-enhanced information) and monetary transactions. An example can be given by eCommerce digital platforms that exploit AI to reach new clients, with new transactions.

AI impacts business value (Enholm et al., 2022) with technological and organizational enablers that use automation and augmentation to produce:

- First-order effects (process efficiency, improved productivity, greater precision and reduction of human errors, decision quality, organizational agility, structural redesign, process reengineering, etc.);
- Second-order effects (operational performance with new and enhanced products and services; higher economic/financial growth and profitability, market-based performance with customer satisfaction, etc.).

New and enhanced products and services represent a cornerstone of AI that can be explained through network theory, where new products are represented by additional nodes and their enhancement by stronger links.

Multilayer networks explain dynamic networks' intertemporal nature that evolve, incorporating AI growth factors. Temporal networks embed dynamic AI features—AI is an incremental and self-learning process that could ideally produce real options, incorporating free-of-charge expansion possibilities.

Scalability can be interpreted with network theory applications, bridging physical nodes with their digital twins. Path-dependent upgrades, ignited by AI and machine learning applications, are dynamically consistent with intertemporal multilayer networks.

As anticipated, AI is a forward-looking technology, fully consistent with the intertemporal nature of multilayer networks, where each "screenshot" represents an instant, dynamically linked to the following one.

Multilayer networks are a type of network that involves multiple kinds of relations with multiplex or multidimensional configurations. In a multiplex network, the same set of nodes is connected through more than one type of link, leading to enhanced scalability and richer representation of relationships (Bianconi, 2018).

1. Multilayer networks go beyond the traditional network framework by incorporating multiple layers or dimensions of connectivity. They provide a more nuanced representation of relationships by capturing various types of relations, such as multiplex, multilayer, multilevel, and multi-relational connections. This extension allows for a more accurate and comprehensive understanding of real-world systems and their interdependencies.
2. Scalability features and bridging nodes: Multilayer networks are intrinsically fit for leveraging the scalability features previously examined. They can accommodate bridging or replica nodes that exist in multiple layers simultaneously. These bridging nodes facilitate connections and interactions across different layers, enabling the study of interlayer dependencies and the flow of information, resources, or influence between layers. This capability enhances the scalability and flexibility of the network representation.
3. Complex multidimensional networks: Multilayer networks, as a type of complex multidimensional network, offer valuable insights across various interdisciplinary fields. Their ability to capture multiple kinds of relations and interdependencies is particularly useful in understanding complex systems and phenomena. Whether analyzing social networks, biological networks, transportation networks, or economic networks, the multidimensional nature of multilayer networks can provide deeper insights into the dynamics, structure, and emergent properties of these systems.
4. Interdisciplinary insight: Multilayer networks serve as a valuable tool for interdisciplinary research. Their application can span diverse fields, including sociology, biology, physics, computer science, economics, and more. By incorporating multiple kinds of relations and interdependencies, multilayer networks enable researchers to study complex phenomena from a holistic perspective. They provide a common language and framework for analyzing and understanding the intricate relationships among elements within complex systems.

Figures 4 and 5 back the "without-with" comparison, showing—with a simplified ecosystem's wiring diagram—a standard company, and, respectively, an AI-driven network.

Network theory can contribute to explaining the nature of AI-driven scalability. AI adds incremental nodes to the existing

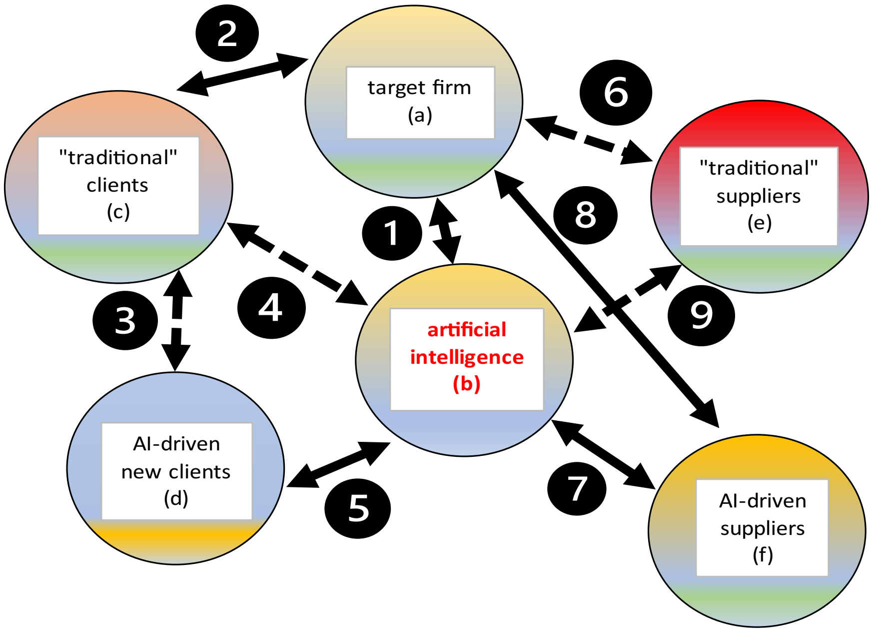

Fig. 5 AI-driven procurement/supply chain. Relationships in a supply chain with traditional and AI-driven firms.

Table 5 The adjacency matrix of a digitized 6 × 6 network.

	a	b	c	d	e	f
a	0	1	1	1	1	1
b	1	0	1	1	0	0
c	1	1	0	0	1	1
d	1	1	0	0	0	0
e	1	0	1	0	0	0
f	1	0	1	0	0	0

ecosystem and improves the interrelation between pre-existing and new nodes.

The model compares a "without" versus "with" scenario, consistent with the IVS 210 evaluation criteria for intangible assets, where a network without AI is compared with the same network when it incorporates AI-driven additional nodes and links (edges). This comparison allows us to sort out the incremental income (and cash flows) derived from the introduction of AI in the model.

The model can be further extended in a dynamic—multilayer—dimension, where AI ignites self-driven growth. Figure 4 is described by the following points:

1. Invoicing to "traditional" clients;
2. Invoicing from "traditional" suppliers.

Figure 5 is described by the following points:

1. Impact of AI on the target company;
2. Invoicing to "traditional" clients;
3. Interaction between "traditional" and AI-driven clients;
4. Interaction between AI and "traditional" clients (that become "augmented" or digitized);
5. AI creates new clients, increasing its revenues;
6. Interaction between the company and its "traditional" suppliers;
7. AI creates new suppliers;
8. The company interacts with AI-driven suppliers (cutting its OPEX);
9. AI interacts with "traditional" suppliers.

The comparison of Figs. 4 and 5 shows that AI acts as a bridging (intermediating) hub which increases the number of nodes (vertices) and, consequently, the overall value and consistency of the network, but especially the quality and quantity of links.

The value added to Fig. 5 (compared to Fig. 4) can be interpreted through the network theory analysis (Barabási, 2016). Network analysis involves measuring the degree of nodes, which refers to the number of links or connections a node has with other nodes in a network. The degree of a node provides insights into its connectivity and prominence within the network.

This process is shown in Tables 4 and 5. In a digital ecosystem, where AI produces its effects, information produces valuable small data that, combined, become "big". Even transactions, using fiat money or cryptocurrencies, convey useful financial information, making the AI-enhanced ecosystem financially sustainable.

The real finite network exemplified in Fig. 5 (or even 4) is a complex system. Interconnectivity can become vulnerable as any "blackout" may give rise to severe problems for the whole ecosystem. The links of Fig. 5 (numbered from 1 to 9) are bi-directional, therefore increasing the potential flow of data and transactions.

In network theory, the relations among nodes in a network are commonly illustrated by using an adjacency matrix, represented by a square matrix that provides a concise representation of the connections or edges between nodes in a finite graph as in Figs. 4 or 5.

The adjacency matrix represents a graph as the elements of the matrix indicate whether a pair of nodes are adjacent or not. Thus, the adjacency matrix is a symmetric and (0,1)-matrix with zeros on its diagonal as each node is not linked to itself.

The degree of each node illustrates the number of links with other nodes and is mathematically expressed with a symmetric adjacency matrix that is Table 4 Fig. 4 (with 3 nodes) and Table 5 for Fig. 5 (6 nodes).

Metcalfe's Law is often used to estimate the value or impact of a network by taking into account the number of connected users or nodes within the system. The law states that the value of a network is proportional to the square of the number of users (n^2). Thus, $\text{network}_{\text{Figure 4}} = 9$, and $\text{network}_{\text{Figure 5}} = 36$ where, for the sake of simplicity, we have assumed that the links in both networks are equally weighted. This underrates the effective value of the links since AI improves the edging intensity between any two linked nodes.

The digital platform driven by AI has the potential to revolutionize network connectivity and efficiency. It minimizes paths and distances, operates continuously, and increases network connectedness. By leveraging AI algorithms, the platform optimizes resource utilization and enables scalability and flexibility. These advancements facilitate seamless interactions, enhance value-creation opportunities, and improve overall network performance. The platform minimizes the number of links among the other nodes and increases the network connectedness. For instance, it creates additional paths between disconnected nodes like banks and sub-contractors which are connected through the platform in Fig. 5 but not in Fig. 4).

The mathematical analysis and comparison between the AI-mastered network and the original simple network can demonstrate the superior performance of the AI network. The advancements brought by the digital platform, coupled with AI capabilities, have the potential to enhance network robustness and resilience.

The specific impact on bankability may depend on various contextual factors, industry dynamics, and the specific implementation of the AI-driven network. Nonetheless, the enhanced network performance and resilience offered by the digital platform and AI technologies provide a strong basis for positive effects on bankability.

Evolving networks

The network model examined in the section "Results" is static and does not incorporate the dynamic features of AI. In effect, the sensitivity analysis applied to evolving networks, describes their change over time, ideally beyond the business planning period.

Several models (such as Erdös and Rényi, 1959; Barabási and Albert, 1999; Bianconi and Barabási, 2001) describe the evolutionary nature of networks. AI-driven extensions of dynamic networks are uneasy to model, and this research just represents a starting point for further inquiries.

The node's ability to acquire additional links affects the network topology. This is consistent with the impact of AI that creates new nodes and additional links, even regarding already existing customers and suppliers, whose edging links are reshaped.

The nodes' intrinsic ability to attract links in the network varies from node to node. The fitters can collect more edges at the expense of others. What matters here is, once again, the AI-driven ability of a node to evolve, be connected to new nodes (additional customers and suppliers), and strengthen the edges with already existing and new nodes.

The Barabási-Albert model postulates that a node's growth rate is determined solely by its degree (number of links with other nodes). These properties are consistent with a scenario reshaped by AI. The degree dynamics, once again likely to be increased by AI, predicts each node's temporal evolution. In many networks, new links are added not only from new nodes but also between pre-existing nodes.

The accelerated growth of a network depends on the number of existing and new (AI-driven) links and their increased links (edge intensity).

In the rest of this subsection, we assume that the network evolves due to the introduction of new nodes and the subsequent dynamics of the weights associated with each edge. Consider a simple economy composed of a company (F) and its clients (C) and suppliers (S), according to the scheme shown in Fig. 6 (called a directed graph). The introduction of AI in this economy has two effects: an increase in the probabilities of payment and the inclusion of new clients and suppliers.

In this graph, the arrows represent the flows of money derived from commercial transactions between, on the one hand, F and C (red arrow), and, on the other hand, between F and S (green arrow). The different risks affecting transactions make payments more difficult.

To represent the probabilities of payment, the graph is further extended by assigning a probability of payment to each arrow (see Fig. 7). The probability of payment from the set of clients to the company is denoted as p, and the probability of payment from the company to the set of suppliers is denoted as q.

A more realistic view considers the probability that the set of clients indirectly pays their debts to the set of suppliers through the company. Thus, the probability that the set of clients indirectly pays for their debts to the set of suppliers (through the company) is $p \times q$.

There is beyond any doubt that the irruption of AI in this economy gives rise to two important effects:

1. An increase in all probabilities of payment, and
2. The consideration of new clients and suppliers.

The introduction of AI leads to an increase in all probabilities of payment and the consideration of new clients and suppliers. This results in a new graph where traditional clients (TC) and suppliers (TS) coexist with new clients (NC) and suppliers (NS). The probabilities of payment between TC and TS in this new context are calculated by using Eqs. (6) and (7), taking into account the new relationships.

Thus, a new graph could be built, as shown in Fig. 8, where:

- TC and NC denote "traditional" and "new" clients, respectively;
- TS and NS represent "traditional" and "new" suppliers, respectively, and
- $p'' > p' > p$ and $q'' > q' > q$.

Obviously, in this new context, the probability of payment from TC to TS is now:

$$p' \times q' > p \times q \tag{6}$$

and so, the value added by the implementation of the AI to the economy is (in percentual terms):

$$\mathrm{AV} := \frac{p' \times q'}{p \times q} - 1 \tag{7}$$

A more realistic scenario involves considering bilateral relationships between TC and NC and between TS and NS (see Fig. 9). The true probabilities of payment between TC and TS are determined by considering the circular relationships between TC and NC, and NS and TS.

In this new situation, it is necessary to determine the true (also called "effective" or "net") probability of payment between TC and TS. Equations (8) and (9) are used to calculate the true probabilities of payment in these circular relationships. The resulting graph in Fig. 10 shows the net probabilities between clients and suppliers. Finally, the true probability of payment between TC and TS is calculated using Eq. (10), which is greater than the probability of payment in the initial graph. The added value (AV) in the economy, resulting from the implementation of

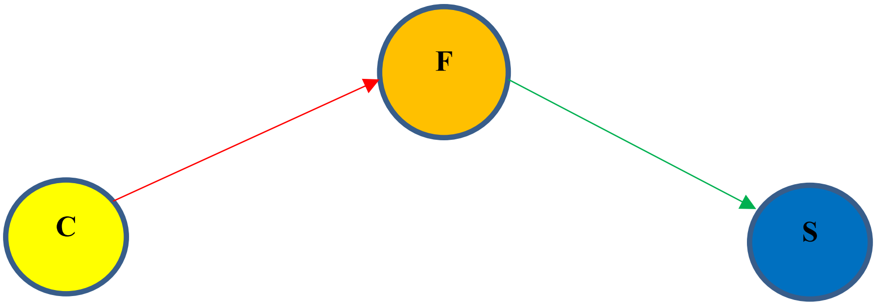

Fig. 6 Directed graph of a simple economy: companies, clients, and suppliers. Simplified network of the payments between traditional firms.

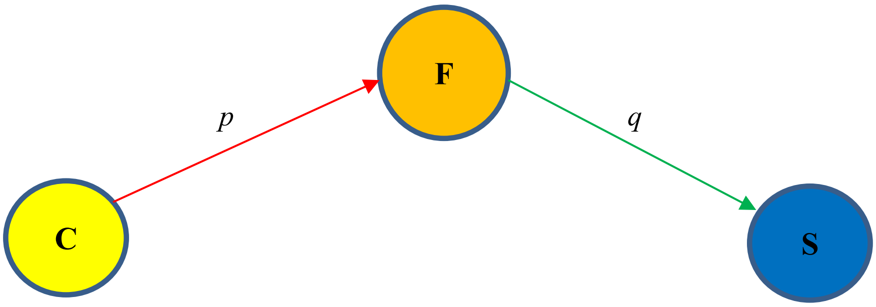

Fig. 7 Directed graph of Fig. 6 with probabilities of payment. Simplified network of the payments between traditional firms, with probabilities.

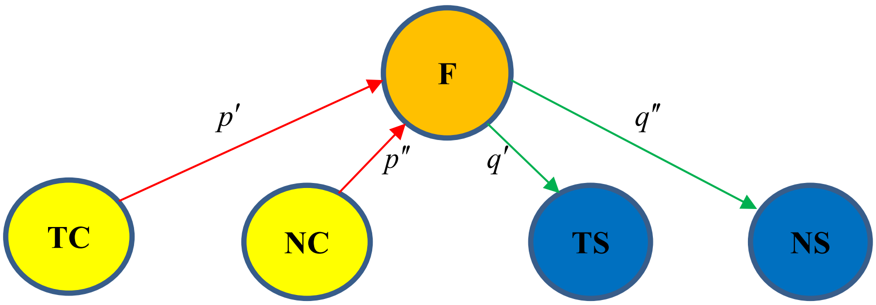

Fig. 8 Directed graph of Fig. 7 with new clients and suppliers. Simplified network of the payments between traditional and AI-driven firms, with probabilities.

AI, is determined by using Eq. (11). Specifically, the steps for this calculation would be the following:

- To determine the true probability (say α) between TC and NC in their circular relationship. In this way, it can be shown that (Cruz Rambaud and Robinson, 2014):

$$\alpha = p' \frac{1 - p''}{1 - p'p''} \tag{8}$$

- To determine the true probability (say β) between NS and TS in their circular relationship. Analogously, it can be shown that:

$$\beta = q'' \frac{1 - q'}{1 - q'q''} \tag{9}$$

Figure 10 exhibits the new probabilities.

Finally, the true probability of payment between TC and TS is:

$$\left(p' + \alpha p''\right) \times \left(q' + \beta q''\right) \tag{10}$$

which is greater than $p \times q$. Therefore, the added value (denoted by AV) in the economy is:

$$\mathrm{AV} := \frac{\left(p' + \alpha p''\right) \times \left(q' + \beta q''\right)}{p \times q} - 1 \tag{11}$$

Discussion

AI can play a significant role in maximizing data value, improving enterprise adoption rates, accelerating time to insight, and providing smart and contextual data-driven advice, through:

a. Data analysis and insights: AI can analyze large volumes of data quickly and efficiently, extracting valuable insights and patterns.
b. Automation and efficiency: AI can automate repetitive and time-consuming tasks involved in data processing, cleansing, and integration. This automation streamlines data management processes, reduces manual errors, and frees up human resources to focus on more strategic and value-adding activities.
c. Personalization and contextual advice: AI can deliver personalized and contextual recommendations and advice based on an individual's or organization's specific needs and goals.

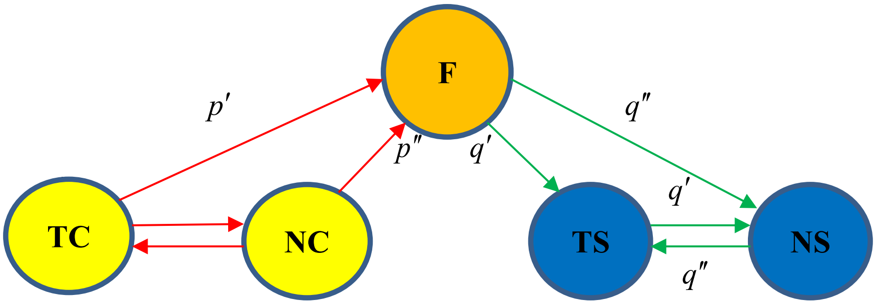

Fig. 9 Directed graph of Fig. 8 with payments between clients and suppliers. Simplified network of the payments between traditional and AI-driven firms: bilateral relationships.

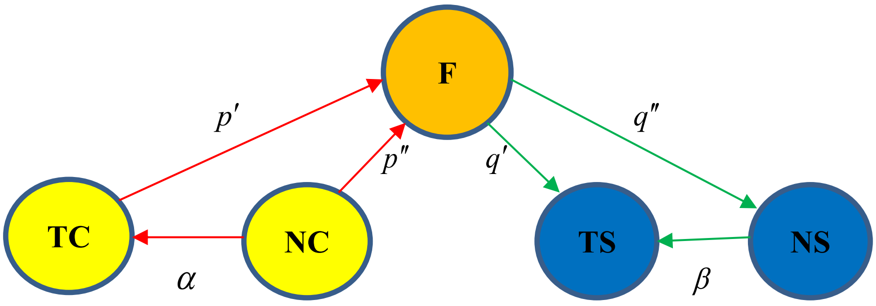

Fig. 10 Directed graph of Fig. 9 with net probabilities between clients and suppliers. Simplified network of the payments between traditional and AI-driven firms: bilateral relationships and net probabilities.

d. Natural language interfaces: AI-powered natural language interfaces, such as chatbots (Moro Visconti, 2023).
e. Continuous learning and adaptability: AI algorithms continuously learn from new data and adapt to changing business conditions.
f. Enhanced decision support: AI can provide decision support by simulating scenarios, running predictive models, and conducting what-if analyses (consistent with paragraph “From standard to AI-driven business planning: a sensitivity simulation”).
g. Augmented analytics: AI can augment human capabilities in data analysis by automating routine tasks and providing suggestions and insights.
h. By leveraging AI technologies, organizations can unlock the full potential of their data, enhance operational efficiency, and gain valuable insights for driving innovation and growth.

The research question of this study addresses the scalability impact of AI on economic/financial margins (proxied by the EBITDA). This impact influences the market value of the company and its sustainability (for a survey of the impact of AI on sustainability, see Kar et al., 2022). The impact of AI on company value is rarely discussed and remains a controversial issue (Lui et al., 2022).

AI fosters growth and improves resource allocation and the company’s knowledge-building proficiency over competitors that may not (fully) adopt AI. This is a source of improved operating performance, and long-term competitive advantage, according to the pragmatic theory of the company (Madden, 2020). This is consistent with the classic model of Solow (1957) according to which technological progress (proxied, in our case, by AI) pushes economic growth without adding more labor and capital.

AI is a core pillar of technological (and digital) innovation, dating back to the Touring test of 1957 (Anyoha, 2017).

Technological investments command a significant premium over traditional businesses. An analysis of stock market trends from 1994 till the end of 2022 shows that technological equities (proxied by the NASDAQ index) behave far better (despite the sharp downturn of 2022) than the World Stock Market Index (Fig. 11). Even if AI represents a small portion of the listed technology stocks, this outlook reflects the incredible growth over standard industries.

The empirical case has been interpreted, consistently with the described outline, with an EBITDA-driven financial and economic performance analysis, showing the impact of AI on the company’s key parameters that are valuation sensitive.

The sensitivity analysis of key indicators can demonstrate the positive impact of AI adoption on overall company performance. By examining the changes in economic marginality and other relevant metrics, it becomes evident how AI-driven improvements contribute to enhanced company performance:

- The joint interaction of sales increase and OPEX decrease substantially improves the EBITDA and the net result;
- The net financial position (NFP) is boosted by growing economic/financial marginality, represented by the EBITDA;
- Both the enterprise and the equity value substantially improve.

Part of this value growth could be dedicated to further AI investments, igniting a virtuous spiral of value creation. More profitable businesses are also more sustainable and ESG-compliant (Moro–Visconti, 2022a).

The value increase resulting from AI adoption can be observed through the cumulative net present value (NPV) and its subsequent distribution among stakeholders, represented in Fig. 5. This is witnessed by the higher enterprise value of the AI-adopting company:

- The adoption of AI can have a positive impact on the debt service capacity of a company, which in turn reduces delinquency risk and improves the likelihood of straightforward debt service.
- The shareholders are the ultimate beneficiaries (after the debt service) of these marginality gains, as shown by the growing

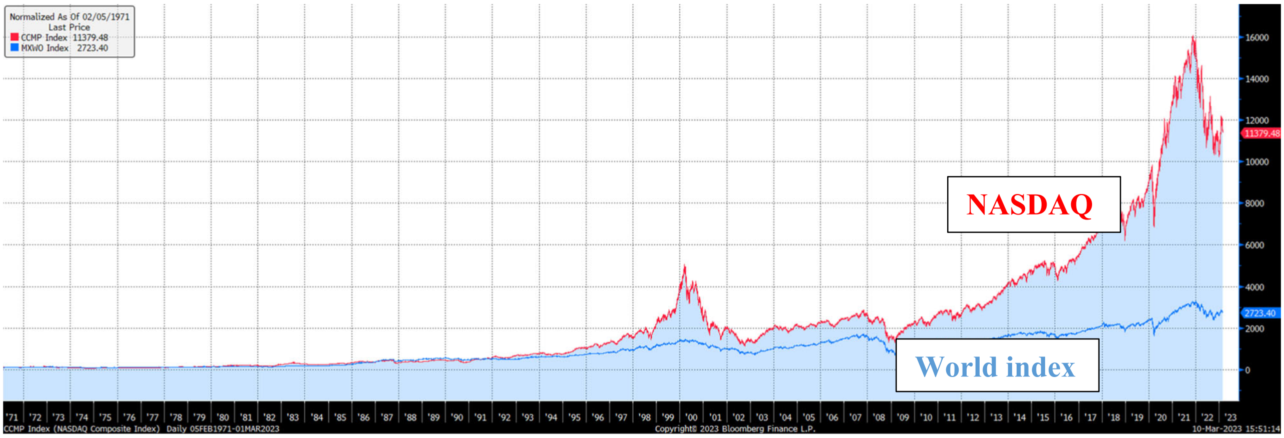

Fig. 11 World versus NASDAQ stock market index 1971–2023—Source: Bloomberg. Observe that, from 1994 to 2022, the technological equities behave better than the World Stock Market Index.

market value of equity. They have the incentive to co-create value, networking with other first-served stakeholders.

This study is focused on the impact of AI on discounted cash flows that represent a proxy for corporate evaluation. AI has a double impact on the EBITDA—the pivotal parameter of cash flows—as it improves the revenues and minimizes the OPEX. The estimate of +5/+10% returns, jointly considered with –5/–10% OPEX, is prudential and does not consider the drag effect that is embedded in self-fulfilling AI (a sort of "real option" that incorporates future expansion fueled by self-learning patterns). This payoff can be examined with sensitivity analysis, embedded in traditional business planning, or using innovative network theory applications. AI's positive impact on network ecosystems is evident through the introduction of new nodes, the strengthening of existing nodes, and the scaling up of links. The flexible nature of expanding networks is fully consistent with the accounting parameters (such as the growing revenues or decreasing OPEX) that represent the backbone of the business plan, including its "without-or-with" sensitivity. The use of network theory as an interpretation tool for the "without-or-with" approach seems innovative and could be further exploited wherever intangibles are assessed for their value-generation potential.

What is still missing in this pioneering research is an analysis of the volatility of cash flows, reflected in the discount factor of formulae (1) and (2), proxied by the cost of capital. The cash flow volatility is sensitive to the belonging industry and is affected by the market timing of the appraisal. The question is to ascertain if and to which extent the volatility of the cash flows is reduced by AI. Whereas the answer seems probably positive (as AI embeds resilient properties), further research is needed to assess its magnitude. Should the discount factor of the DCF reduce, the impact on the overall market value could be significant.

The impact of AI on business model innovation in traditional companies is an area that requires further investigation. Some authors, such as Burström et al. (2021), have focused on manufacturing incumbents finding it difficult to integrate AI into their traditional business models. Therefore, this paper draws on the following research question: *How do manufacturing incumbents use AI to enable business model innovation in industrial ecosystems?*

Also, Sjödin et al. (2021) present empirical insights from a case study of six leading manufacturers engaged in AI. The findings reveal some sets of critical AI capabilities and highlight that firms need to innovate their business models.

Finally, Perifanis and Kitsios (2023) empirically identify a wide range of research about the development of new business models and competitive advantages through the integration of AI in business and IT strategies.

While AI technology holds significant potential for transforming business models, its specific implications and applications within different industries and operational contexts are still being explored (see Reim et al., 2020; Valter et al., 2018), even if it represents a core aspect of the marketability of this technology. Additional research is needed, by segmenting companies according to their industry and by matching their operations with specific AI applications.

It should not be forgotten that AI is a strongly specific technology, uneasy to generalize, and typically not multi-purpose. Simulations of the economic and financial impact of AI on different companies can help AI developers improve their marketing potential (Vlačić et al., 2021), showing the AI benefits to new customers. Appropriate and timely feedback improves the tailor-making of AI solutions.

Conclusion

The research question of this paper addresses the impact of AI on the economic and financial margins of firms by improving revenues and minimizing expenses.

AI can have a significant impact on scalability by improving efficiency and reducing costs. AI-powered systems can help automate many repetitive, time-consuming tasks, allowing companies to scale their operations more quickly and efficiently. For example, it can be used to automate data entry, image and speech recognition, and customer service, among many other applications.

AI can be instrumental in helping companies make more informed decisions by providing real-time data analysis and insights. This capability can greatly assist in identifying and addressing bottlenecks and inefficiencies that hinder scalability.

By leveraging AI-powered analytics tools, companies can gain a deeper understanding of their operations and make data-driven decisions that can help them scale their businesses more effectively.

Moreover, AI can help companies identify new opportunities for growth and innovation. Analyzing data from a variety of sources, AI-powered systems can help companies identify trends and patterns that might be uneasy to detect with traditional methods. These insights can help companies develop new products and services, enter new markets, and innovate in ways that can support long-term scalability.

Overall, AI has the potential to be a key enabler for companies to scale their operations effectively. By improving efficiency, reducing costs, and uncovering growth opportunities, AI can drive sustainable and accelerated growth.

Additional research streams may well consider the impact on the company's valuation metrics of other complementary intangibles, represented—for instance—by validating blockchains (Swan, 2019; Wang et al., 2022) or scalable platforms. Moreover, future research should further explore the complexity of AI to provide a theoretical foundation for the integration of AI in scalable ecosystems.

The impact of AI on business model innovation in traditional companies is an area of great significance and ongoing exploration. As AI technologies continue to evolve and mature, they have the potential to significantly reshape how traditional businesses operate, create value, and engage with their customers. Here are some key points to consider:

1. **Operational efficiency and automation:** AI can enhance operational efficiency by automating repetitive tasks, optimizing processes, and reducing human error. Traditional companies can use AI-powered tools to streamline various aspects of their operations, which can lead to cost savings and improved resource allocation.
2. **Personalized customer experiences:** AI enables companies to analyze large amounts of customer data and provide personalized experiences. This can lead to better customer satisfaction, loyalty, and increased sales. Businesses can utilize AI to recommend products, tailor marketing messages, and anticipate customer needs.
3. **New revenue streams:** AI can unlock new revenue streams by enabling the creation of innovative products and services. For instance, traditional manufacturing companies can leverage AI to offer predictive maintenance solutions, transforming their business from selling products to selling ongoing services.
4. **Data-driven decision-making:** AI-driven analytics can provide actionable insights from vast amounts of data. This empowers decision-makers in traditional companies to make informed choices based on real-time information and trends, leading to better strategic decisions.
5. **Disruption and competition:** Traditional companies face competition from tech-savvy startups that are born with AI and digital capabilities. To remain relevant, traditional companies may need to adapt their business models to integrate AI and respond to changing market dynamics.
6. **Business model innovation:** AI can enable new business models that were previously unfeasible. For instance, subscription-based models, outcome-based pricing, and data monetization strategies can be developed with AI at their core.
7. **Collaboration with AI startups:** Traditional companies can collaborate with AI startups to infuse innovation into their operations. These collaborations can help leverage external expertise and technologies to drive business model innovation.
8. **Reskilling and workforce transformation:** Integrating AI into business models requires reskilling the workforce to effectively collaborate with AI systems. This shift necessitates investing in training programs and creating a culture that embraces technological change.
9. **Ethical and regulatory considerations:** The adoption of AI raises ethical and regulatory challenges that need to be carefully navigated. Companies must consider issues related to privacy, bias, transparency, and accountability when incorporating AI into their business models.
10. **Risk management and security:** With increased reliance on AI systems, companies must also address cybersecurity concerns and ensure the protection of sensitive data from potential breaches or attacks.

In investigating the impact of AI on business model innovation in traditional companies, it is essential to consider both the opportunities and challenges that AI presents. The nature of this impact will depend on factors such as the industry, company size, market dynamics, and the extent to which AI is integrated into various business processes. Companies that proactively embrace AI and leverage it for innovative business models are likely to be better positioned for success in the evolving digital landscape.

Data availability

Data sharing is not applicable to this research as no data were generated or analyzed.

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Author contributions

RMV contributed sections “From artificial intelligence to scalability drivers”, “The model”, and “Results”; SCR provided sections “Evolving networks” and “Discussion”; and finally, JLP contributed sections “Introduction” 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

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