

Article

Drivers and Sustainable Performance Outcomes of AI Adoption Intention: A Multi-Theoretical Analysis in the Entrepreneurial Ecosystem

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Abstract

Artificial Intelligence (AI) will drastically change the way entrepreneurs operate within their respective fields toward sustainable performance. However, although we have some data about how companies will adopt AI and how it is implemented, it is still an under-studied area of research. The goal of this study was to examine the antecedents and consequences of AI Adoption using the Technology–Organization–Environment (TOE) model and Unified Theory of Acceptance and Use of Technology (UTAUT). The researchers collected data from 207 entrepreneurial businesses (including SMEs, startups, and knowledge-based businesses) using a structured questionnaire and analyzed the data using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3. The study's findings suggest that facilitating conditions, social influences, and competitive pressures are all important positive factors contributing to the firm's decision on AI Adoption. On the other hand, the data indicate that performance expectancy is a negative factor related to the company's decision to adopt because of the "reality check" influence of the initial implementation challenges diminishing ease of use. It is also important to mention that several internal factors including effort expectancy and top management support do not have a direct influence. Most importantly, however, the results show that AI Adoption provides companies with an opportunity for strategic renewal (opportunities) and sustainable business models (holistic sustainability). Also, this research provides insight into the Resource-Based View (RBV) and Dynamic Capabilities (DC) theory by showing that AI Adoption creates a significant competitive advantage for companies, making them more successful at creating entrepreneurial and technology-based firms, while providing them increased economic, environmental, and social performance. In conclusion, AI Adoption is a major game-changer for entrepreneurs interested in sustainable practices and the ability to achieve successful, holistic, and sustainable business performance.

Keywords: Artificial Intelligence Adoption Intention; sustainable performance; entrepreneurial ecosystem; TOE framework; UTAUT; entrepreneurial orientation; strategic orientation



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1. Introduction

As AI continues to transform business operations, it is increasingly recognized for its potential to enhance productivity and decision-making accuracy [1,2]. It is believed that, for

SMEs, AI will be a key driver of sustainable performance [3–5]. Sustainable performance encompasses economic sustainability, environmental sustainability, and social sustainability as a multi-faceted objective requiring a technology-based approach to achieving these goals strategically [6]. However, while the Adoption of AI technologies is possible for many SMEs within their current resource-constrained environments or developing countries, the success of AI Adoption for SMEs is a complex issue, with many different factors influencing its implementation [4,7,8].

There are many gaps in the theory and challenges related to ethics and sustainability with the use of AI in Small to Medium Enterprises (SME). Kittipanya-ngam et al. [2] noted that there is still little research into the combined areas of “Ethics” and “Sustainability” and “Small- and Medium-sized Enterprises (SME)” with respect to AI use. Organizations also face other significant hurdles, including the “black box problem”, which is the inability to provide an adequate explanation of AI-generated output, and therefore create distrust from the user [7,9]. They also face data-driven decision-making biases and challenges with integrating AI into their existing systems [7]. Other challenges include a lack of digital skill sets for staff and management not being trained in AI, which creates a barrier for the organization even if the technology is available and is a good fit with organizational strategy [7]. From a broader societal perspective, AI’s potential impact on Sustainable Development Goals (SDG) can have both positive and negative consequences. As noted by Nahar [6], AI can be an enabler of innovation, but uncritically adopting AI can magnify current inequalities in society and create unintended environmental consequences.

The complexity of these issues has led to the identification of the entrepreneurial ecosystem as the fundamental context through which to understand and investigate them. The entrepreneurial ecosystem comprises the multiple interacting components (e.g., Physical Infrastructure, Talent, Finance, and Institutional Arrangements) that create the inlet and outlet of opportunities and obstacles to the entrepreneur who utilizes AI to create solutions for sustainability [10–12]. For example, availability of talent and favorable policies will directly impact an entrepreneur’s ability to successfully deploy AI in their small or medium-sized enterprise (SME) [10]. In addition, entrepreneurial knowledge serves to moderate the entrepreneur’s ability to develop and implement AI for frugal innovation through the use of cost-efficient and resource-efficient solutions in resource-scarce environments [13].

To develop an understanding of what influences the degree of Adoption of this technology ecosystem will require an integrated holistic understanding of the factors that have an impact on the determination of whether or not to adopt the technology. A majority of the existing literature analyses the technological factors affecting Adoption in isolation; however, in this research, we intend to conduct an in-depth analysis of the dynamics and relationships between these factors through a comprehensive framework that combines the Technology–Organization–Environment (TOE) framework [5,7,14,15] and the Unified Theory of Acceptance and Use of Technology (UTAUT) framework [4,5]. The TOE framework provides a macro-level analytical framework for examining the environmental, organizational, and technological issues that may impact technology Adoption, as well as looking at an organization’s willingness to implement the technology based upon their current readiness to adopt the technology [4,5]. In contrast, the UTAUT framework provides a micro-level approach that focuses on the individual’s Intention to adopt the technology, based upon the various factors that influence that Intention, including performance expectancies, effort expectancies, and social influences [16–18].

While all over the UTAUT model has been successfully utilized in many different fields such as Education Management systems as well as general Technology Acceptance [19,20], there still remains a need to integrate UTAUT and other larger factors associated with organizations and environments together in order to fully understand the entrepreneurial

ecosystem [21,22]. This research will fill this gap. Using a Partial Least Squares Structural Equation Model (PLS-SEM), a powerful exploratory theory generation method [3,23], this study will examine the combined effects of this set of drivers on AI Adoption intentions and their ability to catalyze sustainable performance on all economic, environmental and social aspects of sustainable development, thus establishing a comprehensive view of how we can ensure that AI is an enabler of positive impact instead of creating further difficulties [2].

2. Literature Review

It has become clear that Artificial Intelligence (AI) Adoption should not only be seen as a technological improvement, but also as a catalyst for major changes in business strategy and sustainable practices [3,24]. This review intends to provide a rigorous understanding of AI Adoption in the Entrepreneurial Ecosystem through the lens of the Technology–Organization–Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which will serve to illuminate the key drivers of AI Adoption. Additionally, this paper will provide an explanation of the influence of AI on an organization using the Resource-Based View and Dynamic Capabilities framework.

2.1. AI Adoption Intention Drivers: Insights from the Integrated TOE and UTAUT Frameworks

The Adoption of Artificial Intelligence is a complex phenomenon. To understand its complexities, scholars and practitioners must approach the phenomenon through multiple theories. The Technology–Organization–Environment (TOE) framework provides a macro view of this Adoption and supports that the Adoption process occurs through three separate and independent contexts [25]. Within the Technology Context, the literature has clearly established a duality of AI technologies; while some AI-based features (e.g., machine learning) have the potential to significantly automate processes, they are still being weighed against the implementation and operational costs as well as the technology barriers that exist today [2,6]. Innovations in this area tend to emerge at the intersections where AI technologies are used in conjunction with other tools, i.e., Internet of Things (IoT), to produce ‘frugal innovation’ in resource-limited environments [13].

The readiness and ability to adopt AI is addressed in the Organizational Context, where the enabling role of leadership is highlighted, particularly in terms of how chief information officers (CIO) and managers develop ‘absorption capacity’ to assist with the Adoption of new technologies [26]. According to the literature, a continued barrier to AI Adoption is the internal resistance to change and the need for employee upskilling to support implementation [27]. The pace at which companies will adopt AI is driven externally by the Environmental Context. The introduction of disruptive technologies in the marketplace has forced SMEs to significantly change the way they do business whether they want to or not [26]. This ecosystem of Adoption has been made more challenging by regulatory ambiguity and increased competition, increasing the need for companies to adopt AI both to improve their operational efficiency and strategically align themselves with their larger organizational goals such as the SDGs [6,28].

The UTAUT model adds a level of detail to understanding how individuals will act. In contrast to the TOE model that looks at the business aspect of technology Adoption, the UTAUT model considers individual motivators such as performance expectancy and effort expectancy. Understanding individual motivators in the context of larger organizational inhibiting factors gives a fuller understanding of how and why technology is adopted [29].

2.2. Outcomes of AI Adoption Intention: Resource-Based View, Dynamic Capabilities, and Sustainability

In the Resource-Based View (RBV), artificial intelligence (AI) is presented as a strategic resource rather than simply a tool. The valuation of AI capabilities that are valuable,

rare, and not easily replicated corresponds to the development of ongoing competitive advantages within an organization through their use [30]. For small and medium-sized enterprises (SMEs), the incorporation of AI results in proprietary capabilities (e.g., optimized data pipelines) that enable SME firms to differentiate themselves in the marketplace [27]. The RBV also includes the dynamic capabilities framework, which provides additional insight into how AI enhances a firm's dynamic capability to sense, capture, and configure resources according to their environment [30,31]. Specifically, "Green Dynamic Capabilities" leverage AI for enhancing processes that improve environmental performance [32].

The research literature has increasingly linked AI to sustainable business performance and therefore to the concept of the "Triple Bottom Line". In this regard, through improved energy efficiencies, waste management, and the implementation of circular business models, AI operates as an efficiency-enhancing mechanism toward the goal of environmental sustainability [27,32]. At the same time, with attention to the Responsible AI approach, firms can ensure that the environmental performance benefits derived from AI are complemented by social inclusiveness and ethical governance practices [6,33]. Accordingly, there is a theoretical consensus that AI serves as an underlying element that will propel the entrepreneurial ecosystem toward an environmentally sustainable future when AI is managed with a dynamic capabilities approach.

3. Hypothesis Development

3.1. The Drivers of AI Adoption Intention in Entrepreneurial Ecosystems

Entrepreneurial ecosystems increasingly incorporate AI technologies as a way to sustain their performance; therefore, understanding AI Adoption drivers is essential [11,29]. In order to identify these drivers, the UTAUT model provides insight into factors influencing intent to adopt and behaviors in its use [34,35]. Using these UTAUT constructs, the following hypotheses explore the influence of Facilitating Conditions, Effort Expectation, Social Influence, and Performance Expectation on AI Adoption intentions.

3.1.1. Facilitating Conditions

Facilitating conditions represent the extent to which individuals perceive that there are sufficient organizational and technical resources available to support their use of a new system [34,35]. Concerning the Adoption of artificial intelligence, facilitating conditions include access to the necessary resources, technical assistance, and an adequate support system [35]. For entrepreneurs that operate in an ecosystem, having access to these resources, e.g., high-speed internet, computer equipment, and compatible software, may significantly reduce perceived barriers and improve their overall readiness to adopt AI [36].

The importance of facilitating conditions has been documented across many empirical studies, demonstrating that they are an essential component of all Adoption processes. Researchers found that facilitating conditions were a significant predictor of behavioral Intention when adopting AI-enabled lead management systems [34]; similarly, Wu et al. [36] found that facilitating conditions were significantly correlated with the Adoption of AI technologies in construction. Other researchers examining the use of artificial intelligence in both academic librarians' research environments [20,37] and social development organizations [38] have noted that supporting these complex AI applications is critical for integrating these advanced technological systems into these organizational settings. Additionally, Hao et al. [39] reported that the availability of technical support and device compatibility's availability were both critical factors to ensure successful use of mobile learning applications. In light of the above, we offer the following proposition:

H1. *Facilitating Conditions associated with AI Adoption intention.*

3.1.2. Effort Expectancy

Effort expectancy measures how easy it is to use technology [34,35]. Effort expectancy will represent how easy and user-friendly AI tools are to use. The less effort expected when using an AI tool means that the user perceives that the tool is intuitive, easy to learn, and therefore easier to adopt by entrepreneurial users who are pressed for time or have limited experience with technology [35]. To date, empirical studies have provided evidence from multiple disciplines that demonstrate a strong association between perceived ease of use and Intention to adopt technology. For instance, the research found that effort expectancy was a primary predictor of healthcare providers' Intention to use AI-enhanced devices [40] and to use clinical decision support systems [41]. Several studies of ChatGPT Adoption have revealed that perceived ease of use was a dominant predictor of both professional and student behavioral Intentions [42–44]. In the education sector, we also found that an intuitive user interface influenced students' Intention to adopt generative AI applications [45,46]. Hence, our hypothesis is that

H2. *Effort Expectancy is associated with AI Adoption intention.*

3.1.3. Social Influence

According to recent studies, Social Influence refers to how strongly individuals think that their friends/important people think they should start using a new system [34,35]. Within the entrepreneurial ecosystem, perceptions of important stakeholders (investors, partners, and customers), peer pressure, and current trends in an industry can have a major impact on whether or not someone plans to use AI [35]. Another aspect that will motivate entrepreneurs to adopt AI is the actions of their peers, especially if those peers are successful at integrating AI for a competitive advantage.

Researchers have found evidence of the influence of social factors on the Adoption of AI in many areas, including studies exploring AI assistant Adoption for luxury goods that have discovered the role of “social presence” to be a major factor driving these Intentions [47]. Additionally, the impact of Social Influence on the Intention to adopt AI for use in sports, particularly in regard to AI umpires in baseball [48], also shows the significance of social factors. Wu et al. [49] have shown that Social Influence has an important role in determining whether consumers will use digital financial technology (e.g., eWallet). Based on this evidence, we offer the following hypothesis:

H3. *Social Influence is associated with AI Adoption intention.*

3.1.4. Performance Expectancy

The definition of performance expectancy is the extent to which a person believes they will obtain improvements in their work productivity by using the system [34,35]. For those in business, the benefits they perceive from AI (for example, automating repetitive duties and optimizing processes while obtaining analytical insights through data) are significant motivators to use AI; additionally, using AI to help make decisions and cultivate innovative ideas creates an environment in which they can gain a competitive advantage [11,29].

Numerous research articles document performance expectancy as one of the strongest predictors of technology acceptance. Performance expectancy was the most significant predictor of Intentions to utilize an AI-based lead management software solution [34] and AI-enabled health assistants [50]. In educational settings, performance expectancy was an influential factor in the Intentions of students studying technical and vocational education and training (TVET) or science, technology, engineering, and mathematics (STEM) to adopt generative AI [45,46] and to utilize AI in educational administration [51]. Researchers have

established that the expectation of a tool to enhance work efficiency is directly correlated with increased Intentions to adopt that tool [34]. Thus, it is reasonable to hypothesize that:

H4. *Performance Expectancy is associated with AI Adoption intention.*

3.2. The Role of Technological, Organizational, and Environmental Contexts (TOE Framework)

This research builds upon individual-level perceptions provided through the UTAUT model by incorporating the TOE framework, which focuses on the larger context in which AI Adoption occurs [52–54]. While UTAUT emphasizes user acceptance behavior [18,55], the TOE framework examines the multitude of technological, organizational, and environmental conditions impacting one's Intention to embrace new technologies [56,57]. As a result of this analysis, we have developed several hypotheses concerning Technology Competency, Top Management Commitment, and Competition Pressure.

3.2.1. Technology Competency

According to the TOE framework (Technology, Organization, Environment), technology competency describes the level at which an organization can use and integrate new technologies into its operations effectively. Technology competency includes all the things required to develop AI solutions, such as having reliable IT systems, having people with knowledge of how to use IT systems, and being ready for implementation [53]. Technology competencies allow organizations to address technical barriers to the Adoption of AI solutions, thus allowing organizations with higher levels of technology competencies to take full advantage of the opportunities presented by AI solutions [53]. There is substantial empirical support for the importance of having internal technological capabilities. For example, examining AI Adoption among small- and medium-sized enterprises (SMEs) in Malaysia shows successful AI Adoption is heavily dependent on a company's technological proficiency and support infrastructure, including having employees with the required knowledge of AI technologies and having compatible information technology (IT) networks. In addition, many organizations engaged in IT network operations cite technological readiness and compatibility as the most significant factors that contribute to their success with AI solutions [56]. On this basis, our hypothesis is as follows:

H5. *Technology Competency (TC) is associated with AI Adoption intention.*

3.2.2. Top Management Commitment

According to the Technology–Organization–Environment (TOE) framework, one of the fundamental factors in determining the rate of AI Adoption by organizations is Top Management's commitment [58,59]. Top Management's commitment establishes a level of proactive support and direct active participation by the highest level of Top Management necessary to regulate AI Adoption by setting forth an organization's strategic direction and being able to appropriately allocate all the resources required to adopt AI [54]. Executive Management's commitment is also a key driver to establish and support an organizational culture of innovation, which has been shown to effectively reduce resistance to change [54].

Research has shown that organizations with committed leadership are more likely to adopt new technologies. For example, in the context of Egyptian organizations, support from Top Management for AI Adoption has a significant impact [54]. In the Automotive Manufacturing sector, Top Management support for AI Adoption was a strong endorsement of the strategic importance of AI integration, which resulted in a stronger intent to adopt AI technology [52]. Therefore, we would like to propose that:

H6. *Top Management Commitment (OC) is associated with AI Adoption intention.*

3.2.3. Competition Pressure

Competitive pressure is one of the major environmental factors influencing the technology choices of organizations. It is defined as the forces in the external environment created by the competition to which organizations must respond through the Adoption of new and innovative technologies in order to compete or continue to be competitive [58]. In highly competitive industries, companies are forced to utilize AI to increase their efficiency, reduce costs, and provide greater value to customers [52]; therefore, it has been established that competitive pressure from outside organizations has a strong correlation to the use of AI to gain a competitive edge [58]. Research has identified competitive pressure as a major factor contributing to AI Adoption and its positive effect on operational performance in both the automotive and technology industries [52,58]. Based on these findings we propose the following:

H7. *Competition Pressure (EC) is associated with AI Adoption intention.*

3.3. The Consequences of AI Adoption Intention

According to this study, the Intention to adopt AI has downstream effects on strategic orientation—Entrepreneurial Orientation (EO) and Technology Orientation (TO)—and ultimately improves an organization's performance in economic, environmental, and social ways [60–62].

3.3.1. Impact on Strategic Orientations

a. **Entrepreneurial Orientation:** Entrepreneurial Orientation (EO) is defined as the tendency of an organization to innovate, be proactive, and take risks [60]. Recent research suggests that AI technology can help to enhance these characteristics. AI analytics provide better data-based decisions and enable companies to respond quickly to market changes and new opportunities, thus creating a more proactive company image [60,63]. Additionally, through its predictive modeling capabilities, AI technology will facilitate the development of new products and services based on data analytics, thereby supporting an organization's innovativeness [61]. When implementing AI technology in small and medium-sized enterprises (SMEs), AI technology is important for the creation of green innovation/creative ideas that are at the core of entrepreneurial activity [3]. AI technology supports measuring the risk associated with new ventures and makes it possible to make informed decisions on what type of risks are acceptable/effective [60]. Therefore, we would like to propose that:

H8. *AI Adoption Intention is associated with Entrepreneurial Orientation.*

b. **Technology Orientation:** Technology Orientation is an indicator of an Organization's investment and use of advanced technology to achieve strategic objectives [64]. The Intention to adopt AI will naturally drive the organization's orientation toward technology because the implementation of AI will be incorporated into the organization's processes [61,63]. Specifically, an Organization that has a strong technological orientation will have the greatest propensity to deploy AI for operational efficiencies and automation [3]. By doing so, the Organization increases its technological engagement, developing a culture of continuous improvement and innovation within various industries, including finance, education, etc. [36,64]. In addition, digital competencies (which are generally considered a precursor to the Adoption of AI by an organization) also play an important role in enhancing an Organization's overall Technology Orientation [65]. Therefore, we propose the following:

H9. *AI Adoption Intention is associated with Technology Orientation.*

3.3.2. Impact on Sustainable Performance

A. Economic Performance:

Economic Performance includes, but is not limited to, profitability, revenue growth, and cost efficiency as indicators of the financial success of an organization [62,66]. People believe that adopting Artificial Intelligence (AI) will help improve economic performance by increasing operational efficiency and making it easier for companies to manage their supply chain through optimizing processes [3,61]. The automation of many repetitive tasks allows the implementation of accurate demand forecasting using AI. This automation leads to a significant reduction in operational cost as well as increases in productivity and earnings [63]. In addition, AI allows for a more efficient allocation of resources; thus, it creates new opportunities for businesses to obtain funding via large-scale data analysis. Furthermore, factors such as performance expectancy and facilitating conditions also provide the necessary motivation to develop intentions and influence economic performance [67]. Therefore, we propose that:

H10. *AI Adoption Intention is associated with Economic Performance.*

B. Environmental Performance:

The Environmental Performance consists of reducing ecological impact as well as optimizing resource efficiency [62,68]. The opportunities for achieving enhanced environmental sustainability through AI Adoption include the ability to assess environmental performance through predictive maintenance, optimize energy consumption, and manage waste more efficiently [3,61]. In the construction and agriculture sectors, AI-based technologies can enable green tech innovations and provide more accurate ways to manage resources, allowing for reduced environmental footprint [69,70]. Additionally, organizations' ability to analyze environmental data via AI is critical to the generation of environmentally friendly tech innovations that support global sustainability [62]. Therefore, we suggest that:

H11. *AI Adoption Intention is associated with Environmental Performance.*

C. Social Performance:

The Social Performance of an organization is that organization's contribution to the welfare of society, which includes increased customer experience and employee welfare [62,66]. The AI Adoption Intention may promote improvements within this area of social performance through the application of technologies focused on AI-based solutions to solve problems related to the needs of society, including digital telemedicine that allows for remote access to health care [71,72] and the development of AI-based learning and education that enables learners to learn independently and improves access to the learning opportunity at hand [73,74]. AI has also fostered the growth of social responsibility by providing ethical AI development and promoting digital justice through the use of AI-driven metaverse environments [36]. By providing improved human–robot interaction and user satisfaction [75,76], the adoption of AI fosters inclusive social benefits. Thus, we present the following hypotheses (See Figure 1):

H12. *AI Adoption Intention is associated with Social Performance.*

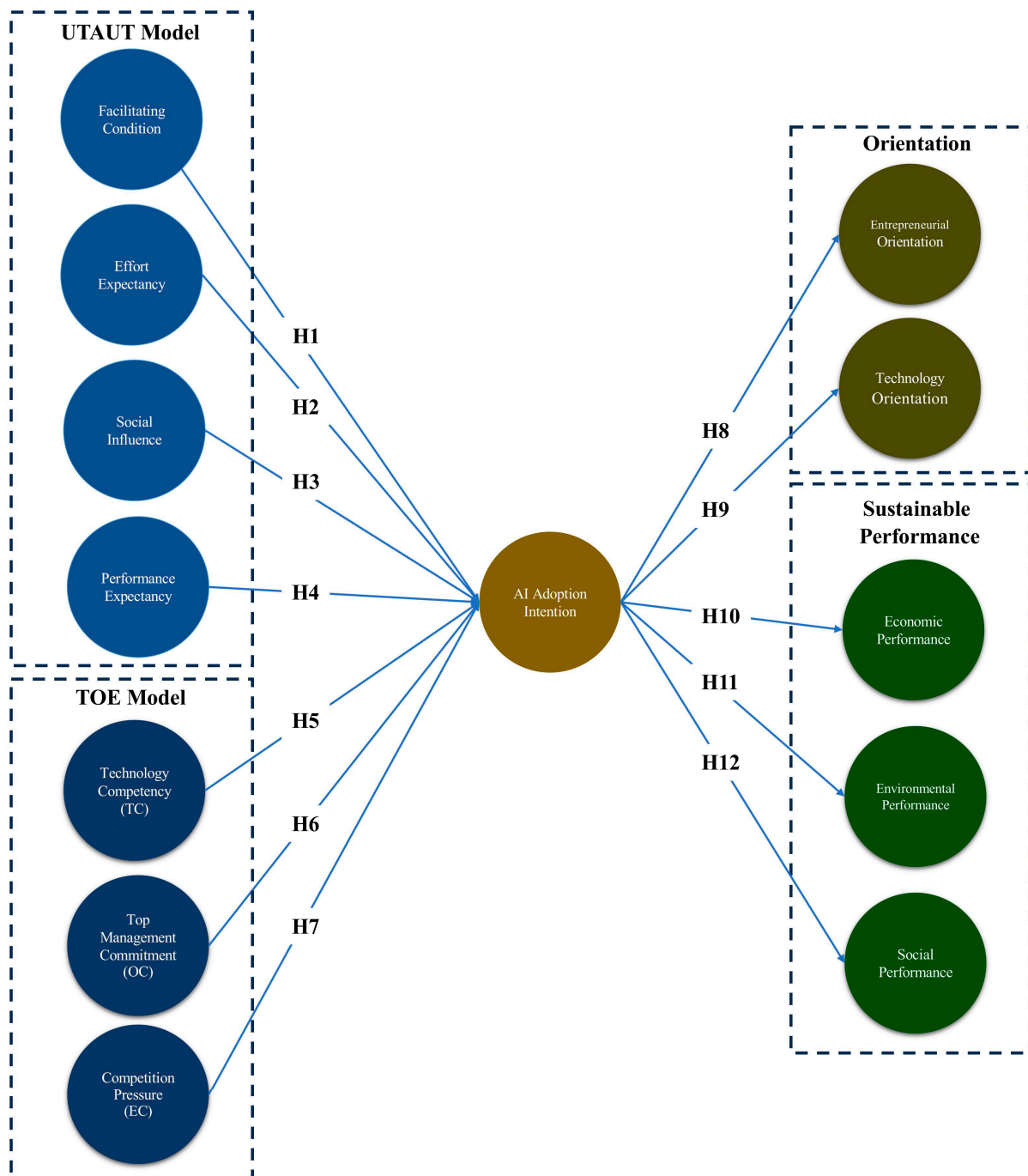


Figure 1. Research conceptual model (researcher-made).

4. Research Methods

4.1. Sample Description

The aim of this empirical research was to investigate the structural dynamics and predictive relationships between adoption drivers and performance outcomes in this study based on data collected from the online (structured) questionnaires. The data collected through this survey provided answers to the research objectives and hypotheses. The statistical population for this study consisted of those members of the Iranian entrepreneurial ecosystem who actively participate as users of AI in their organizations (including start-ups, SMEs, and knowledge-based companies). To make sure that every participant was an active member of this ecosystem, a screening question was added to the questionnaire. The survey

was then sent out to various convenience samples of communities and groups where these individuals congregated. A total of 207 valid questionnaire responses were collected from individuals that completed the survey on a voluntary basis, with all individuals providing their informed consent to participate in this study. Additionally, due to the identified nature of the survey, respondents were not asked any identifying questions and therefore have complete anonymity in their responses to this study.

Organization sectors were classified according to the structure of the local entrepreneurial ecosystem; the demographic and organizational profiles of respondents can be seen in Table 1. The largest group of respondents was those that identified as working in small- and medium-sized businesses, which represented 42.0% of the total respondents; the second largest group of respondents (17.4%) identified as members of the Innovators Accelerators/Innovation Center/Science Parks. Knowledge-Based Companies represented 15.0% of all respondents, along with Technological and Entrepreneurial Companies (14.0%), and Startups (11.6%). Thus, the distribution of the respondents' organizations provides a comprehensive overview of the overall Innovation Ecosystem, creating a solid baseline for understanding how the Adoption of AI will relate to performance, along with how the maturity of each organization will also relate to that performance.

Table 1. Sample demographics and characteristics (N = 207).

Question	Option	Response Frequency	Percentage
Which organization type do you belong to?	Small and Medium-sized Enterprises (SME)	87	42.0%
	Accelerators, Innovation Centers, and Science Parks	36	17.4%
	Knowledge-based Companies	31	15.0%
	Technological/Entrepreneurial Companies	29	14.0%
	Startups	24	11.6%
What is your gender?	Male	115	55.6%
	Female	92	44.4%
How old are you?	Under 20 years	8	3.9%
	20 to 30 years	132	63.8%
	31 to 40 years	42	20.3%
	41 to 50 years	17	8.2%
	51 to 60 years	8	3.9%
What is your level of education?	Diploma or Lower	14	6.8%
	Associate Degree (Advanced Diploma)	8	3.9%
	Bachelor's Degree	63	30.4%
	Master's Degree	101	48.8%
	Doctorate or Higher	21	10.1%
How familiar are you with AI and its tools?	Low	33	15.9%
	Medium	98	47.3%
	High	59	28.5%
	Very High	17	8.2%

Table 1. *Cont.*

Question	Option	Response Frequency	Percentage
How much experience do you have in the ecosystem?	Less than 1 year	89	43.0%
	1 to 3 years	55	26.6%
	4 to 7 years	38	18.4%
	Over 7 years	25	12.1%
How much do you use AI tools in your organization?	Low	53	25.6%
	Medium	79	38.2%
	High	59	28.5%
	Very High	16	7.7%

The sample is highly educated, with nearly 90% of respondents holding a Bachelor's degree or higher, providing a robust technical foundation for evaluating AI technologies. The fact that the majority of respondents hold an advanced academic degree shows us that they likely possess the technical knowledge required to understand and use emerging technologies, such as AI technologies. The demographic profile shows that 55.6% of respondents are males and 44.4% of respondents are females, so the gender distribution is relatively close in ratio.

The sample is primarily composed of a young and dynamic demographic, with over 84% of participants aged between 20 and 40. There is only a small percentage of 16.0% of respondents who are over the age of 40. Therefore, we have a younger population which is dynamic and adaptable to the introduction of new technologies to the workforce. With respect to work experience within the Entrepreneurial Ecosystem, 43.0% of respondents indicated less than 1 Year of experience, 26.6% indicated between 1 and 3 years of experience, 18.4% indicated between 4 and 7 years of experience, and 12.1% indicated more than 7 years of experience. This shows that while there is a large number of individuals who are new to the ecosystem, there are still a large amount of individuals with significant work experience to lend an informed opinion.

The respondents' familiarity with Artificial Intelligence (AI) and the various AI Tools, has been found to be relatively positive. The majority of respondents (84%) demonstrate a high level of technical literacy, reporting moderate to high familiarity with AI tools. However, only 15.9% of the respondents believed they were not familiar with AI Tools. Similarly, 38.2% of the respondents reported that their organization had a Medium Use of AI tools, 28.5% reported that their organization had High Use of AI tools, 7.7% reported that their organization had an Extremely High Use of AI tools, and 25.6% indicated that their organization had Low Use of AI tools. The results confirm that most organizations are now using AI tools to a large extent as a result of the inclusion of staff with reasonable levels of familiarity with AI technology.

4.2. Psychometric Properties of the Measurement Instrument

The questionnaire used for this study relied on academic sources to identify associated scales that represent concepts relating to organizations in the adoption of AI technology (The full questionnaire items, along with their corresponding references, are provided in Table A1 in Appendix A). The questionnaire of this study relied on scales drawn from academic sources, structured as five-point Likert scales, to measure concepts related to AI Adoption [77]. The associated scales for the questionnaire were created using Five-Point Likert Scales, as defined in the data analysis for this study using SmartPLS 3, as well

as Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM assists in developing theoretical models for exploratory research by examining the relationship between variables while measuring the variance in the dependent variable through the use of captively constructed models [77], therefore when bootstrapping to examine the significance of the path coefficients for 5000 subsamples.

Before proceeding with structural relationships, the Reliability, Convergent Validity, and Discriminant Validity of the measurement model were established. The measures of these dependability indicators are provided in Table 2: Cronbach's Alpha, Threshold = 0.7 [78]; Composite Reliability Index (C.R.), Threshold = 0.7 [79]; Average Variance Extracted (AVE), Threshold = 0.5 [79].

Table 2. Reliability and convergent validity of measurement model.

Construct	Item	Loading (t-Value)	Cronbach's α	rho_A	CR	AVE
AI Adoption Intention (AI)	AI1	0.866 (34.296)	0.827	0.847	0.887	0.666
	AI2	0.870 (39.098)				
	AI3	0.868 (43.193)				
	AI4	0.636 (10.998)				
Competitive Pressure (CP)	CP1	0.798 (24.195)	0.658	0.681	0.810	0.589
	CP2	0.812 (18.882)				
	CP3	0.686 (10.924)				
Effort Expectancy (EE)	EE1	0.673 (6.428)	0.699	0.680	0.798	0.497
	EE2	0.782 (14.495)				
	EE3	0.675 (6.226)				
	EE4	0.686 (8.789)				
Entrepreneurial Orientation (EO)	EO1	0.779 (25.191)	0.798	0.808	0.860	0.552
	EO2	0.786 (19.447)				
	EO3	0.717 (14.815)				
	EO4	0.694 (12.757)				
	EO5	0.734 (12.498)				
Economic Performance (EcP)	EcP1	0.850 (31.141)	0.889	0.890	0.923	0.750
	EcP2	0.886 (30.826)				
	EcP3	0.905 (53.992)				
	EcP4	0.822 (27.821)				
Environmental Performance (EnP)	EnP1	0.770 (20.751)	0.854	0.859	0.902	0.696
	EnP2	0.835 (30.464)				
	EnP3	0.863 (38.764)				
	EnP4	0.866 (40.143)				
Facilitating Conditions (FC)	FC1	0.800 (25.216)	0.736	0.767	0.828	0.548
	FC2	0.811 (27.730)				
	FC3	0.704 (13.206)				
	FC4	0.632 (9.428)				

Table 2. Cont.

Construct	Item	Loading (t-Value)	Cronbach's α	rho_A	CR	AVE
Performance Expectancy (PE)	PE1	0.924 (6.431)	0.867	1.274	0.897	0.685
	PE2	0.771 (3.388)				
	PE3	0.804 (3.290)				
	PE4	0.804 (3.443)				
Social Influence (SI)	SI1	0.824 (36.044)	0.783	0.820	0.856	0.599
	SI2	0.789 (19.816)				
	SI3	0.711 (11.185)				
	SI4	0.766 (16.046)				
Social Performance (SP)	SP1	0.757 (20.851)	0.850	0.861	0.893	0.626
	SP2	0.874 (47.254)				
	SP3	0.839 (21.332)				
	SP4	0.759 (17.081)				
	SP5	0.719 (13.799)				
Technology Competency (TC)	TC1	0.778 (16.219)	0.822	0.855	0.893	0.736
	TC2	0.896 (64.778)				
	TC3	0.895 (52.949)				
Top Management Support (TMS)	TMS1	0.852 (35.831)	0.915	0.917	0.936	0.746
	TMS2	0.852 (32.870)				
	TMS3	0.890 (46.078)				
	TMS4	0.867 (45.807)				
	TMS5	0.856 (31.312)				
Technology Orientation (TO)	TO1	0.870 (43.217)	0.860	0.876	0.904	0.703
	TO2	0.884 (47.757)				
	TO3	0.828 (23.202)				
	TO4	0.767 (17.892)				

From the information in Table 2, we can see that we have met or exceeded the minimum standards for each of the measures used in this study. The Cronbach's Alpha and Composite Reliability (CR) values for all constructs were acceptable and ranged from 0.658 to 0.915 for Cronbach's Alpha and 0.798 to 0.936 for CR. This shows that all of the measures possess a high level of internal consistency. Most of the Average Variance Extracted (AVE) values exceeded 0.50, which confirms that we have achieved convergent validity. The only exception to this is Effort Expectancy (EE) which had an AVE in close proximity to 0.50 (0.497); however, this score is acceptable due to the very high Composite Reliability value. We also found that all loadings for items of constructs were statistically significant ($t > 1.96$). Regarding reliability, the rho A for Performance Expectancy (1.274) is an algorithmic estimation result; its reliability is cross-validated by a high Cronbach's Alpha (0.867).

The fit of the estimated model was evaluated using the SRMR (0.130), d_ULS, d_G, Chi-square, and NFI which were evaluated according to Table 3 [80,81]. Although the SRMR (0.130) was marginally above the conservative standard of 0.08 threshold, it is

still commonly viewed to be an acceptable value for these types of complex exploratory models [82,83]. The NFI (0.588) was nearing the acceptable cut-off value of 0.60 [84]. Taken as a whole, these fit indices in conjunction with the rigorous measurement characteristics demonstrated in Table 2 provide evidence to support that the estimated model will offer an adequate representation in testing the proposed hypotheses [85,86].

Table 3. Table of model fit indices.

Metric	Saturated Model	Estimated Model
SRMR	0.086	0.130
d_ULS	10.555	24.136
d_G	2.956	3.609
Chi-square	3184.64	3612.75
NFI	0.637	0.588

As seen in Table 4, we have established the discriminant validity of our measures using the Fornell–Larcker Criterion. A matrix of the construct correlations was created, showing that the square root of the extracted variances on the diagonal of each of the matrix was greater than the correlation between that construct and all other constructs.

Table 4. Discriminant validity (Fornell–Larcker Criterion).

Construct	AI	CP	EE	EO	EcP	EnP	FC	PE	SI	SP	TC	TMS	TO
AI	0.816												
CP	0.567	0.767											
EE	0.424	0.305	0.705										
EO	0.606	0.662	0.351	0.743									
EcP	0.606	0.419	0.335	0.568	0.866								
EnP	0.619	0.457	0.299	0.520	0.737	0.835							
FC	0.721	0.526	0.549	0.613	0.477	0.508	0.740						
PE	0.170	0.323	0.475	0.303	0.119	0.109	0.392	0.828					
SI	0.620	0.511	0.481	0.692	0.441	0.406	0.652	0.424	0.774				
SP	0.564	0.391	0.267	0.505	0.627	0.697	0.461	0.069	0.468	0.791			
TC	0.579	0.627	0.366	0.690	0.443	0.457	0.526	0.201	0.548	0.413	0.858		
TMS	0.636	0.666	0.351	0.786	0.469	0.473	0.618	0.329	0.720	0.466	0.804	0.864	
TO	0.594	0.588	0.343	0.805	0.467	0.478	0.590	0.317	0.649	0.456	0.726	0.801	0.839

In addition to the Fornell–Larcker Criterion, the Heterotrait-Monotrait Ratio (HTMT) was employed to further assess discriminant validity, as it is considered a more stringent and sensitive measure in PLS-SEM. According to Henseler et al. [80], HTMT values should ideally be below 0.85 (conservative) or 0.90 (liberal) to establish distinctiveness between constructs.

As presented in Table 5, the majority of the ratios are below the 0.85 threshold. However, certain values—specifically between Entrepreneurial Orientation (EO) and Technology Orientation (TO) (0.967), and Top Management Support (TMS) and Technology Competency (TC) (0.916)—exceed the 0.90 mark. These high correlations do not indicate a failure of the measurement model but rather reflect the specific strategic landscape of the Iranian entrepreneurial ecosystem. In such contexts, entrepreneurial risk-taking and technological

innovativeness are often mutually reinforcing and deeply integrated strategic postures. Furthermore, since these constructs are theoretically distinct and possess high internal consistency (as shown in Table 2), they were retained to preserve the conceptual integrity of the integrated TOE-UTAUT framework.

Table 5. Heterotrait–Monotrait Ratio (HTMT) Results.

	AI	CP	EE	EO	EcP	EnP	FC	PE	SI	SP	TC	TMS	TO
AI	-												
CP	0.745	-											
EE	0.494	0.396	-										
EO	0.742	0.835	0.435	-									
EcP	0.699	0.540	0.387	0.686	-								
EnP	0.723	0.613	0.338	0.629	0.847	-							
FC	0.885	0.710	0.854	0.768	0.567	0.594	-						
PE	0.222	0.341	0.717	0.316	0.133	0.116	0.545	-					
SI	0.736	0.632	0.638	0.837	0.517	0.455	0.841	0.509	-				
SP	0.655	0.498	0.280	0.623	0.719	0.809	0.533	0.091	0.552	-			
TC	0.680	0.816	0.439	0.836	0.516	0.539	0.636	0.172	0.626	0.484	-		
TMS	0.728	0.802	0.422	0.906	0.513	0.527	0.730	0.328	0.818	0.523	0.916	-	
TO	0.698	0.719	0.429	0.967	0.541	0.558	0.715	0.321	0.752	0.546	0.844	0.896	-

To ensure the integrity of the structural model, we assessed the potential for multicollinearity and Common Method Bias (CMB). We employed the full collinearity assessment approach. According to this method, CMB and multicollinearity are considered non-threats if the Variance Inflation Factor (VIF) values for the indicators are equal to or lower than 3.3.

As shown in Table 6, the VIF values for the indicators in this study range from 1.062 to 3.612. The vast majority of these values fall below the conservative threshold of 3.3. While one indicator (TMS3) exhibited a VIF of 3.612, it remains well below the widely accepted threshold of 5.0 for structural models in exploratory research. Therefore, we conclude that multicollinearity does not distort the findings, and the results are not significantly contaminated by common method variance.

Table 6. Outer VIF values for multicollinearity and CMB assessment.

Construct	Item	VIF	Construct	Item	VIF
AI Adoption	AI1	2.772	Facilitating Conditions	FC1	1.519
	AI2	2.452		FC2	1.571
	AI3	2.232		FC3	1.728
	AI4	1.321		FC4	1.675
Competitive Pressure	CP1	1.217	Performance Expectancy	PE1	1.853
	CP2	1.469		PE2	1.958
	CP3	1.318		PE3	2.517

Table 6. *Cont.*

Construct	Item	VIF	Construct	Item	VIF
Effort Expectancy	EE1	1.921	Social Influence	PE4	2.301
	EE2	1.475		SI1	1.521
	EE3	2.061		SI2	1.557
	EE4	1.062		SI3	1.547
Entrepreneurial Orientation	EO1	1.557	Social Performance	SI4	1.696
	EO2	1.716		SP1	1.576
	EO3	1.487		SP2	2.812
	EO4	1.452		SP3	2.543
	EO5	1.583		SP4	1.789
Economic Performance	EcP1	2.137	Tech Competency	SP5	1.610
	EcP2	2.853		TC1	1.595
	EcP3	3.163		TC2	2.075
	EcP4	1.974		TC3	2.151
Environmental Performance	EnP1	1.570	Top Management Support	TMS1	2.403
	EnP2	2.096		TMS2	2.705
	EnP3	2.208		TMS3	3.612
	EnP4	2.244		TMS4	2.544
Technology Orientation	TO1	2.608		TMS5	2.814
	TO2	2.713			
	TO3	2.133			
	TO4	1.820			

The results of the hypothesis testing using bootstrapping (to derive confidence intervals) on the basis of 5000 subsamples can be found in Table 7. The structural model was evaluated using PLS-SEM to examine the predictive relationships between AI Adoption drivers and sustainability outcomes. The results of the path analysis are summarized in Table 7.

Table 7. Hypothesis testing results.

Hypothesis	Structural Relationship	β (Path Coeff.)	t-Value	p-Value	Result
H1	Facilitating Conditions (FC) → AI Adoption	0.461	5.267	0.000	Supported
H2	Effort Expectancy (EE) → AI Adoption	0.081	1.178	0.239	Not Supported
H3	Social Influence (SI) → AI Adoption	0.181	2.618	0.009	Supported
H4	Performance Expectancy (PE) → AI Adoption	−0.228	3.056	0.002	Supported (Negative)

Table 7. *Cont.*

Hypothesis	Structural Relationship	β (Path Coeff.)	t-Value	p-Value	Result
H5	Technology Competency (TC) → AI Adoption	0.062	0.734	0.463	Not Supported
H6	Top Mgmt Support (TMS) → AI Adoption	0.102	1.013	0.311	Not Supported
H7	Competitive Pressure (CP) → AI Adoption	0.174	3.243	0.001	Supported
H8	AI Adoption → Entrepreneurial Orientation (EO)	0.606	13.595	0.000	Supported
H9	AI Adoption → Technology Orientation (TO)	0.594	11.763	0.000	Supported
H10	AI Adoption → Economic Performance (EcP)	0.606	11.590	0.000	Supported
H11	AI Adoption → Environmental Performance (EnP)	0.619	11.451	0.000	Supported
H12	AI Adoption → Social Performance (SP)	0.564	11.086	0.000	Supported

All hypothesized paths related to the outcomes of interest were found to be statistically significant. Notably, AI Adoption Intention serves as a potent driver for all three dimensions of the triple bottom line. The strongest influence was observed in Environmental Performance (H11) ($\beta = 0.619$), suggesting that AI tools are primarily leveraged for green innovation and resource optimization within the ecosystem. This is followed by significant positive impacts on Economic Performance (H10) ($\beta = 0.606$) and Social Performance (H12) ($\beta = 0.564$).

Regarding the strategic consequences, the data confirms that the Intention to adopt AI significantly strengthens both Entrepreneurial Orientation (H8) and Technology Orientation (H9). These findings indicate that AI integration triggers a strategic renewal, reconfiguring the firm's proactive and technological posture.

In contrast, the analysis of Adoption drivers showed mixed results. While Facilitating Conditions (H4) and Competitive Pressure (H7) emerged as critical antecedents, paths such as Top Management Support (H5) and Complexity (H2) did not reach statistical significance, suggesting that in the studied entrepreneurial context, environmental and individual readiness factors outweigh traditional organizational hierarchy.

5. Results and Discussion

A comprehensive study of AI Adoption Intention in entrepreneurial ecosystems using an integrated Technology–Organization–Environment (TOE) and Unified Theory of Acceptance and Use of Technology (UTAUT) framework, illustrated drivers and positively associate with sustainable performance. Structural Equation Modeling using 5000 bootstrapped subsamples illustrates the specific relationship among these drivers and their correlation with sustainable performance.

In terms of drivers of AI Adoption, Facilitating Conditions (H1)—Resources, Infrastructure, and Technical Support and Social Influence (H3)—Peer Norms, and Organizational Norms are strong, positive predictors [34,35,47,73,87,88] indicating that Availability of resources for AI-driven technology adoption is necessary for entrepreneurial firms to adopt AI-supported technologies. Furthermore, the Competitive Pressure (H7)—Market Competition and Firms' Competitive Advantage also has a positive predictive influence on

AI Adoption. This finding highlights that firms experiencing competitive pressure from external sources (market forces), are incentivized to adopt AI-supported technology to maintain/gain competitive advantage [89,90] which is consistent with previous research that indicates that firms respond to increased market competition by adopting innovative technologies [91].

The negative relationship of Performance Expectancy (H4) on the intended use of Artificial Intelligence (AI) was an interesting finding. The analysis of the data indicated a significant negative relationship between Performance Expectancy and AI Adoption over the time frame studied. This contradicts the large body of forecasting and empirical research on the UTAUT framework, which typically reports a positive association between people's perceptions of technology's benefits and how likely they are to adopt it [34,35,73,87,88]. A negative correlation may suggest that entrepreneurs in a particular ecosystem context are either not experiencing the benefits they anticipated from AI or are being cautious about using it because of the potential risks associated with incorporating new, untried AI technology into their businesses [34,88]. Early expectations of the performance of AI may exceed actual early experiences as businesses run into barriers to successful implementation and realize that promised benefits may not be delivered immediately. Such a scenario could explain the early negative correlation between Performance Expectancy and AI Adoption that this study demonstrated [2,92].

Certain hypothesized motivators did not reveal any statistically significant direct connection to AI Adoption. Specifically, for Effort Expectancy (H2), the data were non-significant, indicating that peoples' perceptions about the ease of use of something are not strong determining factors for that particular kind of technology [34,35,73,87]. This indicates that even when presented with no easy path to use something like AI, entrepreneurially focused companies are willing to make a great deal of effort to learn how to work with these systems and implement them if they have sufficient motivation in some other form. Likewise, Technology Competency (H5) and Top Management Support (H6) did not show any significant direct influences either. Historically, prior research on Technology Competency and Top Management Support stressed the importance of both; however, neither were statistically significantly correlated in this instance. Therefore, it is possible that the lack of statistical significance in either predictor suggests that Technology Competency and Top Management Support do not predict the acceptance of AI Adoption, have a direct relationship between the predictors, and may be located elsewhere within the organization, or that an adequate baseline level of Technology Competency and Top Management Support exists already in the entrepreneurial ecosystem [3,64,93–97].

Unlike the variation in outcomes associated with driver's behaviors, AI Adoption has consistently produced a positive and significant influence. Each of AI's adoptions has influenced enhanced Entrepreneurial Orientation (H8) and enhanced Technology Orientation (H9) [3,33,64,90,91,93–112]. The Adoption of AI serves to advance the ability of firms to innovate, be proactive, and take risks through their entrepreneurial behaviors while extending their technology emphasis [33,93,98].

The structural analysis reveals distinct intensities in the influence of AI Adoption Intention across the three dimensions of sustainability. As evidenced by the results, AI Adoption Intention leads to enhanced performance levels in Environmental Performance (H11), Economic Performance (H10), and Social Performance (H12) [2,3,24,99–102,106,109,113,114]. These findings support the role that AI plays in facilitating a comprehensive approach to sustainability, encompassing improved environmental stewardship, financial performance, and social benefits [2,3,24,113]. Notably, the relationship with Environmental Performance emerged as the strongest among the outcomes. This suggests that for firms within the studied ecosystem, AI is primarily utilized as a vehicle for green innovation and resource

optimization, while the effects on Economic and Social Performance reflect a secondary, yet important, focus on operational profitability and societal welfare.

5.1. Theoretical Implications

There are many theoretical contributions made in this research. For example, we combine the TOE and UTAUT frameworks into one comprehensive framework to gain a wider view of how entrepreneurs adopt AI. The model also illustrates that while individual-level constructs (UTAUTs) and organizational/environmental constructs (TOEs) interact with one another, they will have a different impact based on the specific construct being examined. For example, our negative relationship with performance expectancy illustrates that we need to be more specific about how performance expectancy is defined and measured in rapidly changing technology fields like AI. We also believe that much of the initial hype surrounding the use of AI may have created unrealistically high performance expectations [34,35,92]. Second, the fact that AI has a strong positive association with entrepreneurial orientation and technology orientation further evidences the idea that AI is an integral part of digital transformation and thus will shape and change the strategic posture and innovative capabilities of companies [3,64,93,94,97,99]. Finally, our findings indicate that AI adopts and supports all dimensions of sustainable performance (economic, environmental, and social), which further supports the idea of AI as a dynamic capability that contributes to the resource-based view (RBV) of organizations and enhances/creates traditional performance in traditional areas as well as broader sustainability goals [2,3,24,102,106,113,114].

From the perspective of Capabilities (DC), AI Adoption Intention serves as both a strategic resource and a means for facilitating Strategic Renewal. While AI Adoption is generally viewed as an advancement over previously adopted technologies, in terms of its role within an Entrepreneurial Ecosystem (EE), it is perceived to serve as a catalyst to innovate on the basis of creating Sustainable Business Models (i.e., developing long-term Sustainable Entrepreneurial models). This differentiates AI-Enabled Institutions' ability to create economic and environmental efficiencies through the Adoption of technology and AI-Native Entrepreneurial Models that employ technology as the main means to create social and economic value creation from the resources they provide. Through the combination of creating both Entrepreneurial and Technology Oriented institutions within an Entrepreneurial Ecosystem (EE), it is possible for Companies to restructure their internal operational processes in order to achieve holistic sustainable performance through all three dimensions of the Triple Bottom Line.

5.2. Empirical Implications

The findings from our study provide guidance to both practitioners and policymakers as to how they can increase the use of AI in their firms. Entrepreneurial Firms should invest in infrastructure for supporting AI, such as technical infrastructure, training programs, and skills development, to facilitate the acceptance of AI [34,35,73,87]. Given the influence of Social Factors on the Adoption of new technologies, it is important to create a culture where AI is accepted and used by peers [34,35,47,73]. Therefore, entrepreneurial firms should integrate AI into their business processes as a means of addressing competition, remaining relevant, and being competitive [89,90]. The negative relationship between Performance Expectancy and the Acceptability of AI suggests that in order for firms to continue to adopt AI, they must manage their expectations and demonstrate to the firm the value of their implementation and ongoing utilization of AI. Policymakers must develop an ecosystem of support for the implementation of AI through the creation of AI Resources and the

promotion of Responsible AI Development in order to exploit the benefits of AI towards Sustainable Development [2,3,113].

5.3. Limitations and Suggestions for Future Research

There are multiple limitations to this research. First, the study has a cross-sectional research design which limits our ability to definitively infer causation, even though we built our structural model with theoretical reasoning behind it. Future research can utilize longitudinal methods that track the development of the predictors and outcomes of AI Adoption over time. Second, because this research was conducted in a single ecosystem of entrepreneurs, it may hinder the generalizability of the results to other environments. The negative relationship between performance expectancy and AI Adoption, for instance, may not hold in different entrepreneurial settings. Replicating this research across various sectors and countries will broaden the external validity of this research. Third, while we used a structural model that incorporates the key constructs of AI Adoption, we have not specifically studied other potential influences such as perceived risk [34,115], trust, concerns regarding privacy of data, or the specific forms of AI adopted. Future research should continue to explore these areas more extensively. Furthermore, our findings indicate that we were not able to demonstrate a statistically significant relationship between effort expectancy, technology competency, and support from top management. Future research may define these factors as having an indirect or threshold impact that was not captured by the current model. An area for future research would be examining how technology competency influences how other factors influence the adoption decision. Furthermore, understanding how the use of Artificial Intelligence affects organizational sustainability is likely to be useful in determining how organizations can achieve sustainable performance, through technology innovation (for example) and increasing operational productivity (for example) [3,101,102,113], would be highly beneficial. Lastly, due to the cross-sectional nature of this research, it should be emphasized that the relationships identified between the characteristics of Leadership Styles and AI Adoption Intentions are simply correlations; therefore, more elaborate longitudinal studies would help explain the evolution of these Strategic Orientations over time.

Generally drawing on the Dynamic Capabilities (DC) framework, this study suggests that Entrepreneurial Orientation (EO) and Technology Orientation (TO) may function as intermediary strategic mechanisms. The Intention to adopt AI triggers a ‘strategic renewal’—reconfiguring the firm’s posture to be more proactive and technologically focused—which subsequently drives holistic sustainable performance. While our current model establishes the direct impact of AI on these orientations, future research should formally evaluate this mediation path to further refine the logical sequence of technology-driven sustainability.

6. Conclusions

Through its empirical investigation of how the entrepreneurial community will implement AI, this research develops a comprehensive empirical understanding of what drives AI Adoption in the entrepreneurial ecosystem. The study develops an understanding of how firms navigate the challenges of digital transformation by combining the macro-level view of the Technology–Organization–Environment (TOE) framework with the micro-level behavioral components of the Unified Theory of Acceptance and Use of Technology (UTAUT).

The results of this study show a unique AI Adoption pattern for entrepreneurial firms, as the decision to adopt AI is less dependent on the internal perceptions of ease or managerial support and instead is strongly influenced by Structural Enablement and External Dynamics. The results show that the prominent role of Facilitating Conditions

and Social Influence highlights the importance of Social Influence in AI Adoption, as AI Adoption in this context is a process that is both resource-dependent and socially situated. By developing adequate Technical Infrastructure and receiving social validation from their Peer Networks, entrepreneurs can adopt AI with confidence [34,35,73]. In addition, the significant influence of Competitive Pressure indicates that the competitive intensity of the marketplace makes AI Adoption a strategic necessity rather than optional. As such, in an increasingly competitive world, firms must innovate to remain viable [89].

The report identifies a “wake-up call” in the study highlighting a negative correlation between Performance Expectancy and Adoption. This surprising finding represents a significant contribution to the literature, indicating that the initial excitement for AI may conflict with the actual complexities of implementation within SMEs with limited resources, thus creating a gap between anticipated and realized benefits [34,92]. It is, therefore, important to recognize that in entrepreneurial ecosystems, the journey to maturity with respect to adopting AI is not linear; companies must manage expectations alongside their technology deployment.

Most importantly, our research confirms that AI has the potential to catalyze a transformation in multi-dimensional value creation. The analysis shows definitively that AI Adoption serves as a dual engine of Strategic Renewal and sustainable performance for companies. It enhances the strategic posture of companies by (1) increasing Entrepreneurial Orientation and (2) increasing Technology Orientation, while simultaneously providing significant benefit on the Triple Bottom-line by improving Economic Viability, Environmental Sustainability, and Social Equity [3,24,113].

The findings of this research suggest that while there are many factors affecting an organization’s or an individual’s decision to adopt Artificial Intelligence (AI), the ultimate objective should be achieving sustainable performance. This finding implies that any action by a policymaker or ecosystem builder that promotes the development of AI will need to be combined with activities which will support the creation of a sustainable future. For example, the establishment of an enabling infrastructure to support the creation of AI and AI-related technologies (including support networks that enhance AI development) and developing the infrastructure required for a sustainable future on the Internet. For entrepreneurial companies that are increasingly using AI to deal with today’s challenges, they not only improve their own internal operations but also help support the achievement of a more sustainable future through Digital Development.

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Institutional Review Board Statement: This study is waived for ethical review as researchers to follow specific ethical protocols when conducting studies involving human participants. According to these internal guidelines, formal IRB approval is not mandatory for non-interventional, questionnaire-based studies that collect fully anonymous data, do not involve vulnerable populations, and do not include sensitive personal information, by Institution Committee.

Informed Consent Statement: Participation in the study was entirely voluntary, and informed consent was obtained from all participants prior to data collection through the online survey process. Due to the anonymous and fully online nature of the data collection, no signed or stored consent forms were generated or retained. In line with standard practice for anonymous, non-interventional online surveys, informed consent was obtained through an introductory information page at the beginning of the questionnaire, where participants were informed that proceeding with and completing the questionnaire would indicate their consent to participate.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Measurement of the Variables

Here is the corrected and consolidated Table 1. Summary of Variables, structured to align with your requested constructs and items, citing the specific sources you provided.

Table A1. Summary of variables and measurement Items.

Construct	References	Questionnaire Items
Performance Expectancy (PE)	[116]	PE1: Using AI tools enables me to accomplish tasks more quickly. PE2: Using AI tools increases my productivity. PE3: Using AI tools improves the quality of my work. PE4: Using AI tools makes my job easier.
Effort Expectancy (EE)	[116]	EE1: Learning how to use AI tools is easy for me. EE2: My interaction with AI tools is clear and understandable. EE3: I find AI tools easy to use. EE4: It is easy for me to become skillful at using AI tools.
Social Influence (SI)	[116]	SI1: People who are important to me think that I should use AI tools. SI2: People who influence my behavior think that I should use AI tools. SI3: Senior management has been helpful in the use of AI tools. SI4: In general, the organization has supported the use of AI tools.
Facilitating Conditions (FC)	[116]	FC1: I have the resources necessary to use AI tools. FC2: I have the knowledge necessary to use AI tools. FC3: AI tools are compatible with other systems I use. FC4: A specific person (or group) is available for assistance with AI tool difficulties.
Entrepreneurial Orientation (EO)	[117]	EO1: Our firm emphasizes research and development, technological leadership, and innovation. EO2: Our firm has introduced several new products/services in the past five years. EO3: Our firm is very active in initiating actions to which competitors then respond. EO4: Our firm has a strong proclivity for high-risk projects. EO5: Our firm adopts a bold, aggressive posture in order to maximize the probability of exploiting potential opportunities.
Technology Orientation (TO)	[117]	TO1: Our firm uses the latest technologies in our product development. TO2: Our firm proactively offers technological innovative solutions to customers' needs. TO3: Our firm has the will and capacity to develop and market technological innovative solutions. TO4: Our firm uses innovative technologies to deliver its solutions.
Technology Competency (TC)	[118]	TC1: Our technical infrastructure is available to support AI tools. TC2: Our company has a high level of knowledge and awareness about AI tools. TC3: Our employees have the necessary technical skills to use AI effectively.

Table A1. Cont.

Construct	References	Questionnaire Items
Top Management Support (TMS)	[118]	TMS1: Top managers provide necessary resources (human, financial, material) for AI Adoption. TMS2: Top managers encourage employees to use the latest AI technologies. TMS3: Top managers encourage innovations like AI in the workplace. TMS4: Top managers are willing to take risks related to AI Adoption. TMS5: Top management considers AI implementation strategically important.
Competitive Pressure (CP)	[118]	CP1: Our company believes AI Adoption affects industry competitiveness. CP2: Our company is under pressure from competitors to adopt AI. CP3: Some competitors have already used AI for risk prediction and premium calculation.
AI Adoption Intention (AI)	[118]	AI1: Our organization intends to use AI tools for business tasks. AI2: We plan to increase the use of AI tools in the near future. AI3: We predict we will use AI tools regularly in our operations. AI4: We are committed to adopting AI technologies to improve our processes.
Economic Performance (EcP)	[119]	EcP1: Our return on investment has been higher than the industry average. EcP2: Our sales growth has been higher than the industry average. EcP3: Our profit growth rate has been higher than the industry average. EcP4: Our market share has increased over the last three years.
Environmental Performance (EnP)	[119]	EnP1: Raw material usage efficiency has improved in the last three years. EnP2: Resource consumption (energy, water) has decreased in the last three years. EnP3: The share of recycled materials used has increased in the last three years. EnP4: Waste ratio per product has decreased in the last three years.
Social Performance (SP)	[119]	SP1: Employee turnover rate has decreased in the last three years. SP2: Employee satisfaction has increased in the last three years. SP3: Employee motivation has increased in the last three years. SP4: Health and safety performance has improved in the last three years. SP5: Employee training (days per employee) has increased in the last three years.

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