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Artificial Intelligence and the Great Reset: Impacts and Perspectives for Italian SMEs Business Model Innovation

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Abstract: The rise of artificial intelligence is fundamentally transforming the competitive landscape across various sectors, offering visionary enterprises new pathways to innovation development and to get a competitive edge. AI leverages data, analysis, and observations to perform tasks without hard coding, and benefits from self-learning and continuous improvement. We use Systems Thinking to frame how managers may adopt and integrate AI in business activities. We also investigate the motivations driving entrepreneurs to adopt AI solutions, and how they may impact on sustainable business model innovation, by administering a questionnaire to a sample of innovative Italian SMEs to get a comprehensive overview of the dynamics influencing AI adoption in business. This study sheds light on the intricate relationship between technology, sustainability, and corporate innovation. It offers both valuable insights for future research and for strategic managerial decisions on AI integration. Furthermore, it helps the development of innovative, sustainable business models in the evolving landscape of the Great Reset.

Keywords: artificial intelligence; great reset; system theory; business model innovation; PLS-SEM; survey; technology adoption

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1. Introduction

The idea of the Great Reset was first introduced by the World Economic Forum on 3 June 2020, through a multi-step process that involved strategic communication aimed at stimulating global debate and encouraging the adoption of new policies and practices to address the challenges of the 21st century [1].

This initiative emerged during the COVID-19 crisis as a strategic response to fill a significant gap in the global media landscape and to leverage the crisis as an opportunity to enhance global conditions [2]. The Great Reset asks for a comprehensive overhaul of economic and social systems capitalizing on the advantages offered by the Fourth Industrial Revolution [3]. Among these challenges are steering markets towards more equitable goals, supporting green infrastructure, and capitalizing on the momentum of digitalization [4]; addressing these challenges will necessitate changes in industries and businesses [5]. In this scenario, it is crucial to examine the factors motivating small and medium-sized enterprises (SMEs) to implement systemic digital innovations, such as those related to artificial intelligence (AI).

To understand the role of AI in the Great Reset, it is essential to apply Systems Thinking [4]. Systems Thinking involves comprehending the interconnectedness and interdependencies within a system and recognizing how components influence one another within the whole [6,7]. This approach is vital when considering the broad implications of integrating AI into business models, particularly within the context of the Great Reset, as it allows businesses to see beyond immediate gains and consider long-term impacts on the environment and society [8].

Disruptive innovations—a concept that refers to innovations that create a new market or transform an existing one, shifting market dynamics and often surpassing existing technologies, such as artificial intelligence [9]—redefine various industries' competitive dynamics. AI can be defined as the application of advanced algorithms and computing technologies to automate complex decision-making processes, enhance operational efficiency, and create added value for organizations [10]. AI has been recognized as one of the most significant technological innovations due to its enormous potential in creating added value and ensuring a competitive advantage [11]. Accordingly, AI development, and its implementation, has been able to leverage many financial and human resources. It possesses the ability to self-learn, continuously improve, and scale rapidly [12]. This potential stems from its ability to automate decision-making processes, drawing on human-like reasoning, which has sparked significant interest across numerous industries and companies.

Currently, the global AI market is valued at $150.2 billion, with an expected annual growth rate of 36.8% until 2030 [13]. According to a recent 2023 report, AI startups are achieving valuations of over $1 billion in significantly less time than their counterparts in other sectors [14]; in just 2023, 15 new companies in the AI sector achieved unicorn status, generating over $21 billion in total market value, driven by major Large Language Models (LLMs). Projections indicate a global expenditure on AI of $110 billion in 2024, compared to a modest $2 billion in 2015 [15]. This phenomenon, described as the "AI revolution", is considered crucial for innovation in sectors such as Fintech, healthcare, and credit services. Continuous innovation in AI can also lead to new business models and market opportunities. A PwC report underscores that AI is one of the keys enabling technologies for business innovation [16]. In conclusion, despite ethical challenges and potential risks, the responsible implementation of AI in business offers fertile ground for positive outcomes, operational improvements, and a continuous cycle of innovation.

In recent decades, research on the evolution of business models and on their role in innovation (BMI) processes has gained relevance in management studies [17]. Scholars have described BMI as a process aimed at creating, implementing, and sustaining strategies by companies to generate, deliver, and capture value [18,19]. Innovation in this context involves restructuring or merging components and activities within a business model [16,20]. According to several scholars [21,22], these technologies can significantly influence BMI, including those related to sustainability and sustainable development [23,24]. AI can act as an accelerator for BMI, offering companies the opportunity to adapt their current strategies [25]. Furthermore, AI is considered a necessary resource for companies to remain competitive [26].

The rest of the paper is structured as follows: First, we present a literature review and develop our hypotheses. Next, we outline the methodology and provide a detailed analysis of the data and results. Finally, we discuss the conclusions and implications.

2. Literature Review

2.1. Systems Thinking and the Great Reset

The Great Reset, proposed by the World Economic Forum, deals with the transformative impacts on societies of the COVID-19 pandemic and the Fourth Industrial Revolution [27]. Digital innovation stands as the third and final priority of the Great Reset. The pandemic has acted as a digital transformation catalyst as an outcome of lockdown measures has been the digital realm's robust and often irreversible expansion.

Systems Thinking, which emphasizes understanding the interconnectedness and interdependencies within systems, is crucial for comprehending the broader implications of the Great Reset [3,4]. This approach is essential for analyzing how digital innovations, such as AI, can contribute to sustainable BMI [23,28].

The Great Reset transformed not just individual businesses but entire economic systems, and companies may require a holistic understanding of how technologies, such as AI, can enhance sustainability through systemic changes. One of the principal impacts the pandemic has had on businesses has been to force managers to accelerate the automation transition [29]. Even if the diffusion of automation had begun previously, the Great Reset in the post-pandemic world is further accelerating, leveraging technologies such as AI and robotics to reduce employee health risks [4].

Thus, the focal point is the aggregation of digital technologies such as artificial intelligence, nanotechnology, biotechnology, and quantum computing [2]. Companies that miss the opportunity for digitalization risk their very same existence [27]. The changes brought about by technology are inevitable; hence, people have no control over technology and its impacts [30]. Specifically, this concerns small businesses, which have been severely affected by the pandemic's effects and are a vital source of employment growth, accounting for about half of all private-sector jobs in most advanced economies.

The Great Reset could signify the leading revolution in information technology, with artificial intelligence as its pivotal component [5]. For this reason, it is crucial to examine the factors that influence its integration into business practices. Advanced IT solutions such as AI could assist in managing complex challenges and contribute to enhanced stability [31].

2.2. Artificial Intelligence and Sustainable Business Model Innovation

Artificial intelligence is the branch of computer science dedicated to developing systems to perform tasks normally requiring humans to act. Fundamental characteristics of AI include machine learning, adaptation to new data, the analysis of complex patterns, and decision-making based on information [32–34]. In the context of management, AI uses algorithms to learn from data, interpret complex models, and provide predictions or suggestions to support managerial decisions and optimize business performance [35]. This ability to automate decision-making processes has sparked significant interest in both academic and managerial fields, as it enables the creation of integrated systems and the simplification of complex mechanisms through advanced automation [36,37]. AI has been defined as "the ability of a system to correctly interpret external data, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation" [38]. However, the term AI is a broad one, and it encompasses advanced technologies such as machine learning, robotics, autonomous vehicles, computer vision, natural language processing, virtual agents, and neural networks [39].

Unlike traditional computer programs with a fixed set of pre-programmed instructions, AI systems can learn and improve based on experience and even through self-learning [40,41]. Recent developments allow machines to process large sets of unstructured data using complex algorithms to perform specific tasks [42,43].

Furthermore, commercial applications of AI are increasingly visible, and they attract significant venture capital funding [44]. According to [39], after a series of AI "winters", the technology is gaining substantial commercial traction, ensuring sustained development.

Finally, analysts increasingly agree that AI could bring significant changes to the entrepreneurial landscape. Despite numerous positive aspects, current AI literature focuses on how new technologies will impact entrepreneurs and consumers in the creative, cognitive, and physical processes of new ventures [45,46].

AI adoption may be hindered by individuals' reluctance to use it due to discomfort with the unknown [47,48]. At the same time, AI systems resembling humans may struggle to elicit emotional attachment and empathetic responses, limiting their effectiveness in providing emotional support [49]. This can lead to cognitive dissonance, reducing user engagement, satisfaction, and trust [50]. The efficiency of AI-performed tasks can increase users' perceived discomfort [51] and raise privacy concerns [52]. Finally, discomfort with AI negatively affects the intention to continue using it [50].

In recent years, there has been an increased focus on integrating sustainability into business models, giving rise to the concept of Sustainable Business Model Innovation (SBMI) [53,54]. SBMI aims to integrate sustainability goals directly into business models, creating value for multiple stakeholders, including customers, shareholders, suppliers, partners, the environment, and society [55].

AI adoption can play a crucial role in SBMI. AI supports decision-making and management processes by improving forecasts and reducing costs [56]. Recently, some studies have explored the role of AI in business model innovation [57,58]. AI can accelerate SBMI, and it is a relevant competitive factor [25,26]. Integrating AI into companies' business models requires a deep understanding of its applications [59] and ways to adapt communication strategies to stay relevant and competitive [60]. AI has facilitated business model innovation in various sectors [61], going beyond incremental process improvements and revolutionizing companies' value propositions through co-creation with customers [62–64]. However, there is a research gap on how companies can create value using AI [11,65]. Although there are examples of AI applications in corporate business models, developing new business models remains a challenge [66,67]. Companies must reflect on their values and embrace sustainability to implement effective strategies [68,69]. In this context, AI is a key catalyst for developing sustainable business models [70,71].

3. Research Framework and Hypothesis Development

The adoption of AI and sustainable business model innovation are highly relevant topics for modern companies [23,41]. With the advancement of AI technologies, organizations are increasingly interested in understanding how to integrate these technologies into their business models to enhance sustainability and competitiveness [22,25].

A combination of theoretical relevance, empirical support, and the topicality of the subject matter has driven the definition of our research model. First of all, we defined our hypotheses by looking at the theoretical concepts widely discussed in existing managerial literature on AI adoption and on its connection between them and SBMI, such as the attitude managers have towards AI adoption [72,73], how much they are interdependent with their partners [74,75], entrepreneurial orientation [76,77], and sustainability orientation [23,44].

Then, we investigated the substantial empirical support for the relationships between the variables in question [25,73,76]. Previous studies have shown that a positive attitude towards AI promotes the adoption of innovative and sustainable practices [78,79], while a negative attitude can hinder them [22,80]. Similarly, interdependence with partners and entrepreneurial orientation have been identified as key factors influencing AI adoption and business model innovation [23,74–76].

Furthermore, the hypotheses reflect the complexity and multidimensionality of the business decision-making process. It is not enough to consider only the general attitude towards AI; it is also important to examine how interdependence with partners and entrepreneurial orientation influence this attitude.

Finally, these hypotheses aim to address specific gaps in the existing literature. Although many studies explore individual aspects of AI adoption and sustainable innovation [77,78], few research efforts examine how these factors interact with one another in an integrated manner [73,79].

3.1. Relationship between the Attitude towards Adopting AI Solutions and Sustainable Business Model Innovation

The construct known as General Attitude Towards Artificial Intelligence (GAAIS) pertains to the overall evaluation and opinions of individuals towards AI, including feelings, beliefs, and emotions [72,73].

The general attitude towards AI is influenced by various factors, such as personal experiences, media information, social group opinions, and perceptions of the social and economic impacts of artificial intelligence [41,80,81]. Understanding this attitude is crucial to develop effective communication strategies, appropriate educational and regulatory interventions, and guide the responsible development and adoption of artificial intelligence in different sectors [82].

A positive attitude towards AI can foster innovation and sustainability in business models of organizations [23,83]. Managers who are optimistic about artificial intelligence see opportunities to improve efficiency, productivity, and the quality of products and services, creating a conducive environment for implementing advanced solutions. Organizations that promote a positive approach to artificial intelligence tend to invest more in research and development, identifying new technological applications and orienting themselves towards sustainability [41,84].

AI facilitates the transition towards more sustainable processes [81,85] and promotes an organizational culture based on research and innovation. Companies that value AI tend to have teams more inclined to experiment and propose new ideas, adapting business models to market needs and sustainability demands [25,83]. In summary, a positive attitude towards AI can act as a catalyst for innovation and the adaptation of business models, making organizations more competitive in an ever-evolving business landscape [25,41,82].

Based on this literature, we propose the following hypothesis:

H1a: *A positive general attitude towards AI by managers positively influences sustainable business model innovation.*

A generally negative attitude towards AI can represent a significant obstacle to BMI within organizations [22,86,87]. Concerns and fears related to the implementation of artificial intelligence, such as potential job loss, data privacy issues, and ethical implications, can undermine trust in new technologies and discourage the adoption of innovative business models. Firstly, the fear of job loss due to automation can generate resistance to the adoption of innovative technologies [22,87,88]. Employees might fear that AI-based solutions could replace their roles, creating uncertainty and resistance to change within the organization. Additionally, concerns about data privacy and information security can hinder the adoption of artificial intelligence [89,90]. Ethical considerations related to the use of artificial intelligence, such as the risk of algorithmic discrimination or lack of transparency in automated decision-making processes, can generate doubts about its acceptance and adoption within organizations [91]. In a context of suspicion or fear, leaders might be reluctant to invest in new strategies or technologies perceived as controversial or risky [41,75,82]. Finally, this climate of distrust can slow down innovation and digital transformation, limiting the ability of organizations to adapt to market changes and remain competitive in the long term.

Based on this literature, we propose the following hypothesis:

H1b: *A negative general attitude towards AI by managers negatively influences sustainable business model innovation.*

3.2. Relationship between Interdependence with Partners and the Attitude towards the Adoption of AI Solutions

The interdependence with partner companies plays a crucial role in the adoption and acceptance of artificial intelligence within organizations. As emphasized by some scholars [74,75], close and collaborative relationships with business partners is essential to shape companies' attitudes towards emerging technologies like AI. One of the key advantages of this interdependence is the sharing of resources and knowledge, as highlighted by [92]. In a context where AI requires continuous access to specialized data and skills, companies can combine their resources and expertise with those of their partners to address common challenges and develop advanced AI solutions. This collaboration not only facilitates the companies' best practices exchange and the processes to access otherwise unavailable resources, speeding up the adoption and implementation of AI [93], but it also fosters the creation of technological synergies. A strong degree of interdependence with partner companies enables collaborative addressing of ethical and social challenges related to AI [94]. Sharing best practices and developing common guidelines can help mitigate concerns regarding data privacy, security, and the social impact of AI.

As it emerges, the following hypothesis is established:

H2a: *Strong interdependence among partner companies positively influences the positive general attitude towards AI.*

Interdependence among partners influences the adoption of AI in organizations, but at the same time, it poses significant challenges. Excessive reliance on partner resources and decisions can compromise the organization's strategic control, limiting its ability to innovate autonomously [83,95]. Additionally, interdependence can lead to rigidity in commercial relationships, hindering the adoption of new technologies [96] such as conflict of interest among partners [97]. To mitigate these negative effects, organizations must balance collaboration and strategic autonomy [98]. Diversifying partnership sources and promoting an internal culture of innovation are crucial [99]. Furthermore, establish transparent governance mechanisms to responsibly manage partner relationships [100]. In conclusion, while partner interdependence offers collaboration opportunities, it requires careful management to ensure effective adoption aligned with organizational goals.

As it emerges, the following hypothesis is established:

H2b: *Strong interdependence among partner companies negatively influences the negative general attitude towards AI.*

3.3. Relationship between Entrepreneurial Orientation and Propensity to Adopt AI Solutions

Entrepreneurial orientation (EO) is a concept in management that indicates an organization's attitude toward innovation, risk-taking, and proactivity in seizing market opportunities [82].

Organizations with a strong entrepreneurial orientation tend to embrace risk and innovation [76]. Artificial intelligence is seen as a key element to enhance operational efficiency and creatively address market challenges. Companies that adopt a positive approach towards AI believe that this technology can become a source of competitive advantages and help companies to discover new business opportunities [23,41]. This entrepreneurial attitude drives organizations to explore the potential of AI in various areas, from improving operational performance to creating innovative products and services that meet the needs of an evolving market [23]. Entrepreneurially oriented companies are more inclined to experiment with new AI applications and quickly adapt their operational strategies in response to changes in the competitive environment [77,80]. Moreover, this inclination towards innovation can foster a corporate culture focused on continuous learning and adaptation, creating a favorable environment for the development and implementation of cutting-edge AI-based solutions [65].

In summary, companies with a strong entrepreneurial orientation tend to view AI as an opportunity for innovation and progress rather than a threat or source of uncertainty. This positive outlook can significantly impact corporate strategy and the ability of organizations to adapt in dynamic and continuously evolving markets.

From what has been previously stated, we define the following hypothesis:

H3a: *A strong entrepreneurial orientation positively influences the general positive attitude towards AI.*

A strong entrepreneurial orientation can positively impact fears and anxieties related to the adoption of artificial intelligence in companies in various ways [101,102]. Entrepreneurially oriented organizations tackle challenges with a problem-solving mindset rather than focusing solely on the fears and anxieties of change, encouraging the exploration of innovative solutions [41]. This can positively affect the negative propensity to adopt AI, in addition to the fact that these companies are more inclined to experiment and take calculated risks in adopting AI [103], mitigating fears through exploration and learning from failures. Entrepreneurial orientation also drives companies to focus on innovation and the adoption of new technologies to remain competitive [28]. Companies with a strong entrepreneurial orientation are more agile and adaptable to changes, enabling them to swiftly address AI-related fears by adapting strategies and business operations [104]. Lastly, these organizations tend to foster a culture of trust and collaboration, facilitating the sharing of concerns and the pursuit of group solutions [105], thus reducing individual anxieties through knowledge and experience sharing. In summary, entrepreneurial orientation can alleviate fears and anxieties related to AI by promoting a problem-solving mindset, an experimental approach, innovation, agility, adaptability, and a culture of trust and collaboration.

From what emerges in the literature, we establish the following hypothesis:

H3b: *A strong entrepreneurial orientation positively influences the negative general attitude towards AI.*

3.4. Relationship between Entrepreneurial Orientation and Sustainable Business Model Innovation

The individual entrepreneurial orientation is crucial in developing an entrepreneur sustainable orientation [106,107]. When company leaders embrace an entrepreneurial orientation focused on sustainability, they not only foster innovation in business models but also cultivate solutions mindful of environmental, social, and economic impacts, as illuminated by [108]. Primarily, entrepreneurs oriented towards sustainability prompt companies to assess the environmental and societal ramifications of their operations, as highlighted by [109]. Moreover, companies guided by a robust entrepreneurial orientation tend to engage stakeholders to develop sustainable solutions addressing global challenges like climate change, poverty, and social inequality [110]. The integration of artificial intelligence within companies may also serve as a catalyst at the intersection of entrepreneurial orientation and SBMI [79,88,106]. AI not only streamlines business operations, enhancing energy efficiency and waste reduction, but also facilitates the development of innovative products and services that sustainably cater to customer needs [111,112].

From what emerges in the literature, we establish the following hypothesis:

H4: *A strong entrepreneurial orientation positively influences sustainable business model innovation.*

3.5. Relationship between Partners with Interdependent Activities and Tasks and Sustainable Business Model Innovation

Task-initiated interdependence encapsulates the mutual reliance seen when companies actively collaborate toward shared goals [113,114]. This collaboration fosters efficient resource sharing and facilitates the development of innovative solutions for sustainability challenges [115]. Trust among partner companies is nurtured through collaboration and the exchange of knowledge and resources [116]. Such collaboration results in business models that effectively integrate sustainability, thereby enhancing competitiveness and resilience in the business landscape [117]. The adoption of AI plays a significant role in enhancing task-initiated interdependence by providing tools and platforms for efficient collaboration, data analysis, and process automation [25]. Moreover, AI aids in identifying emerging trends and opportunities, supporting the implementation of sustainable business models [84,86]. In essence, AI enhances interdependence, fostering collaboration and innovation for sustainable business models, benefiting both companies and communities.

Therefore, we establish the following hypothesis:

H5: *A high level of task-initiated interdependence among partner companies positively influences sustainable business model innovation.*

3.6. Relationship between Sustainability Orientation and Entrepreneurial Orientation

The literature highlights that sustainability-oriented companies often exhibit a strong inclination towards entrepreneurship [118]. These companies, sensitive to environmental, social, and economic needs, are driven to seek innovative and sustainable solutions [119]. This mindset can stimulate developing an entrepreneurial culture valuing innovation and flexibility, fostering collaboration and co-creation with both organizations and institutions [120]. Companies that integrate sustainability into their entrepreneurial strategies tend to develop innovative business models that generate economic, social, and environmental value, promoting collaboration and innovation in the sector [44]. In conclusion, within the realm of sustainable business model innovation, the integration of AI adds complexity and potential to the relationship between sustainability and entrepreneurial culture [94]. AI provides sustainable solutions to address environmental, social, and economic challenges, and stimulates new business opportunities for sustainability-oriented companies [121]. By supporting predictive decisions oriented towards sustainability and automating business processes, AI amplifies the effectiveness of the relationship between sustainability orientation and entrepreneurial orientation, facilitating innovation and collaboration [23]. Accordingly, we establish the following hypothesis:

H6: *Strong sustainability orientation positively influences entrepreneurial culture within firms.*

Accordingly, our hypotheses let us define the following research model (see Figure 1).

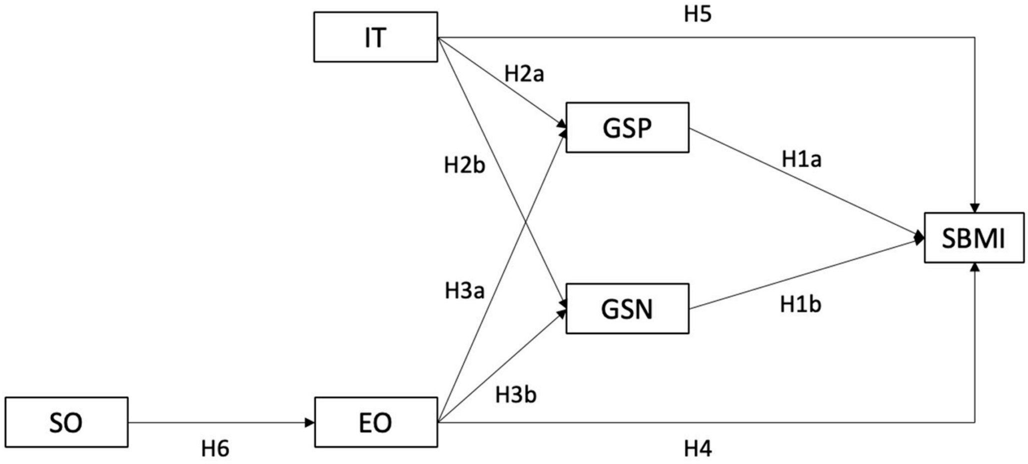

Figure 1. The proposed research model. Source: Authors' elaboration.

4. Materials and Methods

4.1. Sample Selection

To explore the viability of our research model, we adopted a quantitative approach to gather data with a survey. We chose the survey as this investigative tool as it offers flexibility and efficiency in the data-gathering process [122]. To facilitate and expedite data collection from subjects distributed across various Italian regions, we used an online platform (www.limesurvey.com) to administer it [123].

As the focus of our model is related to the Business Model Innovation, we targeted our data-gathering process to a specific type of Italian SME: the innovative SME. These companies have to meet at least two of the following criteria: (1) they have to spend at least 3% of the highest between turnover and production costs in R&D or Innovation expenses; (2) at least 1 out of 5 their employees must have a Ph.D., or they have to be Ph.D. Students, or they work a Academic Researchers, or at least 1 out of 3 has to have a master's degree; (3) the company own, has filed, or has a license to at least one patent, or it owns a registered software. As a consequence, targeting these companies allowed us to test our model with companies with a high potential for innovation and readiness to adopt new technologies. The decision to select this type of business stems from several considerations. Firstly, some scholars have highlighted the need to delve deeper into research on the implementation of artificial intelligence solutions in innovative SMEs, emphasizing the necessity of using a quantitative approach that holistically comprehends the drivers and enabling factors behind the development and implementation of this innovative technology [72,124]. Moreover, compared to large enterprises, SMEs face greater obstacles during the implementation of artificial intelligence solutions due to limited resources or the lack of qualified professionals with adequate IT/technical skills to manage and use these systems [125].

Furthermore, as these companies have been started all over Italy, targeting them helped us to reach companies from various sectors, regions, and sizes.

4.2. Measures

The questionnaire was developed by considering the knowledge and theories already present in academic literature. To ensure the validity and reliability of the measures, only previously validated scales used in similar research were utilized.

Following the usual guidelines [123], we adopted the "translation back to translation" method to adapt the scales from English to Italian. We used the construct of "General Attitude Towards Artificial Intelligence", (20 items in total, 12 positive and eight negative attitudes). In both cases, the items were adapted from previous works [72,126].

Entrepreneurial orientation (EO) was adapted from previous literature [127,128]; sustainability orientation (SO), was measured through six items [129,130].

We adapted the sustainable business model innovation (SBMI) from previous studies [131,132]. "Initiated-task interdependence" was measured with four items [113,114].

All variables were measured using a seven-point Likert scale ranging from 1 = Not at all true to 7 = Perfectly true.

To mitigate possible distortions in data acquisition, such as retrieval bias and common method bias (CMB), the items related to the different constructs were reversed and presented in a random order, following the usual indications [133]. Before the official distribution of the questionnaire, a group of experts, consisting of about 10 academics and managers, reviewed its content to evaluate the clarity and adequacy of the proposed questions. Their observations contributed to targeted modifications to improve the structure and comprehensibility of the questionnaire.

4.3. Data Collection

As we said before, we targeted Italian Innovative SMEs for this study. Furthermore, in order to get a comprehensive overview of the practices and challenges related to AI adoption, we tried to engage companies in various industrial sectors. Our main target, considering the scope of this research, were companies in manufacturing, services, information technology, healthcare, and energy, as these sectors are known to be more open to adopting new technologies and therefore are relevant to our study. By examining the responses from these diverse sectors, we hoped to gain a comprehensive view of the opportunities and hurdles related to AI adoption as each sector presents unique practices and challenges, highlighting the multifaceted nature of AI implementation across different industries. This understanding is crucial to develop strategies that can facilitate successful AI integration and maximize its benefits.

Moreover, to avoid regional biases and ensure diversity, we selected SMEs from different geographical regions. This approach allowed us to consider regional differences in AI adoption and sustainability practices. The data-collection period ran from January to May 2024. During this period, we collected 85 valid survey responses.

Our study is mostly exploratory, aiming at understanding if AI is related to Sustainable Business Model Innovation in these themes of Great Reset. For such studies, the minimum sample size required for the application of structural equation models is calculated considering the most complex multiple regression. This means that either the construct with the largest number of items or the construct with the largest number of antecedents is considered (with the general rule of 10 cases for each of the most complex regression independent variables in the model) or, using a more modern ex-post measurement approach for a model with the lowest path coefficient between 0.2 and 0.3 with a 5% significance level, the minimum sample size is 69 cases [134]. In our study, as the largest set of predictors is given by the four SBMI predictors, both minimum requirements may be considered to be satisfied.

In the following Table 1, we report the main characteristics of the sample.

Table 1. Characteristics of the sample.

Characteristics	Types	Value	%
Industry	Manufacturing	14	16.47
	Service	17	20
	Information technology	21	24.70
	Healthcare	11	12.94
	Energy	14	16.47
	Other	8	9.41
Area	North	35	41.17
	Center	26	30.58
	South	24	28.23
Requisites	At least 3% R&D	26	30.58
	At least 20% qualified staff	34	40
	At least one patent	25	29.41

Source: Authors' elaboration.

5. Results and Discussions

5.1. Analysis of Reliability and Convergent Validity

The first step in evaluating the reflective measurement model is to examine the reliability of the indicators and constructs. In this regard, two aspects of reliability were examined: the reliability of individual items and the reliability of internal consistency.

The reliability of the individual item is considered adequate when an item has a factor loading greater than 0.6 on its respective construct [135]. Specifically, during the construct analysis, items GSN1, GSN2, GSN4, GSN7, GSN8, GSP2, GSP3, SO6, PRO1, VP1, and VCR4 presented a factor loading less than 0.6 and were therefore eliminated. When evaluating the reliability of an individual item, a factor loading above 0.6 is generally considered adequate. This means that more than 36% of the item's variance is explained by the construct being measured. As for the reliability of internal consistency, both Cronbach's alpha (α) coefficient and composite reliability (CR) were used. For internal consistency to exist among constructs, both Cronbach's alpha and CR should be equal to or greater than 0.7 [136]. As shown in Table 2, all measures are robust in terms of their reliability, as the factor loading of each item is above 0.6, and both Cronbach's alpha and CR are above 0.70.

The analysis of validity aims to determine whether the items can measure the latent construct [137]. This is specifically assessed through convergent validity and discriminant validity. The metric used to assess convergent validity is the average variance extracted (AVE) for all elements in each construct. The AVE is the average percentage of explained variance (extracted variance) among the elements of a construct. For convergent validity to exist, the AVE of each construct must be at least 0.5, indicating that the construct explains at least 50% of the variance of its items [138]. As shown in Table 2, the AVEs of all constructs are greater than 0.5, meaning that all latent variables in the model can explain, on average, more than 50% of the variance of their indicators.

Table 2. The analysis of reliability.

Construct	Latent	Items		Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
General Attitude Towards AI—Negative	GSN	GSN3	0.9140	0.943	0.959	0.887
		GSN5	0.9360			
		GSN6	0.9634			

Table 2. *Cont.*

Construct	Latent	Items		Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
General Attitude Towards AI—Positive	GSP	GSP1	0.8393	0.963	0.963	0.725
		GSP4	0.7825			
		GSP5	0.9181			
		GSP6	0.8358			
		GSP7	0.8712			
		GSP8	0.7943			
		GSP9	0.8317			
		GSP10	0.8785			
		GSP11	0.8661			
		GSP12	0.8891			
Initiated-Task Interdependence	IT	IT1	0.8991	0.887	0.92	0.742
		IT2	0.8490			
		IT3	0.8580			
		IT4	0.8379			
Sustainability Orientation	SO	SO1	0.9454	0.96	0.969	0.863
		SO2	0.9087			
		SO3	0.9593			
		SO4	0.9057			
		SO5	0.9242			
Entrepreneurship Orientation	INN	INN1	0.9207	0.809	0.884	0.721
		INN2	0.6846			
		INN3	0.9188			
	PRO	PRO2	0.9077	0.831	0.921	0.854
		PRO3	0.9403			
	RT	RT1	0.9422	0.842	0.91	0.836
		RT2	0.7821			
		RT3	0.9098			
Sustainable Business Model Innovation	VCA	VCA1	0.7833	0.738	0.882	0.789
		VCA2	0.8102			
		VCA3	0.6857			
	VCR	VCR1	0.9082	0.872	0.922	0.797
		VCR2	0.9088			
		VCR3	0.8602			
	VP	VP2	0.9332	0.84	0.926	0.862
		VP3	0.9236			

Source: Authors' elaboration.

5.2. Discriminant Validity Analysis

Discriminant validity, instead, is the extent to which a construct is distinct from other standard empirical constructs. Therefore, establishing discriminant validity implies that a construct is unique and captures phenomena not represented by other constructs in the model. We use the Fornell–Larcker criterion [138] to assess discriminant validity. According to this criterion, a latent construct should share more variance with its assigned indicator than with any other latent construct. As shown in Table 3 in the case of our analysis, the criterion is met.

Table 3. The analysis of convergent validity (Fornell–Larcker criterion).

	GSN	GSP	IT	SO	INN	PRO	RT	VCA	VCR	VP
GSN	**0.942**	.	.	.	.	.	.	.	.	.
GSP	−0.235	**0.828**	.	.	.	.	.	.	.	.
IT	0.333	0.612	**0.861**	.	.	.	.	.	.	.
SO	−0.058	0.384	0.286	**0.929**	.	.	.	.	.	.
INN	−0.244	0.614	0.328	0.781	**0.849**	.	.	.	.	.
PRO	−0.228	0.432	0.066	0.642	0.816	**0.924**	.	.	.	.
RT	−0.295	0.254	−0.012	−0.013	0.026	0.171	**0.915**	.	.	.
VCA	0.31	0.399	0.476	0.472	0.422	0.362	−0.173	**0.888**	.	.
VCR	0.225	0.383	0.387	0.784	0.699	0.655	−0.082	0.76	**0.893**	.
VP	0.459	0.204	0.483	0.553	0.903	0.382	0.236	−0.272	0.766	**0.928**

Source: Authors' elaboration. Note: The table values are the correlation between the variables—the value on the diagonal (in bold) are the square root of AVEs.

5.3. Evaluation of the Structural Model

Fundamental criteria for evaluating the quality of the structural model include the coefficient of determination (R^2) and the statistical significance of the path coefficients [136]. To assess the explanatory and predictive effectiveness of a model, we rely on the coefficient of determination, denoted by R^2. This value measures the proportion of explained variance in the endogenous constructs, thus providing a measure of the overall explanatory power of the model. Note that, regarding our analysis, all R^2 values are above 0.25, implying that the model exhibits good predictive ability. In this case, the SBMI construct has an R^2 of 0.57; therefore, this R^2 value means that the model exhibits good predictive ability.

The following Table 4 and Figure 2 report the results of the hypotheses testing

Table 4. The testing of hypotheses.

HP	Relationship	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
HP1a	GSP → SBMI	−0.293	−0.28	0.163	−1.797	−0.602	0.042
HP1b	GSN → SBMI	−0.339	−0.336	0.091	3.711	−0.148	−0.511
HP2a	IT → GSP	0.456	0.459	0.063	7.258	0.336	0.585
HP2b	IT → GSN	0.426	0.424	0.083	5.153	0.253	0.576
HP3a	EO → GSP	0.517	0.507	0.078	6.601	0.338	0.645
HP3b	EO → GSN	−0.419	−0.407	0.103	−4.078	−0.583	−0.189
HP4	EO → SBMI	0.725	0.719	0.093	7.775	0.532	0.896
HP5	IT → SBMI	0.359	0.345	0.157	2.283	0.011	0.636
HP6	SO → EO	0.73	0.727	0.058	12.558	0.599	0.824

Source: Authors' elaboration.

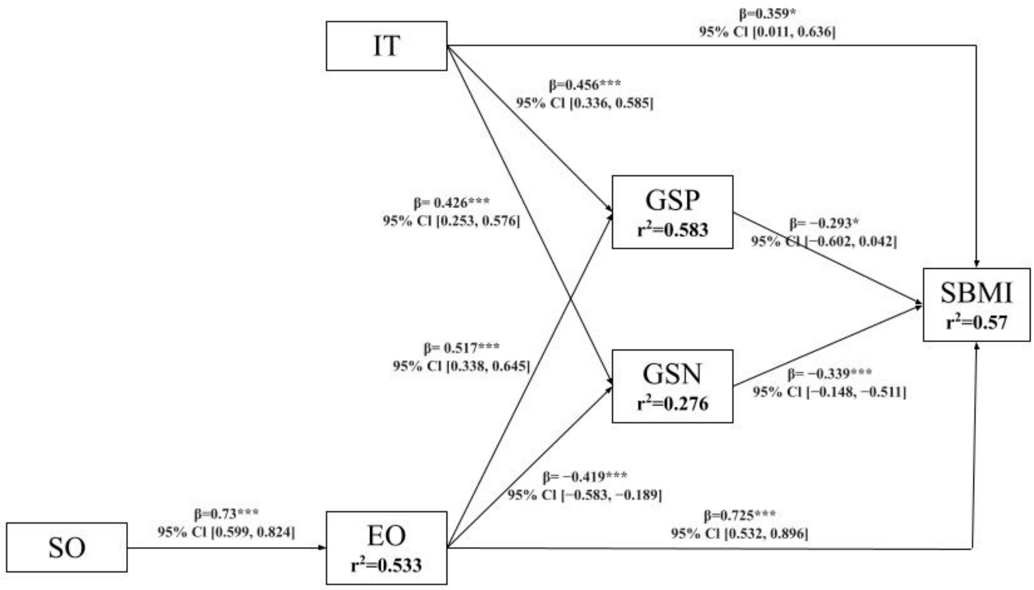

Figure 2. The results of the verification of the hypotheses. Source: Authors' elaboration. Notes: *: p-value ≤ 0.1; ***: p-value ≤ 0.001.

The results show that all research hypotheses are confirmed, except for HP1a, for which there is no evidence.

5.4. Discussion of Results

The study results indicate partial support for the hypotheses linking the propensity to adopt AI solutions and SBMI. In particular, we have found that a negative inclination towards AI adoption adversely impacts SBMI (H1b: −0.339 ***), but at the same time, the study found no significant evidence linking a positive inclination towards AI adoption to SBMI.

All the other hypotheses in our research framework are significant.

Regarding H2 (both a and b, respectively, 0.456 *** and 0.426 ***), our results have found that IT has a significant and positive impact on both dimensions of General Attitude Towards AI without a significant difference between them. Furthermore, regarding H5 (0.359 *), the negative effect that H2 highlights of the relationship between IT and SBMI, considering that GSP has not a significant effect on SBMI, gets balanced by a similar positive direct effect driving to a moderately positive total effect.

On the contrary, EO shows the strongest effect on SBMI as the sum of two different effects, a direct one (H4: 0.725 ***) and an indirect one, through a negative effect on GSN (H3b: −0.419 ***). Similarly, even SO has a positive effect on SBMI, even if it is fully dependent on its effect on EO (H6: 0.73 ***).

6. Implication, Limitation, and Future Research

6.1. Theoretical Implications

This study significantly contributes to academic research. Regarding Systems Thinking, it emphasizes the importance of interconnections among business elements in AI adoption and business model innovation, confirming the need for integrated approaches in support of previous results [27,139]. When we consider our results under the lens of the Great Reset, it empirically analyzes business strategies in the context of socio-economic change, highlighting how AI can promote sustainability and innovation, aligning with studies on the convergence of emerging technologies and socio-economic restructuring [4,5,29].

The theoretical implications of our research in the field of digital entrepreneurship highlight critical aspects for the adoption of sustainable business models. We have found no support for H1a, not aligning our results with those previous studies that have highlighted how creating an environment conducive to the development and implementation of cutting-edge solutions based on artificial intelligence (AI) is crucial for corporate success [23,41,76].

Looking at H1b, our results confirm what is reported in the literature regarding the importance of further studies on the negative attitudes of managers towards SBMI and the associated risks [140]. Previous studies [79,83,85] have emphasized how a negative attitude from managers can hinder the adoption of sustainable business models, thus limiting the ability of companies to innovate sustainably [22,87,89].

Regarding open innovation, our research provides significant contributions on the importance of managing collaboration and interdependence among partner companies. Close collaboration and the interdependence of activities performed between partners can enhance the effectiveness of innovation, as evidenced by hypothesis H5. In general, well-structured interdependence with partners promotes SBMI, as demonstrated by several authors [115,117].

We have found mixed evidence on the relationship between interdependence with partners and AI adoption. On the one hand, results for H2a show that collaboration with partners may facilitate the exchange of best practices and access to otherwise unavailable resources, accelerating AI adoption and implementation [22]. Accordingly, our results support previous findings [64,74,92] that companies embedded in innovative networks or open to change exhibit a greater capacity to implement innovation such as those related to AI.

On the other hand, looking at the results for H2b, excessive dependence on partners can cause organizations to lose control over their strategic and operational paths, limiting their ability to adapt to market changes and innovate autonomously [83]. As a consequence, a high degree of collaboration and interdependence must be carefully evaluated during the agreement phase, considering both benefits and potential risks. Overly stringent partnership agreements can compromise strategic control and limit the ability to innovate independently, as indicated by previous research [83,96,99].

Our research also confirms the importance of promoting a corporate and entrepreneurial culture focused on continuous learning and adaptation. A strong entrepreneurial orientation (EO) is correlated with a positive attitude towards AI (H3a), as companies see AI as helping to reach competitive advantages and to develop new business opportunities [41]. Additionally, organizations with high EO can mitigate managers' negative attitudes towards AI by fostering a culture of collective problem-solving and knowledge-sharing [105]. A strong entrepreneurial orientation, as shown by the results for H3b, can also alleviate fears and anxieties related to the adoption of AI, as suggested by previous studies [41,101,102], thus indirectly promoting SBMI.

The positive correlation between EO and SBMI is further supported by literature [106,108], which suggests that sustainability-oriented EO within firms creates an environment conducive to business model innovation that integrates economic, social, and environmental considerations. Such models embrace circular economy practices, responsible production, and sustainability-oriented services, addressing customer needs and global challenges [120].

Finally, our research confirms the importance of the positive relationship between sustainability orientation and entrepreneurial orientation in fostering sustainable innovation in business models (H6). Previous studies [44,119,121] have demonstrated how a strong sustainability orientation can be a fundamental driver for business model innovation, enabling companies to develop innovative solutions that are also sustainable. Our research reinforces this theory, suggesting that companies must integrate sustainability into their entrepreneurial strategies to maximize their innovative potential.

6.2. Economic Implication

Based on these results, the economic implications for companies adopting technologies for business model innovation, based on the verified hypotheses, are significant. A negative attitude of managers towards AI (H1b) can hinder innovation, leading to high opportunity costs and lower operational efficiency, resulting in lost competitiveness and new market opportunities. Conversely, strong interdependence among partners (H2a, H2b) both enhances positive attitudes towards AI and reduces resistance to change, leading to faster and integrated innovations, with savings on development costs, while improving the negative aspects towards it. At the same time, interdependence among partners (H5) facilitates the development of innovative and sustainable solutions, improving the effectiveness of innovations and reducing research and development costs. Sharing best practices contributes to more sustainable operations and less environmental impact.

A strong entrepreneurial orientation (H3a, H3b, H4) fosters an innovation culture, encouraging AI adoption and supporting sustainable innovation. These companies tend to invest in new technologies and processes, increasing competitiveness and long-term growth. An informed negative attitude can also manage risks, avoiding ill-considered investments and preventing financial losses.

A strong sustainability orientation (H6) integrates sustainable practices that attract talent and investment, promoting responsible innovation and creating long-term value. In summary, the adoption of AI technologies and business model innovation brings significant economic benefits, including cost reduction, revenue growth, improved competitiveness, and long-term sustainability.

6.3. Managerial Implications

Managerial implications encompass four critical areas. Firstly, as demonstrated by the results, a negative attitude towards AI is more likely to be associated with the non-adoption of a sustainable business model (H1b). Managers must therefore recognize the role of AI in transforming business models towards sustainability by creating an integrated strategy for AI adoption that aligns with sustainability goals, such as the Great Reset. These results highlight the necessity for managers to adopt an approach aligned with the Systems Thinking perspective, which emphasizes understanding the interconnectedness of organizational components [139].

Secondly, fostering an innovative corporate culture is essential. Managers should promote an entrepreneurial mindset and encourage continuous learning to mitigate resistance to AI and harness its potential for sustainability [103]. Indeed, a strong entrepreneurial orientation not only enhances the propensity to adopt AI (H3a) but also increases the likelihood of adopting a sustainable business model (H4 and, indirectly, H3b).

Thirdly, effective collaboration and partnerships are crucial. Engaging partners can facilitate AI adoption by sharing resources and expertise, accelerating technological advancements [139]. Although a strong interdependence with partners might create an obstacle to AI adoption, it has an overall greater effect in transitioning from a traditional business model to a sustainable one (H2b, H5). This aligns with the collaborative goals of the Great Reset, promoting sustainable and equitable economic systems [4]. Companies that effectively address these challenges can leverage AI to enhance operational efficiency, make informed decisions, and innovate within their sectors.

Managers must communicate the benefits of AI, address concerns, and seamlessly integrate the technology into existing processes [29]. Systems Thinking advocates for a holistic approach to change, considering both internal and external dynamics [108], while monitoring systems evaluate sustainability impacts and inform strategic adjustments [141].

Based on these premises, managers should adopt an integrated strategy for AI adoption to facilitate the transition to a sustainable business model. Firstly, they should cultivate an innovative culture by encouraging continuous learning to mitigate resistance to AI. Secondly, they should implement partnerships and collaborations to share resources and expertise, thereby accelerating technological progress. Lastly, they must communicate the benefits of AI, address concerns, and integrate the technology into existing processes.

6.4. Limitation and Future Research

The research has limitations, including a small sample size of 85 observations, potentially limiting generalizability. It is possible to suppose that the lack of support for H1a was probably due to this constraint.

Future studies should expand samples and test models across larger enterprises and diverse countries, considering regulatory and cultural impacts on AI adoption drivers. Comprehensive longitudinal and comparative studies are needed to explore AI adoption's relationship with sustainable business, analyzing barriers, facilitators, and ethical impacts. New theoretical frameworks based on Systems Thinking and the Great Reset could provide essential guidance for understanding AI's interaction with sustainable business models, shaping future research and managerial strategies.

7. Conclusions

Below is a summary of the main conclusions of the research:

- AI adoption is affected by collaboration and knowledge sharing among organizations; it is influenced by processes promoting access to external resources and those related to open innovation. Engaging with partners facilitates AI adoption by sharing resources and expertise, accelerating technological advancements. This supports the collaborative goals of the Great Reset (H2b, H5).
- A negative attitude towards AI from managers adversely impacts the adoption of a sustainable business model. Consequently, companies should try to reduce its effects by reducing the fears related to these new technologies and those related to implementing disruptive innovations in company's processes (H1b).
- The adoption of AI influences entrepreneurial strategies towards sustainability and innovation, confirming the necessity for digital entrepreneurs to integrate AI into decision-making processes. Therefore, on one hand, a strong entrepreneurial orientation facilitates the adoption of AI, while on the other hand, it can help manage risks by avoiding uncalculated investments and preventing financial losses (H3a, H3b, H4).
- Fostering an entrepreneurial mindset and promoting continuous learning can mitigate resistance to AI (H3b) and harness its potential for sustainability (H4, H6).
- Although collaboration is essential for business model innovation from the perspectives of open innovation, excessive dependence on partners can lead organizations to lose control over their strategic and operational directions, thereby limiting their ability to respond to market changes and innovate autonomously (H2b).

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