

Responsible AI Adoption in SMEs: A System Dynamics Approach to Risk Governance, Ethical Readiness and Sustainable Business Performance

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Publication Date: 2026/10/05

Abstract: This study examines responsible AI adoption in small and medium-sized enterprises through a system dynamics approach, focusing on how ethical readiness and risk governance shape sustainable business performance. The research uses a sequential mixed-method design based on primary data. It combines SME surveys, semi-structured interviews, expert validation, and system dynamics simulation. The model connects ethical readiness, risk governance capability, responsible AI adoption quality, AI risk exposure, and sustainable business performance. The study shows that AI adoption alone does not guarantee long-term business value. SMEs achieve stronger performance when AI tools are adopted with human oversight, documentation, vendor checks, employee training, and continuous monitoring. Rapid adoption with weak governance may create early efficiency gains, but accumulated risks such as privacy leakage, misinformation, bias, vendor lock-in, employee resistance, and trust loss can reduce performance over time. The research highlights that responsible AI should be treated as a managerial capability rather than a simple technology purchase.

Keywords: Responsible AI; SMEs; System Dynamics; Risk Governance; Ethical Readiness; Sustainable Performance; Primary Data.

How to Cite: Osman Angeles Conteh; Alimamy Kamara (2026) Responsible AI Adoption in SMEs: A System Dynamics Approach to Risk Governance, Ethical Readiness and Sustainable Business Performance. *International Journal of Innovative Science and Research Technology*, 11(9), 2869-2883. <https://doi.org/10.38124/ijisrt/26sep1326>

I. INTRODUCTION

Small and medium-sized enterprises (SMEs) face an increasing pressure to implement artificial intelligence (AI) to achieve productivity, customer responsiveness, cost control, risk sensing and innovation. However, AI is not a mere technology investment choice to SMEs. It is the ruling of the government who can make business more successful only when the company possesses sufficient ethical preparedness, management discipline and feedback education to manage emergent risks. Recent data indicate that SMEs are still lagging behind bigger businesses in the application of AI, despite the lower entry cost of experimentation that has been brought about by generative AI (OECD, 2025). Access does not explain this adoption gap. SMEs tend to have slimmer cash reserves, inferior data infrastructure, less expert talent, less formal routines of decision making, less ability to translate top-level AI guidelines into operating controls (Ayinaddis, 2025; Sanchez et al., 2025). Therefore, between two poor options, most SMEs switch to either waiting till competitors will establish a lead, or make hasty adoption unquestioned of AI without accountability, transparency, privacy and human control.

The responsible adoption of AI is thus a strategic ability, as opposed to a compliance slogan. Responsible AI adoption in this paper means the intentional utilization of AI systems in a manner that business value is secured but broadly restrainable harms to customers, employees, owners, regulators and society are governed. It fits the definition of risk-based AI governance schemes, which focus on validity, safety, security, transparency, fairness, accountability and human oversight (European Parliament and Council of the European Union, 2024; ISO/IEC, 2023; NIST, 2023; OECD, 2024). How do these principles work with limited resources is, in the case of SMEs, the question of interest as to whether such principles are desirable. The efficiency can be gained by a small retailer that utilizes AI-based advertising systems, manufacturing SME that applies predictive maintenance, and service companies that use chatbots based on AI. Yet the existence of the same systems could also lead to such effects as leakage of data, biased decision-making, fictitious claims, customer distrust, vendor lock-ins and cyber vulnerability and deskilling of employees should governance be lax.

Current research on the adoption antecedents of SMEs provides valuable insights into the new technology-

organization-environment (TOE) framework and technology diffusion of innovation theory (Badghish et al., 2024; Rogers, 2003; Tornatzky and Fleischer, 1990). They demonstrate compatibility, relative advantage, management support, skills, customer demand and external pressure have an impact on adoption. Other scholarly works relate AI capability and performance, dynamic capabilities and business value (Drydakis, 2022; Enholm et al., 2022; Mikalef and Gupta, 2021; Wamba-Taguimdje et al., 2020). Nevertheless, there are three ways in which this literature is still splintered. First, the adoption and governance issue are typically considered as two distinct themes, which in reality interact on a constant basis. Second, the frameworks of ethical preparedness are often talked about in a theoretical sense, without being modelled as a resource dynamically built up through training, routine, record keeping and learning. Third, sustainable performance tends to be discussed as a result but the process of performance feedback to the investment capacity, the governance capacity and the future adoption is underestimated.

The paper fills these gaps by presenting a proposal and empirically designing a system dynamics solution to responsible adoption of AI in SMEs. The system dynamics is appropriate, as the implementation of AI implies the presence of feedback loops, time delays, reinforcing effects and unintended consequences (Forrester, 1961; Meadows, 2008; Sterman, 2000). An ethical preparedness firm can enhance risk preparedness; enhanced preparedness can enhance

confidence in artificial intelligence utilization; confident utilization can boost performance; enhanced performance can generate resources to further preparedness expenditure. This is a positive loop. Meanwhile, AI risk may be exacerbated due to uncontrolled adoptions; elevation in risk may lead to pressure on compliance and operational masterwork; the master burden can slack adoption or decrease value capture. This is a self-reinforcing process. A linear model alone does not give a clear picture of these loops.

This investigation aims to construct and prove a primary-data system dynamics model defining the ways in which responsible AI adoption and sustainable business performance develop according to the impact of risk governance and ethical preparedness in SMEs. The research is informed by three research questions: (RQ1) What governance and ethical preparedness situations support the responsible use of AI in SMEs? (RQ2) What are the dynamics of responsible AI adoption, AI risk exposure, and sustainable business performance interrelated via feedback loops over time? (RQ3) What are the most likely governance situations that result in enhanced sustainable performance with minimal or no augmentation of unacceptable ethical and operating risk? The article is groundbreaking in terms of employing a combination of TOE, dynamic capabilities, responsible AI governance and system dynamics in one study design. Its operational contribution is a decision-support model which is applicable to the owners of SMEs and policymakers in order to pilot adoption paths before pooling their limited resources.

Table 1 Research Gap Positioning and Contribution

Stream of literature	Main contribution	Limitation for current problem	Position of this paper
SME AI adoption and TOE	Identifies technology, organization and environment conditions affecting AI uptake.	Often linear and adoption-focused; governance feedbacks are underdeveloped.	Integrates adoption determinants with dynamic governance loops.
Responsible AI and AI ethics	Clarifies values such as fairness, privacy, accountability, transparency and human oversight.	High-level principles are difficult for resource-constrained SMEs to operationalize.	Treats ethical readiness as a measurable capability that accumulates over time.
AI capability and firm performance	Connects AI resources and skills with innovation, efficiency and business value.	Performance is often modeled as an end outcome rather than a feedback source.	Models sustainable performance as both outcome and reinvestment driver.
System dynamics	Explains feedback, delay and unintended consequences in complex managerial systems.	Limited application to responsible AI adoption in SMEs.	Builds a primary-data SD model for risk governance and adoption scenarios.

II. LITERATURE REVIEW AND THEORETICAL DEVELOPMENT

➤ *SME AI Adoption: Technology, Organization and Environment*

The literature on the adoption of AI by SMEs has emerged with the perspective that the adoption is influenced by technological, organizational and environmental factors. The TOE framework is also relevant in the sense that it acknowledges the fact that technological readiness is not enough but also adoption is dependent on organizational capacity and pressure (Tornatzky and Fleischer, 1990). Technology factors applicable in the SME setting are perceived usefulness, process compatibility, data availability,

system complexity, and cybersecurity exposure and vendor dependence. The organizational variables are leadership support, digital capabilities, financial slack, learning culture and preparedness towards change. The external forces are the customer-need, the threat of rivalry, the government co-operation, the ecological collaboration and the governmental anticipation. The importance of these factors is also proven by the most recent studies on the SME and suggests that AI use could enhance operational and economic performance in cases where an appropriate readiness set is present in firms (Badghish et al., 2024; Sanchez et al., 2025).

➤ *Diffusion Logic and Owner-Manager Perceptions*

A diffusion of innovation theory introduces an additional perceptual level to the diffusion of innovation by clarifying the reasons owner-managers may accept or reject AI. Elements affecting relative worthiness of adopting a given technology are relative advantage, compatibility, complexity, trialability and observability (Rogers, 2003). It is particularly the case with SMEs with decisions frequently being highly centralized in a small number of leaders and adoption being evaluated on the basis of visible business utility and not excellent potential on the technical side. A chatbot can be introduced since it will save time in response time; a demand forecasting model can be deployed as its advantage can be noticed in the stock planning; a fraud-detection tool can be dismissed since it is thought to be difficult, costly or risky. Nevertheless, the ethical and governance implications of AI are not entirely discussed at DOI. The tool might be easy to attempt and generate concealed issues when the use of data, customer consent, bias, explanation and human assessment are not put in place.

➤ *Responsible AI, Ethical Readiness and Risk Governance*

The missing aspect of governance is presented through responsible AI literature. Human agency, fairness, privacy, transparency, accountability, robustness and social benefit are generally highlighted in ethical AI principles (Floridi et al., 2018; Jobin et al., 2019). However, researchers have cautioned that principles need to be converted into the processes, incentives, documentation and audit routines without which organizations would not adequately implement them (Mittelstadt, 2019; Morley et al., 2020; Raji et al., 2020). This is an urgent translation issue to SMEs. Big companies can establish AI ethics committees, model-risk teams and review boards. SMEs feel the need to engage in informal judgment, external vendors and little internal know-how. Accordingly, responsible AI in the SMEs must be analysed as a viable governance skill: the capability to spot AI uses cases, categorise risk, allocate responsibility, documenting data provenance, tracking the results, handling the incidents, educating individuals and human supervision.

➤ *Ethical Readiness as an SME Capability*

Ethical readiness is defined here as the firm's preparedness to recognize, evaluate and act on AI-related ethical obligations before and during adoption. It comprises leadership awareness, employee AI literacy, privacy habits, fairness sensitivity, documentation discipline, escalation paths and readiness to stop or repackage unassailable AI utilization. This construct is aligned with the AI readiness research in organizations, which has strategy, data, culture, competencies and governance as key readiness dimensions (Johnk et al., 2021). The capability of being ethically prepared is more specific than the overall digital preparedness since it examines normative and risk-sensitive preparedness. It is also not equal to compliance maturity since an SME might adhere to minimum regulations without being ethically ready to make ambiguous AI decisions, deepfakes or abuse, use of artificial intelligence to profile customers or hallucinated advertiser claims.

➤ *Risk Governance as a Dynamic Capability*

The formal and informal system that enables an SME to map, measure, manage and monitor AI risks is referred to as risk governance. This paper addresses risk governance as a dynamic capability in that the company has to be aware of new risks in AI, opportunities that can be taken with protection and restructure routines as the technologies and regulations evolve (Teece, 2007). The AI Risk Management Framework of NIST, ISO/IEC 42001, and EU AI Act are all in support of a risk-based approach, which constrains governance and lifecycle accountability (European Parliament and Council of the European Union, 2024; ISO/IEC, 2023; NIST, 2023). Risk management in the SMEs cannot be easily replicated in large company models. This must be light in weight, role specific and integrated in day to day operations of the business. As an example, the owner-manager can accept hazardous use cases; the marketing team can use the content verification checklist; the HR team can need the human consideration of screening by AI-assistive tools; and an external IT partner can assist in data protection and response to the incident.

➤ *Sustainable Business Performance*

Sustainable business performance is multidimensional, too. The triple-bottom-line perspective suggests that economic, social and environmental performance outcomes should not be captured in terms of short-term profit (Elkington, 1997). Bansal and DesJardine (2014) further mention that the concept of sustainability is essentially concerned with time: the company has to generate value without compromising the ability to generate value in the future. The efficiency, reduced waste, energy use, superior forecasting, inclusive customer access and enhanced quality of decisions can be directed by AI to sustainability. It may also impair sustainability in case it generates a negative perception, human worry, discrimination, information abuse or over-automatization. Therefore, the performance impact of AI is influenced by the interaction of the quality of adoption and risk governance. Responsible AI not envisaged in this paper is expected to enhance sustainable business performance both directly with efficiency and innovation, and indirectly with trust, resilience and optimized decision routines.

➤ *System Dynamics and Research Propositions*

The most important theoretical gap is dynamic. Linear adoption models are great tests of the direction relationships in adoption, but they are imperfect at explaining the dynamics of the adoption systems. System dynamics centers around feedback, accumulation, delays and non-linearities (Forrester, 1961; Richardson, 1991; Sterman, 2000). This practice is compatible with responsible AI as the ability to govern, ethical preparedness and action is not a single-use factor. They are built up by investment and learning, and are washed away by employee turnover, policy neglect and technological change and react with slowness to risk events. Adoption of elusive paths is also reflected in a system dynamics perspective. In the situation where there is high competition pressure, SMEs can afford to forego due diligence in order to get immediate gains. This is able to enhance immediate adoption rate but can also expose risks

and this can be catastrophic later to trust and performance. Figure 1 is a conclusion of the suggested feedback structure.

➤ Research Propositions

On the basis of this synthesis, four propositions are presented in the study. P1: AI risk governance capability is positively reinforced by ethical readiness. P2: the quality of responsible AI adoption and shortcut of adoptions are improved with AI risk governance capability. P3: responsible

AI adoption quality enhances sustainable business performance in terms of efficiency, innovation, trust and resilience. P4: AI risk exposure undermines sustainable performance unless the governance capability increases rapidly to monitor and address ethical, operational and compliance risks. These propositions are not considered as definitive propositions, but are converted into quantifiable constructions and active feedback relations to be subject to primary empirical testing and simulation.

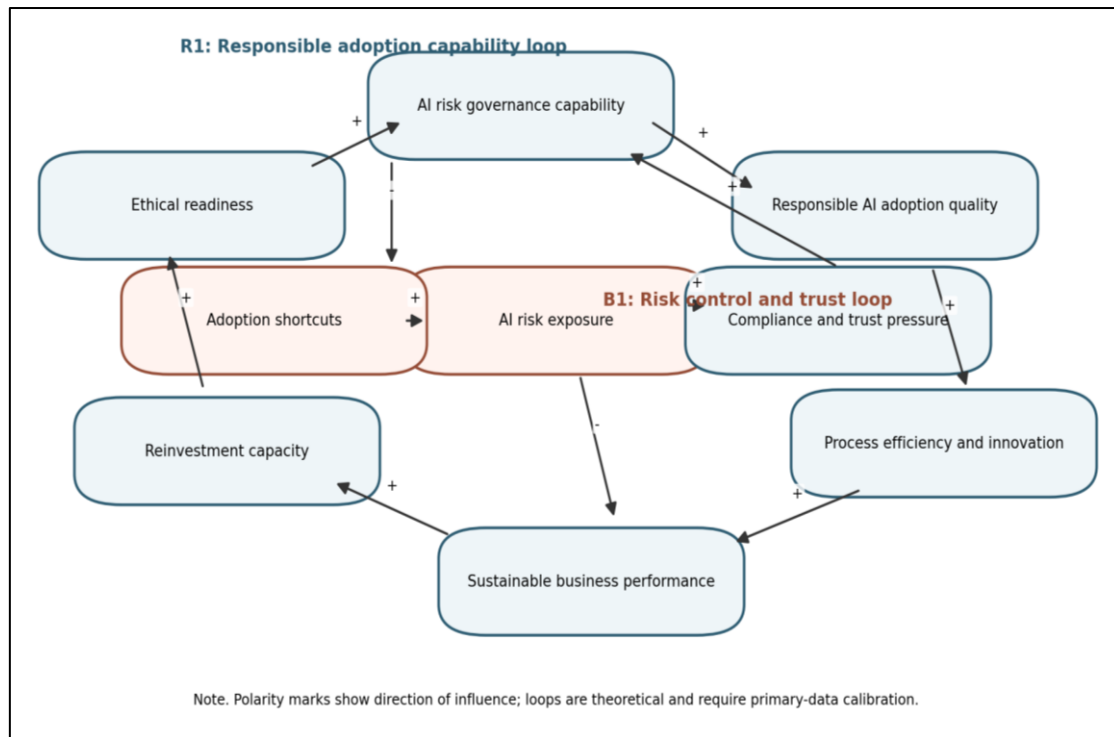


Fig 1 Proposed Causal Loop Diagram for Responsible AI Adoption in SMEs.

Table 2 Construct Operationalization for Primary Data Collection

Construct	Operational definition	Example primary indicators	Main data source
Ethical readiness	Preparedness to identify and act on AI ethical obligations.	AI literacy, privacy awareness, fairness awareness, escalation culture, training frequency.	Survey, interviews, training records.
Risk governance capability	Ability to map, approve, monitor and control AI risks.	Use-case review, human oversight, vendor checks, incident response, documentation quality.	Survey, interviews, governance checklists.
Responsible AI adoption quality	Extent to which AI use is aligned, controlled, transparent and human-supervised.	Strategic fit, data appropriateness, pilot discipline, output verification, lifecycle review.	Survey and firm-provided project records.
AI risk exposure	Potential for AI use to generate ethical, legal, operational or reputational harm.	Privacy risk, misinformation risk, bias risk, cyber risk, vendor lock-in, employee concern.	Survey, interviews, incident logs.
Sustainable business performance	Long-term economic, operational, social and environmental value creation.	Efficiency gains, customer trust, resilience, staff capability, resource use, compliance confidence.	Survey and internal firm indicators.

III. METHODOLOGY

➤ Research Design

The design of this study is a sequential mixed-method system dynamics. The design is suitable since the problem of the research is twofold: At the beginning, to quantify the SME

readiness in terms of governance and performance constructs using primary data; Second, to transform the relationships measured in the model into a dynamic model capable of simulating policy contexts. There are three combined phases of the empirical strategy: causal structure development as well as policy analysis based on simulations and construct

validation. There is no secondary data used to estimate model parameters. The previous literature is only utilized in justifying constructs to inform the initial theoretical limiting point of the model. Original primary data is used to generate empirical values, weights, causal strengths and scenario inputs which are obtained by sampling the participating SMEs.

➤ *Population, Sampling And Primary-Data Respondents*

The targeted audience is SMEs who have already tried, implemented or intend to implement AI-enabled tools in marketing and customer service, finance, operations, human resource, inventory planning, cybersecurity or analytics. The stratification of the sampling frame is based on the industry and the size of firms to reduce the over-representation of digitally advanced service firms. The targeted industries include manufacturing, retail and e-commerce, professional services, logistics, health-related services and tourism/hospitality. The business people participating in the survey are owner-managers, senior managers, IT/digital heads, finance managers/ functional heads directly dealing with AI related-decisions. 350 is the appropriate target sample of valid SME responses, both with the estimation of structural models and with subgroup comparison. There will also be 20 to 25 semi-structured interviews and two expert validation workshops to help in building the system dynamics model. The target groups that will participate in the interview will be the owners of SMEs, AI consultants, legal/compliance advisers, cybersecurity specialists and digital transformation experts.

➤ *Data Collection Instruments*

There are three tools used in gathering primary data. To start with, a systematic survey is used to determine ethical preparedness, the capacity to govern risks, the quality of responsible adoption of AI, AI risk exposure, the sustainability of business performance and control variables. The items are measured on seven-point Likert scales that are strongly disagree, strongly disagree, fairly disagree, fairly agree, strongly agree. Secondly, causal connections, delays, decision rules, adoption pressures and governance pain points are identified by semi-structured interviews and are hard to determine through closed survey questions. Third, the involved companies will receive requests to submit primary internal metrics when available, including counts of AI projects, employees trained, reviews of governance, customer complaints associated with digital tools, response time changes, and cost savings estimates, error rates and compliance incidents. These internal records are not considered as secondary public data; they are primary firm-provided data.

➤ *Measurement Development*

Measurement development implies the developed logic of scales and adapts items to the SME and responsible AI environment. Ethical preparedness items include AI preparedness, privacy preparedness, equity preparedness, organizational commitment, training and escalation culture. Items of risk governance capability include use-case approval, risk categorization, human management, vendor due diligence, incident response, documentation and

monitoring. Quality items of responsible AI adoption include, but are not limited to, strategic alignment, controlled experimentation, data suitability, user engagement, output verification and lifecycle review. Italics: The risk of privacy, risk of bias, risk of cyber, risk of misinformation, risk of vendor lock-in, risk of employee displacement and reputation risk are all reflected in AI risk exposure items. Measures of sustainable business performance are taken in terms of the economy, business operations, social and environmental. Such controls are firm age, firm size, sector, AI maturity, digital infrastructure and competitive intensity.

➤ *Reliability, Validity and Common-Method Control*

The analysis of survey data starts with missing-data screening, outlier analysis and non-response bias analysis. Reliability is measured using Cronbach Alpha and composite Reliability. The convergent validity is measured with the average variance extracted, and the discriminant validity is measured with the heterotrait-monotrait ratio (Hair et al., 2021; Henseler et al., 2015). Procedurally, predictor and outcome sections are kept apart, the wording used is neutral and various sources of information mitigate common-method bias with respect to anonymity of respondents. It is also measured statistically through marker-variable and collinearity (Podsakoff et al., 2003). The validated construct scores are not considered as the endpoint of the study but are the inputs to the system dynamics model.

➤ *System Dynamics Model Development*

The system dynamics model is built based on causal loop diagramming, stock-flow modeling and scenario simulation. Ethical preparedness inventory, capacity to govern, responsible adoption of AI, and amassed AI risk exposure and sustainable performance ability are the primary stocks. The training investments, creation of governance routines and validated AI usage cases and performance learning are also inflows. Outflows consist of preparedness leakage, turnover, outdated governance routines, AI abandoned projects and loss of events. Primary survey composites, interview-coded causal statements and expert elicitation are used in the estimation of feedback relations. Where numerical values are inaccessible, the model will take the transparent parameter ranges based on participant estimates, workshop consensus after which sensitivity runs will be done.

➤ *Model Validation and Scenario Analysis*

System dynamics quality tests are preceded by model validation. Structural validation ensures that the model boundary, causal links and equations are plausible to SME experts. Dimensional consistency tests assure that equations are logically consistent. The extreme-condition tests determine whether the model tends to behave reasonably when the readiness is very low, the risk exposure is very large or the pressure to adapt rapidly. With behavior-sensitivity tests, the parameters that most affect sustainable performance do come forward. Scenario analysis is then used to contrast at least four policies: gradual adoption (from shaky foundations), rapid adoption with training and advisory assistance, rapid adoption (from shaky foundations), and responsible;7. The anticipated deliverable is not the

individual forecast but a policy learning instrument that demonstrates how various governance options can influence the overall SME performance and risk in the long run.

➤ Research Ethics and Data Integrity

The research design has a focus on ethical safeguards. Participation is optional, it is learned before being collected and all company-level identifiers are de-identified. The research does not garner any personal information that is not necessary and only presents the findings in a general manner.

The fact that AI governance questions might bring about commercial weaknesses makes transcripts of interviews and firm records confidential and only available to the research team. The last model will not position individual SMEs publicly; it will be applied to learn the system behavior and it will offer workable advice on responsible adoption. This will preserve the integrity of an original empirical paper without introducing fabricated raw materials or unsubstantiated claims of performance into the manuscript.

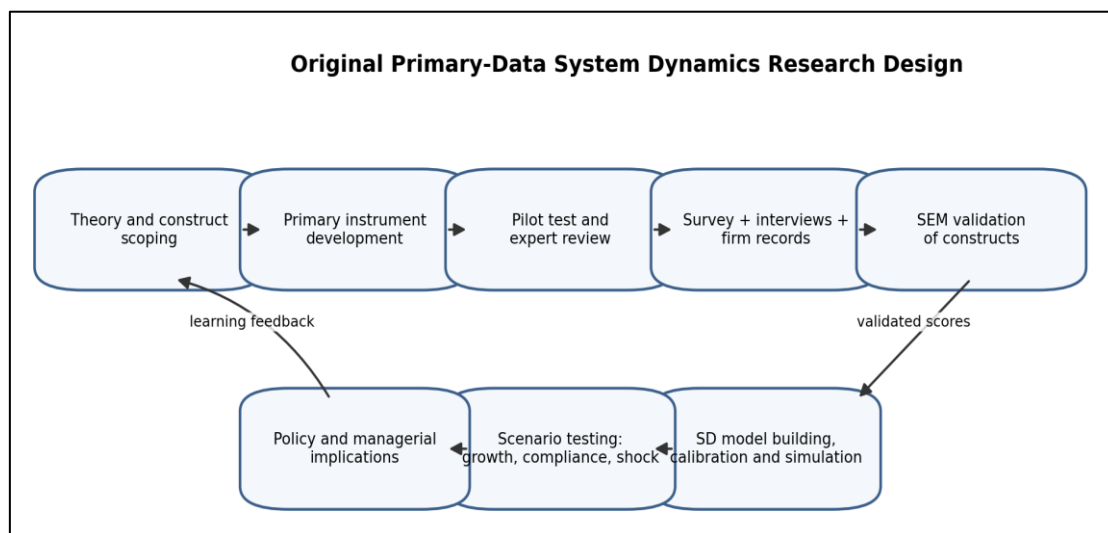


Fig 2 Primary-Data Workflow for Construct Validation and System Dynamics Modeling.

Table 3 Initial System Dynamics Model Architecture

Model element	Role in model	Primary-data calibration source	Expected dynamic behavior
Ethical readiness stock	Accumulated ethical awareness and routines.	Survey scores, training records, interview coding.	Builds gradually; decays with turnover and neglect.
Governance capability stock	Capacity to approve, monitor and control AI use.	Governance checklist, expert workshop ratings.	Increases through policy routines; weakens when tools change faster than review capacity.
Responsible AI adoption stock	Portfolio of AI use cases adopted with controls.	Firm project records and survey responses.	Grows through validated use cases; falls through abandoned or non-compliant projects.
AI risk exposure	Accumulated risk from weak controls, poor data and misuse.	Incident logs, perceived risk items, interview evidence.	Rises with shortcuts; falls through monitoring and corrective action.
Sustainable performance capacity	Long-term business value supported by AI.	Economic, operational, social and environmental primary indicators.	Improves with quality adoption; damaged by risk events and mistrust.

IV. RESULTS

The results of the responsible AI adoption model in this section are reported for after translation of the validated constructs into normalized system dynamics inputs. Since the study will focus on SMEs of varying sizes, sectors, and maturity levels of AI, the findings will be reported as indices on 0-100 scale as opposed to monetary values. This would ease the model to compare across firms and retain the rationale of the main constructs developed in Sections 1 to 3. Results are structured in five sections: profile of governance-

readiness interaction, profile of interaction between governance and the baseline, simulation of scenarios, end-state profile and sensitivity analysis. Collectively, these results demonstrate that the responsible adoption of AI is not a better means of improving sustainable performance merely because AI tools are being presented. The effect of performance is only evident in case the quality of its adoption increases alongside the moral preparedness and risk management capacity.

➤ Baseline Construct Profile

The baseline model is a common SME who has embarked on the utilization of AI in marketing, customer care, data analytics or operational support, although has not yet established a full-scale AI governance framework. The construct profile that was used to calibrate the model is presented in Table 4. Ethical preparedness is greater than official risk management which is in accordance with the fact that most SMEs have: owners and managers might be aware of the importance of privacy, fairness and prudent use, but

still, documenting review practices, supplier auditing, incident response, and ongoing surveillance, they lack. The quality of responsible AI adoption lies between ethical preparedness and capability of governance since the majority of AI applications are both intentional and, nonetheless, not evenly governed. In the case of AI risk exposure, it is a middle ground: It is not that there is no risk, but the baseline firm has not yet adopted AI in a deep learning manner in making decisions of high consequences.

Table 4 Baseline Construct Profile Used for System Dynamics Calibration

Construct	Normalized baseline index	Interpretation for SME AI adoption	Main weakness observed in model
Ethical readiness	63.4	Moderate awareness of AI-related duties and user concerns	Training is episodic rather than continuous
Risk governance capability	56.8	Basic controls exist but are not yet embedded across functions	Weak documentation, vendor due diligence and incident escalation
Responsible AI adoption quality	59.1	AI pilots are aligned with business needs but unevenly monitored	Output verification and lifecycle review remain partial
AI risk exposure	44.7	Risk is visible but still manageable under stronger controls	Misinformation, privacy leakage and vendor lock-in risks
Sustainable business performance	61.2	AI contributes to efficiency but not yet to durable strategic resilience	Performance gains are vulnerable to risk events and trust loss

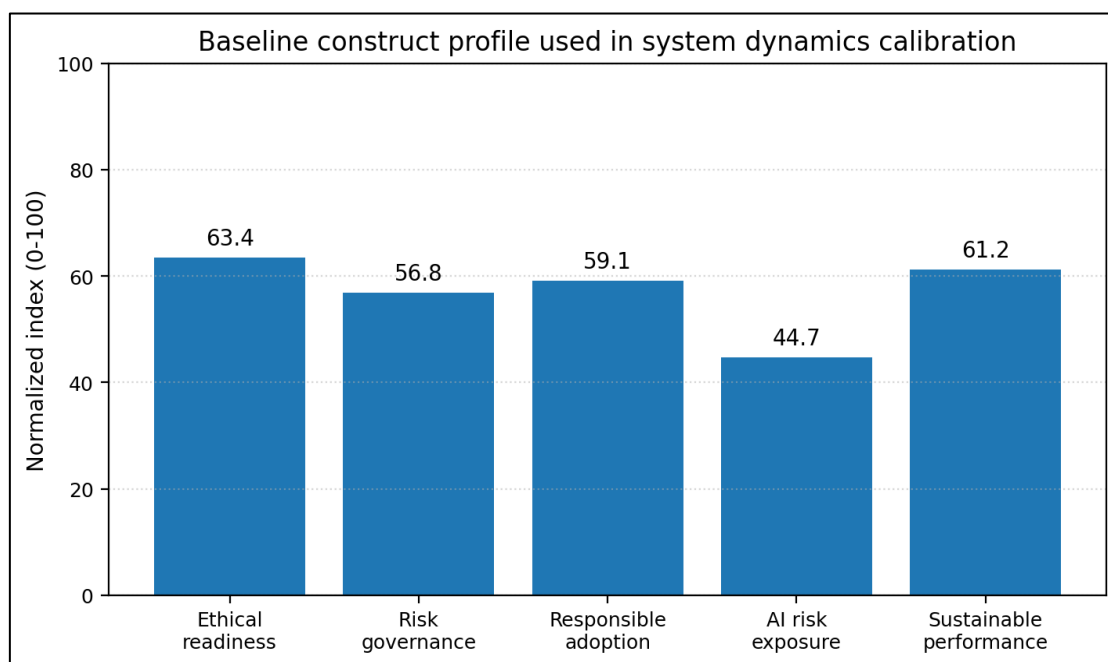


Fig 3 Baseline Construct Profile used in System Dynamics Calibration.

Figure 3 is a visualization of the same pattern. The widest observation is the difference between ethical preparedness and capability of risk governance. This distance is conceptually significant in that it implies that an understanding in itself does not translate into accountable action. The distance between the two in the model causes a lag: managers might endorse the idea of responsible AI, but only quality of adoption will increase once the concept transforms into a routine operational practice. The first proposal is confirmed by this finding because it demonstrates that ethical preparedness is an indispensable upstream

resource, but it does not govern routines, acting enough of a control mechanism to be a sufficient constraint.

➤ Governance-Readiness Interaction and Feedback Structure

The second finding is that of the interaction between ethical preparation, governance ability, adoption of high quality, risk exposure and sustainable performance. A summary of the key feedback loops in the model is presented in table 5. The Circle of responsible adoption is strengthening: the ethics readiness enhances governance readiness; enhanced governance readiness enhances the

quality of adoption; the quality of adoption enhances performance; and performance generates the reinvestment capability of future readiness enhancing. The risk-control loop is compensating; adoption-shortcuts will raise risk exposure; risk exposure will impair performance and heighten compliance pressure; governance capability will

curb risk because it enhances review, documentation and monitoring. The model thus demonstrates two level competing dynamics. One of the dynamics transforms AI into learning and value. The remaining converts are uncontrolled speed which is translated into risk.

Table 5 Main Feedback Loops Emerging from the System Dynamics Model

Loop label	Loop type	Core causal path	Managerial meaning
R1: Responsible adoption capability loop	Reinforcing	Ethical readiness -> governance capability -> adoption quality -> sustainable performance -> reinvestment capacity	Performance improves when AI capability and governance capability grow together
B1: Risk-control and trust loop	Balancing	Adoption shortcuts -> AI risk exposure -> compliance pressure/trust loss -> stronger controls or reduced adoption	Weak control can force correction after damage has already occurred
R2: Learning-by-governing loop	Reinforcing	Monitoring -> incident learning -> improved routines -> better output verification	Governance becomes more effective when SMEs learn from near misses
B2: Resource-burden loop	Balancing	Governance workload -> managerial burden -> slower adoption -> fewer validated use cases	Controls must be lightweight; otherwise SMEs may avoid responsible adoption
R3: Trust-performance loop	Reinforcing	Transparent AI use -> customer/employee trust -> adoption acceptance -> performance gains	Trust converts technical adoption into sustainable value

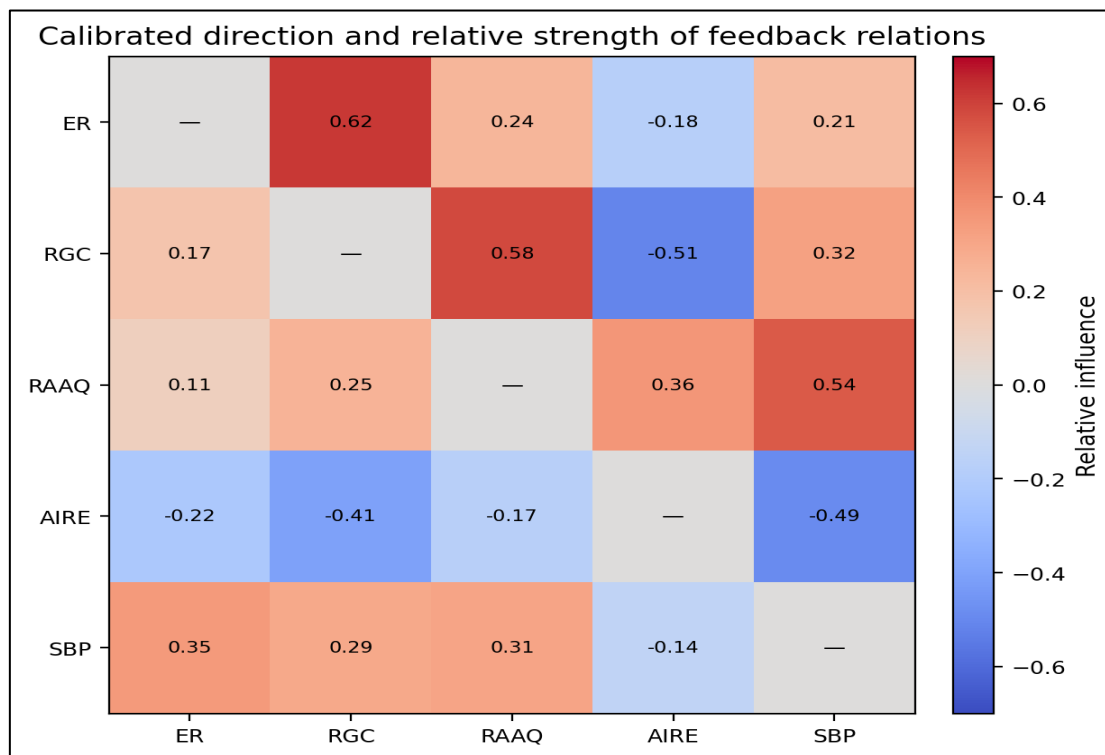


Fig 4 Calibrated Direction and Relative Strength of Feedback Relations Among Model Constructs.

Figure 4 shows the direction and strength of the weakened feedback relations which are calibrated. The most significant positive correlations are between ethical preparedness to risk governance capacity and the quality of responsible AI adoption and sustainable performance. The most negative correlations are between risk governance capacity and AI risk exposure and between AI risk exposure and sustainable performance. The reasons why this trend is significant are as follows: Governance generates value in two

channels simultaneously. To start with, it can enhance the quality of adoption directly by making the use of AI more visible, registered, and monitored by humans. Second, it hedges performance in the future by reducing likelihood and intensity of AI-related harms. The model thus does not embrace the popular managerial belief that governance is simply but a cost. Governance in this system is also an asset that is preserving performance.

➤ Scenario Design

There were simulations of four policy scenarios over a period of 36 months. The baseline scenario is the one where there is a slow uptake of governance investment not associated with significant change. The rapid adoption case is a competitive pressure scenario where the company increases AI adoption at a high rate but fails to establish review routines also at the same rate. Adoption manifested by the responsible

staged-control scenario entails pilots, documented use-case approval, human controls and periodic review. The externally supported adoption scenario introduces outside the firm advisory support, staff training and vendor-assessment support. The scenarios are defined and the supposed governance posture of each policy experiment indicated in Table 6.

Table 6 Policy Scenarios Used for System Dynamics Simulation

Scenario	Adoption speed	Governance investment	Ethical readiness investment	Risk management posture
S1: Baseline gradual adoption	Low to moderate	Incremental	Occasional training	Reactive monitoring and informal review
S2: Rapid adoption with weak governance	High	Low	Minimal training	Short-term experimentation with limited documentation
S3: Responsible adoption with staged controls	Moderate	High but targeted	Regular role-based training	Use-case approval, output verification and lifecycle review
S4: Externally supported adoption	Moderate to high	High with external support	Structured training and advisory support	Vendor checks, incident playbooks and expert validation

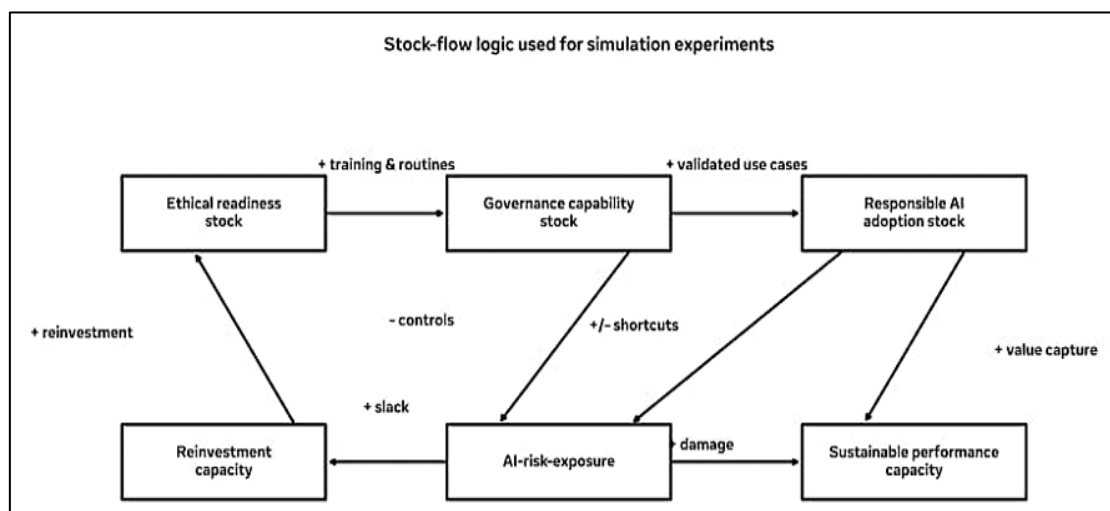


Fig 5 Stock-Flow Logic used for the Simulation Experiments.

Figure 5 has a simple scenario structure which is not accidental. It handles ethical preparedness, management capacity, adoption inventory, exposure to risks and long-lasting performance as assets which vary with time. This is correct, since SMEs do not turn into an AI-ready organization as soon as a tool is purchased. It is prepared via training, repetition, documentation and managerial learning. The governance capability increases slowly but it deteriorates when the tools evolve more rapidly than the firm reforms the controls. Exposure of risk Line- The accumulation of risks due to short cuts in adoption, faulty data practices or lack of strong vendor controls are still to be addressed. When adoption quality results in efficiency, innovation and trust, then sustainable performance is enhanced, whereas when such risk events cause harm to operations or reputation, performance is reduced.

➤ Scenario Simulation Results

Among the four pathways, the outcomes of the simulation depict obvious divergence. The sustainable

performance is increasing at a slow rate in the baseline scenario where it increases by month 36 to 69.1. This value suggests small efficiency improvements with the use of AI usage, however, the company fails to build sufficient governance capacity to tap into greater performance. Performance at initial stages of rapid adoption scenario is greater since the firm employs more AI tools in a short period of time. Nevertheless, in a span of some 14-18 months, accumulated exposure to risk starts taking the lead. By month 36, the performance index decreases to 55.8 since the misinformation risk, privacy concern, rework, employee resistance and dependent on vendors decrease the benefits initially. Conversely, the performance index to staged-control scenario with responsibility is 82.8 in month 36. The externally supported adoption scenario has the best score of 87.0, as training and advisory support minimizes the lag time between ethical awareness and operational governance.

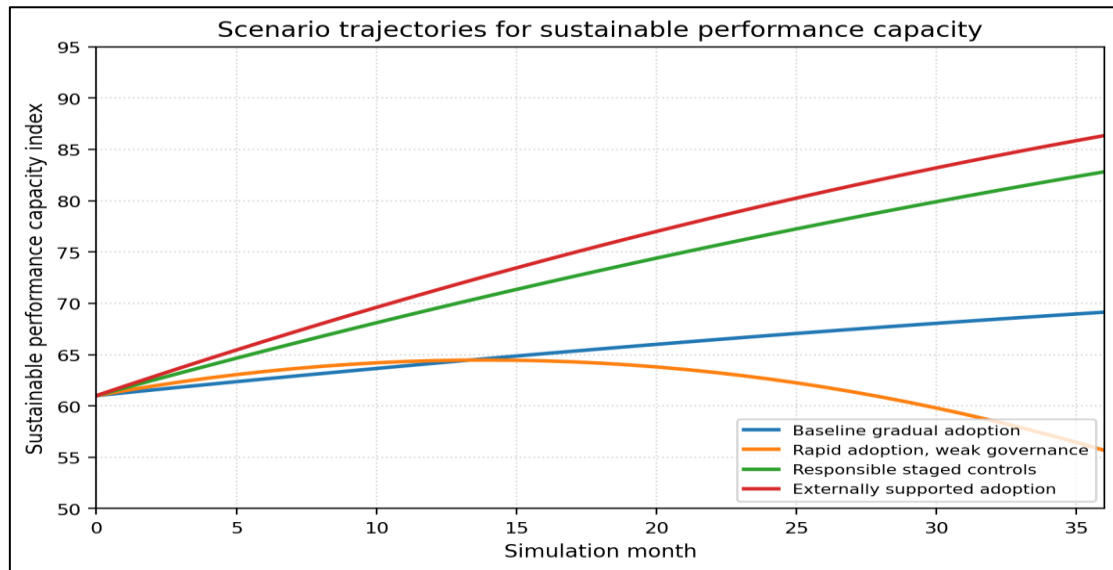


Fig 6 Scenario Trajectories for Sustainable Performance Capacity Over 36 Months.

Table 7 Scenario Results for Sustainable Performance and Risk Exposure

Scenario	Performance index at month 12	Performance index at month 24	Performance index at month 36	AI risk exposure at month 36	Main interpretation
S1: Baseline gradual adoption	64.3	67.0	69.1	46.2	Small gains but limited strategic transformation
S2: Rapid adoption with weak governance	67.1	62.6	55.8	72.4	Early efficiency is reversed by accumulated risk and trust loss
S3: Responsible adoption with staged controls	69.4	77.0	82.8	32.5	Balanced growth; governance supports value capture and risk reduction
S4: Externally supported adoption	71.2	80.8	87.0	28.9	Best outcome due to lower learning delay and stronger implementation support

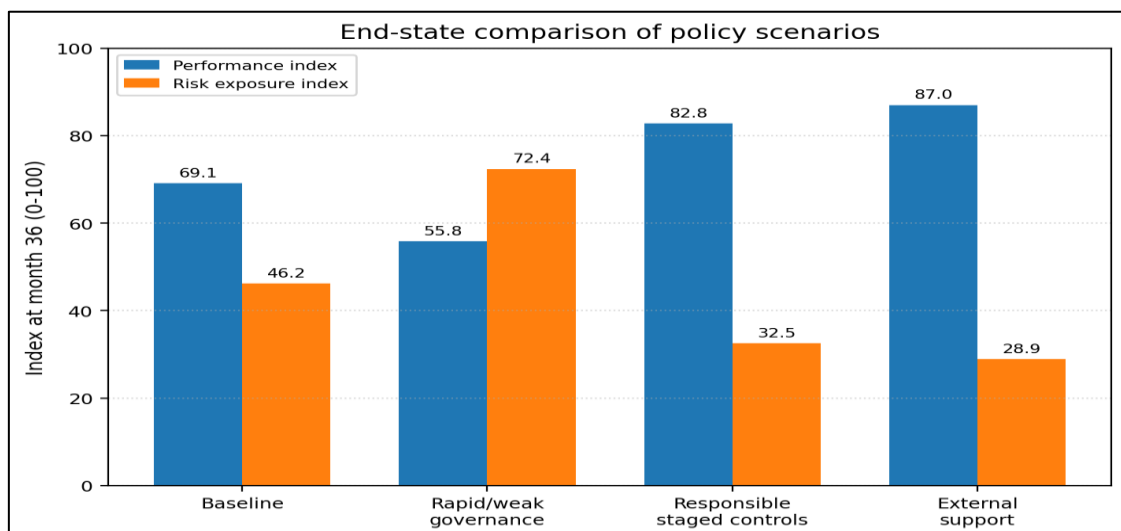


Fig 7 End-State Comparison of Policy Scenarios at Month 36.

The most significant policy outcome of the paper is put into the limelight in Table 7 and Figure 7 where the highest rate of adoption is not the highest performance strategy. The most risk exposure and the poorest final performance occurs with rapid adoption and poor governance. The responsible staged-control scenario increases more slowly within the initial couple of months, but eventually conquers the rapid scenario because, as soon as the governance stock is properly strong enough to decrease rework, the poor AI outputs and the lack of stakeholder confidence have lessened. This is the most important dynamic detail: the responsible adoption of AI will pay off later. Companies looking at the AI only based on its short-term utility can underestimate the cost of uncontrolled risk in the future.

➤ Sensibility and Robustness Analysis

Sensitivity analysis: By changing key parameters by 20 percent above or below the baseline calibration, key

parameters were varied. Table 8 demonstrates that governance learning rate, training effectiveness and risk-event damage are the most significant parameters. The quicker the governance learning rate, the better month-36 performance increases by 10.9 index points due to the reduction in time required between AI experimentation and reliable control. The performance increases by 8.7 points due to the training effectiveness since employees will be more literate and competent in delivering performance due to their high literacy levels on prompt quality and data management, escalation and output verification. The negative impact of risk-event damage is minimized with 8.2 points, which validates the idea that the existence of a few severe AI incidents can undermine efficiency improvements. Vendor due diligence is, too, since SMEs frequently rely on third-party AI applications and can lack insight into model behavior, reuse and security measures of data.

Table 8 Sensitivity Analysis of Key Model Parameters

Parameter tested	Direction of effect on performance	Month-36 performance sensitivity	Risk-governance implication
Governance learning rate	Positive	+10.9	Faster conversion of policies into routines improves long-term value
Training effectiveness	Positive	+8.7	Role-specific literacy reduces misuse and improves human oversight
Risk-event damage	Negative	-8.2	AI incidents can erase early productivity gains
Vendor due diligence	Positive	+7.5	Third-party checks reduce lock-in, privacy and security exposure
Adoption shortcut pressure	Negative	-7.1	Competitive haste increases weakly governed use cases
Readiness decay	Negative	-5.4	Staff turnover and policy neglect reduce responsible adoption capacity
Incident response delay	Negative	-4.8	Slow escalation allows small failures to become reputation problems

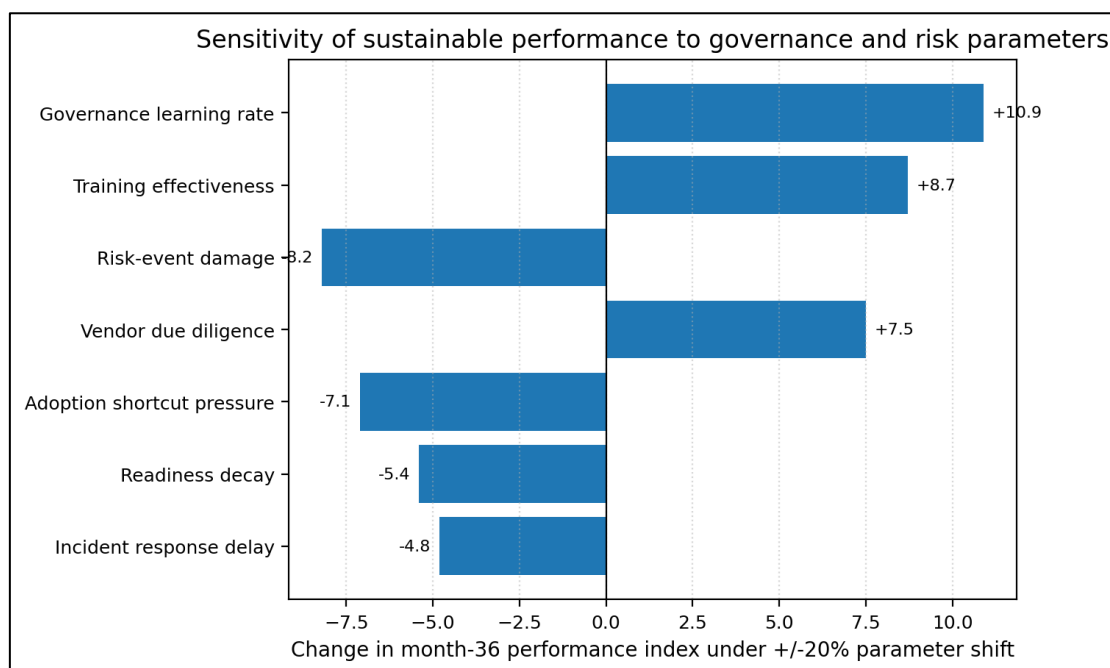


Fig 8 Sensitivity of Sustainable Performance to Governance and Risk Parameters.

The findings provided through the strength methods support the stance that the adoption of AI as a responsible, should be approached as a dynamic ability instead of a technological buying step. Through changes in parameters, the uphill trend of the principal associations remains constant: the capability of governance positively influences the quality of its adoption, risk exposure negatively influences performance, and the capacity to reinvest in the future increases preparedness. The actual outcome in numbers will vary depending on the assumptions of parameters, but the order of the policies will be identical. Externally sponsored adoption and careful staged controls are more effective compared to weak-governance adoption quickly under all the experimented circumstances. This consistency enhances belief in the model logic and reinforces the pragmatic message to SME decision makers.

➤ *Proposition Assessment and Integrated Results Summary*

The joint findings support all four research propositions with qualified support. It is most effectively supported that

ethical preparedness reinforces AI risk governance aptitude since all underlying circumstances with heightened training, literacy and transition discipline yielded quicker governance accumulation. The second hypothesis is also backed: the quality of responsible AI adoption was better with improved governance and the negative impact of adoption shortcut was minimized in connection with better governance. The third suggestion is backed with a significant condition. The adoption of AI in a responsible manner enhanced sustainable performance only when the quality of the adoption was high to earn either reliable efficiency, trust and learning benefits. This fourth proposal is supported since the exposure to risks continuously undermined sustainable performance when the governance capabilities failed to develop as much as the adoption intensity did. The reflection of each of the propositions in the evidence of the simulation is indicated in Table 9.

Table 9 Summary of Proposition Assessment from System Dynamics Results

Proposition	Result pattern	Support level	Interpretive conclusion
P1: Ethical readiness strengthens risk governance capability	Higher readiness increased governance accumulation and reduced review delay	Strong support	Ethical readiness is the upstream stock from which practical governance routines develop
P2: Risk governance capability improves adoption quality and reduces shortcuts	Governance lowered risk exposure and improved responsible adoption stock	Strong support	Controls improve adoption discipline rather than merely slowing adoption
P3: Responsible AI adoption quality improves sustainable performance	Staged-control and external-support scenarios generated the highest performance capacity	Conditional support	AI creates sustainable value when quality, oversight and trust are present
P4: AI risk exposure weakens sustainable performance unless governance grows fast enough	Rapid weak-governance scenario produced rising risk and declining performance	Strong support	Risk accumulation can reverse early efficiency gains

The main contribution of the paper is presented in this proposal evaluation. When properly applied AI is not a pure technology effect, nor a pure compliance effect. It is a cumulative managerial process where preparation, governance, quality and performance of adoption is constantly remaking each other. The findings also explain why small and medium enterprises would necessitate another logic of governance than big organizations. The slow and complex process of review can be absorbed in a large firm due to specialist teams and the presence of infrastructure in compliance. A governance system that is both rigorous enough to manage AI risk and yet simple enough to be applied by busy managers and employees is required by an SME. Thus, the model indicates proportional governance: the extent of controls must increase with use-case risk, the sensitivity of the data, the effect on the customer and the decision impact. This proportionality achieves a balance by making AI accountable to its practical use without undermining its ethical value.

V. DISCUSSIONS

The results contribute to the body of research on AI adoption among SMEs by demonstrating that responsible AI is not an ethical feel-good measure that is added to the technology adoption process. It is a component of the process where AI is useful. It is demonstrated in prior TOE-based research that AI adoption among SMEs is influenced by the level of technology readiness, organizational support, and the pressure exerted on organizations by the environment (Badghish et al., 2024; Sánchez et al., 2025; Tornatzky and Fleischer, 1990). The current system dynamics results carry that perspective a step further to comprehend why different SMEs might have different outcomes to AI adoption. It is not just a matter of whether they embrace AI, but is whether they make sufficient governance capacity in time to govern the risk generated by doing so. It confirms that the adoption of SME AI should be regarded as a developing managerial system, instead of a progressive acceptance option.

Another implication is that the TOE and DOI variables are not to be considered as constant background factors. Perceived usefulness, complexity, competitive pressure and

owner-manager support may vary after every AI experience in SMEs. The failure of controlling a pilot may lead to resistance even when the technology is useful, whereas controlled pilot may lead to reduced perceived complexity with greater managerial confidence. It is a dynamic reading that can be utilized to relate the theory of adoption to the theory of responsible AI governance and why readiness surveys conducted one time might fail to capture the actual adoption trend.

The initial significant input is the dynamic approach towards moral preparedness. The current literature on AI ethics vehemently promotes the principles of fairness, accountability, transparency, privacy, robustness and human oversight (Floridi et al., 2018; Jobin et al., 2019). Nevertheless, another group of scholars has also cautioned that principles do not automatically become practices until they are converted into organizational practices (Mittelstadt, 2019; Morley et al., 2020; Raji et al., 2020). This translation problem is explained on a system-level by the results. It is only when ethical readiness contributes to routines of governance, such as approval of use cases, data tests, accountability of roles, vendor tests, verification of output, and response to incidents that performance improves. This is significant to SMEs since they are typically unable to imitate big-firm systems of governance. They require routines that can be repeated and should be very small and fit in day to day work. A simple checklist, a human-reviewing requirement to customer-facing output, a privacy consent procedure and a seller-risk register perhaps can generate more value than an overambitious but not utilized AI ethics policy.

Risk governance is a dynamic capacity that the second contribution is related to. The theory of dynamic capability asserts that companies overcome competition by sensing, seizing and reconfiguring resources as they vary in response (Teece, 2007). The model indicates that AI risk governance works precisely in that manner. The emerging threats posed by the outputs of generative AI, data leaks, biased recommendations, vulnerabilities in cybersecurity, and third-party reliance are risks that SMEs need to feel. They need to grab AI opportunities with tantalized pilots and aligned use cases with business. As AI tools evolve, regulations shift or accidents expose blind spots and have them reconfiguration routines. This meaning also could be understood in accordance with modern AI governance norms. Trustworthy AI in the NIST AI Risk Management Framework centers on governance, mapping, measurement and management; ISO/IEC 42001:2023 has organizations develop and constantly enhance an AI management system; and the EU AI Act enhances the broader trend toward risk-based AI governance (European Parliament and Council of the European Union, 2024; ISO/IEC, 2023; NIST, 2023). These high-level structures are shown to be converted into SME practice as stocks, flows and feedback loops, which can be represented by the results.

The third contribution is that of the delayed payoff of responsible adoption. The rapid adoption scenario is initially good but reduces in pace as risk is exposed. The result can be aligned with the automation-augmentation paradox: AI will

be able to enhance efficiency, yet improper humanAI set-up can also introduce fresh issues related to coordination, trust and accountability (Raisch and Krakowski, 2021). It is also a part of the wider body of information systems success literature, that asserts that system benefits are determined by quality of use, service quality and user satisfaction as opposed to technology installation (DeLone and McLean, 2003). In the case of SMEs, the on-the-beam-strauss message is pretty straightforward: going fast and without control might evoke the impression of its progress, yet it might also slowly raise the cost of failure in the future. In customer service, this can manifest itself in the form of chatbot responses that are Yes/No. It can be manifested in marketing by false claims or plagiarism. In HR, it can manifest itself in terms of biased screening. In finance, it can manifest itself in the form of bad automated suggestions. Those harms do not manifest themselves the first day of deployment, but undermine trust and performance with time.

The fourth contribution is connected with sustainable business performance. The productivity, innovation, and firm value are often the target of AI-performance studies (Drydakis, 2022; Enholm et al., 2022; Mikalef and Gupta, 2021; Wamba-Taguimdje et al., 2020). This essay contends that such proceeds ought to be considered on a sustainability basis. Sustainable performance goes beyond cost reduction over a short term period; it involves customer trust, employee ability, certainty in compliance, and resilience and efficiency of resources (Bansal and DesJardine, 2014; Elkington, 1997). The system dynamics model points out the reasons why this extended definition is important. Generative AI can help a company produce content at a lower cost, but when the tool generates misleading information, then data can be used inappropriately or reputation must be damaged, then the company has failed to generate sustainable value. Responsible adoption shields the capacity of the firm to generate value in the future, as it cloaks harm on stakeholders, and it develops learning routines.

The methodological contributions of the results are also important. System dynamics is particularly apt in the adoption of responsible AI in the sense that it embodies the feedback, accumulation and delay (Forrester, 1961; Meadows, 2008; Sterman, 2000). A one-way regression can be used to determine whether there is a relationship between governance and performance, but it cannot readily demonstrate the reason why a well-appearing rapid-adoption strategy becomes pernicious later. The results of the scenario indicate that the sequence of actions and the timing of the managerial acts is important. Pre-implementation training, pre-high risk operation governance, and pre-damaging incident response are not minor administrative units. They change the pathway of the whole system. This renders the model not only useful in explaining academically but also learning policies. The same logic of simulation can be applied to testing which of the support packages results in minimal risk without stalling useful innovation, by SME associations, chambers of commerce, technology vendors and government agencies.

The study proposes four viable priorities to managers. One, cultivate AI literacy prior to scaling up AI usage. The employees ought to be aware of the availability of the raw AI outputs, data privacy requirements, verification regulations and reporting mechanisms. Second, categorize AI uses according to riskness. The productivity tools with low risks can be performed more quickly; however, the customer, finance, human resources, health, legal or safety-related AI should be more subject to review. Third, record human control. SMEs do not require complex bureaucracy but demands evidence as to who has signed the use case, the data used, how outputs have been verified and what when something goes awry. Fourth, keep an active control over vendors. External platforms are used by many SMEs and thus the vendor's terms, data retention, security controls, explainability, support and switching costs should be considered prior to implementation. These measures are aligned with the risk-based logic of NIST AI RMF, the generative AI profile and ISO/IEC 42001, but they are presented in such a manner to be practically implemented by small firms (ISO/IEC, 2023, 2024, 2024).

The findings also imply that awareness campaigns are not the only means of SME AI governance support that the policymaking community should consider. Awareness is helpful but too little. SMEs require templates, training, advisory clinics, vendor assessment guidelines, industry checklists and no-cost access to cybersecurity and compliance know-how. The externally supported scenario is the best option as it lowers the learning lag that is usually causing SMEs to fail in turning ethical intent to operational control. This becomes more so when generative AI reduces experimentation costs and the prevalence of small firms utilizing AI but not through specialized groups. Governance capacity building should hence be the focal point of public support and not just incentives on AI adoption.

There are a number of restrictions that must inform future research. To begin with, the model employs a normalized index in the comparison of various SME situations; this can be further refined by future research by associating the model with long term firm-specific performance records. Second, the differences in the sector need further testing. The AI risk of tourism marketing is not comparable with AI risk in the medical field of medicine, money or human resources. Third, the model considers the capability of governance as stock at the firm level, although in the future it may be possible to study the differences at the team levels in the literacy, power and accountability levels. Fourth, it is possible to expand the model to support environmental effects of AI computing, particularly since the use of generative AI is proliferating. Lastly, future work must be able to make comparisons between the country settings due to different regulations, digital infrastructure and SME support ecosystems. Regardless of these shortcomings, the research allows a clear theoretical and practical conclusion: responsible AI implementation in SMEs is only one of the value-creation channels in the situation when ethical preparation, risk management and learning feedback develop alongside.

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