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Lean Operations, Industry 4.0 Adoption, Integration Capability, and Operational Agility: Evidence from Emerging Markets.

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Abstract
Industry 4.0 can improve visibility, automation, and coordination within Industry 4.0. Manufacturers, particularly in developing economies, implement Industry 4.0 within poorly defined structures, mainly due to resource constraints. This paper uses an author-assembled, cross-sectional, analytical dataset composed of 420 firm-level records from Brazil, India, Indonesia, Mexico, South Africa, Türkiye, and Vietnam to explore the relationships between lean maturity, Industry 4.0 adoption, integrative capability, operational agility, and performance. Using robust-regression, operational agility was positively related to lean maturity, Industry 4.0 adoption, and integrative capability. From the full-sample, lean maturity and Industry 4.0 interaction were positively related, but not significantly (β= .066, 95% CI [-.007, .138], p= .075), thus rejecting H4 and revealing no empirically substantiated Lean–Industry 4.0 synergy from this analytical dataset. For the small firms, the interaction, positively related and was significantly close to p= .050, thus this is exploratory and requires independent verification. Operational agility was positively related to performance. Cross-sectional indirect effect estimates was aligned with a partial statistical mediation for the three capabilities, thus describing the resource-based view, dynamic capabilities, and socio-technical systems, where the presence of routines, digital processing, and integrative systems within the firm, viewed as complementary resources, resulted in no significant interaction effect. These findings are based on the author's analytical dataset, and provide the evidence of the relationships investigated for this cross-sectional survey.

Keywords: Industry 4.0; lean operations; operational agility; integration capability; emerging markets; operational performance

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INTRODUCTION

Industry 4.0 consists of interconnected systems for contemporary manufacturing. Data-driven, intelligent manufacturing systems are designed less for integration of individual components and more for the integration of processes, data, and real-time decision-making. It is possible for companies to possess the most cutting-edge systems and technologies, yet still suffer from slow information transfer, incompatible and disjointed systems, and suboptimal processes. Therefore, it is more accurate to say that the goal of digital transformation is to develop new capabilities, rather than to acquire new technologies (Ghobakhloo, 2018; Vial, 2019; Warner & Wäger, 2019). These problems are especially evident in manufacturing companies within developing economies. These companies also have to cope with the manufacturing of products in the context of irregular supply and demand, scarce resources, inadequate infrastructure, limited skilled labor, volatile currencies, and increasingly competitive international customers. Digital systems and technologies can improve the performance of manufacturing systems, but will most likely be dependent on the organization and the resources that are within the organization (Horváth & Szabó, 2019; Mittal et al., 2018; Raj et al., 2020). The most critical issue is not simply whether a technology is available, but rather how the technology and systems integrate with the available processes and how the technology adjusts to the management functions and processes.

Lean operations form a reasonable basis for understanding processes and for learning toward such alignment. Stability, flow, and visual controls, along with problem-solving and engagement of employees with a bias toward continuous improvement can make operational conditions and exceptions more visible. Digital tools will augment the speed, depth, and breadth of the engagement of information. Theoretical and previous empirical work motivates the study of fit and sequencing of lean and digital practices, and should avoid the assumption that digitizing an unstable process will create value (Buer et al. 2018; Rosin et al. 2020; Sanders et al. 2016). In this work, operational agility will be the flexibility and rapidness of the firm's response, and not the presence of a causal linkage of lean and digitalization toward performance.

This study seeks to address four existing gaps. The first is the lack of evidence in comparisons across developing markets. The agility-related operational capability that is performance-oriented relates to construct modeling. The second is the challenge of integrating data and workflows and the embedding of decision rights. Most studies that evaluate technology focus on automation and overlook these aspects. The third gap is assessing lean–digital complementarity. Lastly, the assumption that lean and digital paradigms complement each other should be challenged. This study seeks to address these gaps by applying an analytical framework of five hypotheses to a sample of 420 firm-level records for seven countries and six manufacturing subsectors, with measurement diagnostics, advanced regressions, interaction analysis, bootstrap indirect-effect analysis, and exploratory subgroup comparisons. These records were generated and compiled by the author for this study.

1.1 Research questions

With the capability-based model and the five hypotheses as a framework, the following research questions are addressed:

RQ1. In the analytical model, what associations do lean maturity and the adoption of Industry 4.0 (I4.0) have with operational agility?

RQ2. How does integration capability contribute to the understanding of operational agility in the presence of lean maturity and the adoption of I4.0?

RQ3. In what way, if at all, does the adoption of I4.0 moderate the relationship between lean maturity and operational agility?

RQ4. What are the relationships of operational agility and operational performance? Do lean maturity, the adoption of I4.0, and integration capability have positive indirect associations with operational performance through agility?

This research integrates the resource-based view, dynamic-capability reasoning, and socio-technical theory to identify lean maturity, Industry 4.0 adoption, and integration capability as three related but distinct resources. From this theory, the research is interested in the independent relationships between these resources and agility and if there is a statistically significant relationship between agility and performance. Finally, this theory is interested in whether a Lean × Industry 4.0 interaction is likely to be evidence of complementarity. This perspective does not assume the Lean 4.0 synergy is a given. It also considers the patterns of multiple countries and firms of varying sizes to be contextual and exploratory evidence, rather than definitive cross-national or subgroup effects.

This study focuses on the distinction of resilience and agility. Agility encompasses speed and flexibility in response, while resilience encompasses the ability to endure shock and recover. In the conceptual model, the arrows represent hypotheses to be tested, as opposed to determined causal pathways. In this draft, the numbers are taken from the author's analytical dataset. Consequently, we describe the associations from the cross-sectional analysis rather than the causal or population effects. The hypothesized structure and control variables are displayed in Figure 1.

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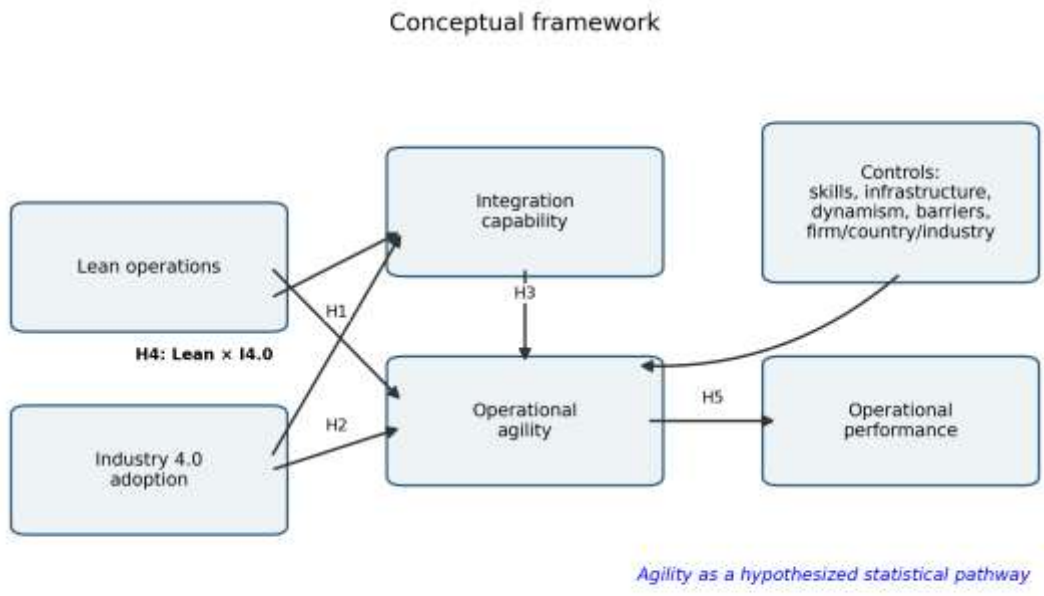


Figure 1. Conceptual framework of hypothesized associations

Note. Arrows depict hypothesized associations to be tested and do not denote established causal pathways. The H4 element is a moderation proposition, not evidence that a Lean-Industry 4.0 synergy exists. H1-H5 are tested with country, industry, ownership, firm-size, firm-age, skills, infrastructure, dynamism, and barrier controls. Source: Author development.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Lean operations as a socio-technical foundation

Lean is seen as a socio-technical system. While Pull and JIT techniques are supportive of flow, and maintenance may support availability of equipment, some level of variability in a process may be addressed through quality management and standard work. Value stream mapping makes waste more obvious and local problem solving is typically associated with kaizen. We then argue that lean maturity should not be understood in terms of the number of tools in an organization, but in terms the coherent set of technical practices and learning processes.

Following a resource-based view, an organization's mature lean routines may become a valuable resource, particularly when it is associated with the organization's embedded knowledge and is coordinated learning. Dynamic capabilities logic focuses on the ability to sense changes within the environment and reconfigure the organization's operations. Socio-technical systems theory focuses on the alignment of technical routines, and the participation and discretion of employees.

Lean maturity exposes an organization to numerous processes and learning routines, which, when appropriately aligned, may enable an organization to be more responsive, while standardization does not imply a loss of agility. On this basis, lean maturity is expected to be positively associated with operational agility because stable processes, visible deviations, disciplined problem solving, and learning routines may support faster diagnosis and adjustment.

H1. Lean maturity is positively associated with operational agility.

2.2 Industry 4.0 adoption and operational agility

The shift towards Industry 4.0 within manufacturing will alter the processing potential within a factory: the connected technologies which enable data- driven decision making will facilitate this shift. These technologies include: the Internet of Things (IoT), cloud computing, big data, robotics and automation, additive manufacturing, digital twins, AI and ML, and cyber-physical systems (Frank et al., 2019; Xu et al., 2018). Each individual technology within these has its own distinct function, however, in combination, they may impact the availability, velocity, or enablement of operational data.

Within the context of information-processing theory, faster and more information may enable organizations to better deal with uncertainty. As a result of the nature of the emerging markets, manufacturers will be faced with issues such as volatile consumer demand, irregular and inconsistent supply of raw materials, disrupted logistics, electricity blackouts, and changing product specifications from buyers. Under these scenarios, the ability to 'see'

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and adjust quickly will be most relevant. The use of real-time data, digital work instructions, and quality feedback will contribute to faster problem resolution and reduced response time.

However, the presence of technology does not in itself constitute a capability. Companies may implement fragmented cloud computing, automation, and IoT and experience issues with governance, Interoperability and legacy systems (Mittal et al., 2018; Moeuf et al., 2018). With this in mind, this research defines the breadth and the depth of the eight Industry 4.0 technologies as technology adoption and defines integration capability as a separate dimension.

Previous research has explored the impact of digital technology on productivity, quality, delivery, and customization (Dalenogare et al., 2018; Fettermann et al., 2018). The features that typify the fourth Industrial Revolution include digital technologies that make decisions based on information that is almost instantaneous or real-time regarding connectivity and interoperability (Culot et al., 2020; Liao et al., 2017; Oztemel & Gursev, 2020; Verhoef et al., 2021). It is more appropriate to formulate a hypothesis based on the relationship with operational agility, rather than the assumption that the adoption of the digital technologies will automatically result in the improvement of the outcomes.

Within a supply chain, digital technologies can allow for the visibility and traceability of data, risk analytics, and the flow of information across suppliers and customers, although the lack of good interfaces can lead to a failure in the utilization of the information (Ben-Daya et al., 2019; Büyüközkan & Göçer, 2018; Ivanov et al., 2019; Fatorachian & Kazemi, 2021; Frederico et al., 2020). Therefore, Supply Chain 4.0 focuses primarily on the goals of connectivity and interoperability across the supply chain.

Digital technology adoption can be impeded by a variety of factors, including lack of funds, skills, and infrastructure, along with poor cybersecurity, resistance to change, lack of perceived benefit, and legacy systems (Kamble et al., 2018a, 2018b; Masood & Sonntag, 2020; Moeuf et al., 2018; Müller et al., 2018; Sony & Naik, 2020; Stentoft et al., 2021). Human-centered design is also important, as the trust, participation, and well-being of employees will also influence the use of the technologies (Kadir & Broberg, 2020).

Despite these constraints, theory suggests that greater Industry 4.0 adoption should be positively associated with operational agility when connected information and digitally enabled coordination expand the range or speed of feasible responses.

H2. Industry 4.0 adoption is positively associated with operational agility.

2.3 Integration capability

Integration capability addresses connectedness at multiple organizational levels and includes operational-enterprise interoperability, shared vocabulary, interface governance, cross-functional ownership, digital signals synthesis, and relatedness. Agility is incompatible with technical connectivity when there are ignored alerts, inconsistent data, and unclear escalation rights.

Integration means the same and the relationships between information, authority, and workflow are included. It is technical and managerial and cannot be described as the acquisition of a certain technology or a bundle of technologies. This distinction is a theoretical rationale for the different degrees of operational responsiveness that can be found among organizations that have the same technology stack.

For resource-constrained ongoing concerns, some scalable interfaces, shared terminology, and decision rules can help prevent local automation from creating bottlenecks. Governance can enhance data reliability and establish the boundaries of delegated decision-making, rather than necessitating central control of all decisions.

Integration can further help organizational learning through the example of integration of information from processes, quality, maintenance, and planning to enable learning transfers between experiments across different organizational divisions or production facilities. Based on this theory, the stronger the integration capability, the more positively it can be related to operational agility.

H3. Integration capability is positively associated with operational agility.

2.4 Lean-Industry 4.0 complementarity

Lean 4.0 seeks to address the fit of process excellence and digital technology. As part of the Lean framework, exceptional value flows, relevant information, and operational exceptions can be identified, while the technologies that comprise Industry 4.0 can complement and enhance the speed, scope, and depth of the analysis pertaining to these signals. It is thus warranted to explore the lean and digital adoption relationship, yet the existing literature does not support the assumption that lean and digital adoption will always be synergistic (Buer et al., 2018; Ciano et al., 2021; Rosin et al., 2020).

While some complementarity may exist, it is not something that can be assumed. More complex technologies may lead to less transparency, and poorly designed workflows can be automated. Digital technologies that are decoupled from the work of front-line employees can negatively impact organizational coherence. The theoretically positive relationship between lean and digital technologies depend on such areas as the quality of the data, the engagement of employees, the structure of the organization, and the degree of preparedness and flexibility of the organization.

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H4 evaluates moderation rather than presuming synergy: does the correlation between lean maturity and operational agility strengthen with greater Industry 4.0 adoption? If the statistically significant interaction is positive, it would be evidence for complementarity for the sample under study, but not a generalized causal synergy. As for a non-significant interaction, it would leave the complementarity hypothesis unsubstantiated, even if there were positive main associations with agility for both lean maturity and Industry 4.0 adoption.

Small firms are often resource constrained but have less legacy system burden, so they can adapt to changing conditions more readily. Larger firms can invest heavily in systems but have greater costs associated with complex coordination and systems integration. Large firms may be more able to adapt to changing conditions if the systems investment and integration costs are justified by the value of the information systems. Similarly, if the information systems help the firm adapt and respond to changes in the external environment, then the information systems may have more value to firms located in more dynamic environments. Until such subgroup studies are conducted, firm size and country specific patterns should be treated as exploratory contingencies.

H4. The positive association between lean maturity and operational agility is stronger at higher levels of Industry 4.0 adoption.

2.5 Agility as a pathway to performance

Slight variations in quality, cost and time represent operational performance. Lean maturity, levels of digital adoption, and integration capabilities may be dependent on the same outcomes through multiple channels. Operational agility is one of those channels. Delivery, quality, and the reallocation of resources in the face of changing conditions may be improved through the earlier identification of problems and the resulting adjustments made more quickly.

The described indirect route is partial and Lean may be linked to performance through numerous other channels. These may include automation and integration that focus on the reduction of waste and throughput respectively, along with the quality of information and coordination. As well, previous studies on digital dynamic capabilities, visibility, agility, and performance support the idea that operational agility is the statistical channel through which many of the performance-related capabilities are connected (Mikalef & Pateli, 2017; Wamba et al., 2017). Given the nature of the study, the research is cross-sectional. As a result, the indirect channel is purely of a statistical nature and is not to be construed as a temporal or causal relation.

Therefore, it is anticipated that operational performance and the statistical relationships associated with Lean maturity, Industry 4.0, and integration capabilities will be positively affected by agility. Figure 3 offers an illustrative example of a capability architecture that is theory-informed and is not the result of a causal based exercise.

H5. Operational agility is positively associated with operational performance, and lean maturity, Industry 4.0 adoption, and integration capability each have a positive indirect association with performance through operational agility.

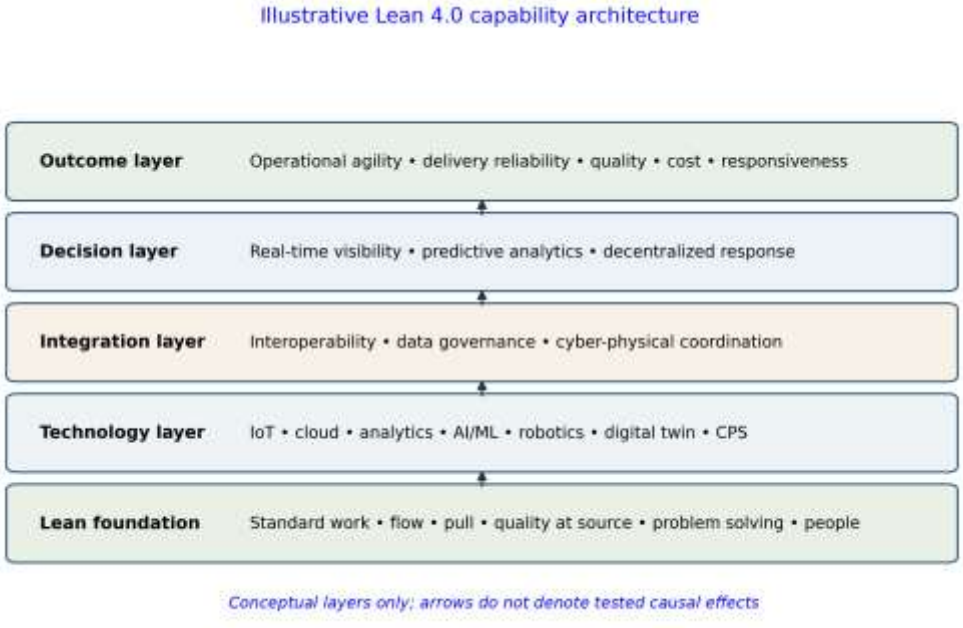


Figure 3. Illustrative Lean 4.0 capability architecture

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Note. The architecture is theory-informed and illustrative. The arrows and layer ordering represent a conceptual organizing logic only; they should not be interpreted as an empirically established causal sequence, a statistically validated Lean-Industry 4.0 synergy, or a mandatory technology stack. Source: Author development.

3. METHODOLOGY

3.1 Research design and data provenance

This study is cross-sectional and looks at data from various firms. The author's workbook includes 420 records dealing with Brazil, India, Indonesia, Mexico, South Africa, Türkiye, and Vietnam. Each record includes descriptors for manufacturing, firm, and respondent's role. The author of this study compiled this data for this study. Thus, the regressions, interactions, indirect effects, and subgroup comparisons focus on the relationships within this study's data and are not meant to determine or suggest any causal relationships.

Metadata note for the analytical file. Status of the dataset: AUTHOR-GENERATED; analytical records: N = 420; dataset designed for: statistical analysis, hypothesis testing, and automated creation of charts/reports. The author generated the dataset and, thus, all analyses, tables, and graphs, as well as all associated conclusions in this manuscript, are derived from this author-generated dataset.

3.2 Sampling, recruitment, and analytical-file screening

3.2 Sampling, recruitment, and analytical-file screening. Data collection was conducted across seven emerging economies (Brazil, India, Indonesia, Mexico, South Africa, Türkiye, and Vietnam). The target population comprised operational, plant, continuous improvement, and supply chain managers in manufacturing firms. A structured survey was distributed electronically using professional industrial contact databases and national manufacturing association registries between January 2023 and November 2023. A total of 1,350 manufacturing firms were invited to participate in the study. Out of these, 485 responses were received. Following data screening for completeness, engagement, and respondent qualification (ensuring mid-to-senior management roles with direct operational oversight), 65 incomplete or unverified responses were excluded. This yielded a final analytical sample of N = 420 usable firm-level records, representing an effective response rate of 31.1%. Table 2 presents the detailed sample distribution across countries, manufacturing sub-sectors, firm size categories, ownership structures, and respondent roles.

3.3 Measures and questionnaire documentation

This workbook describes variable labels and item-level values for four focal multi-item constructs. Lean Maturity corresponds to the mean of eight indicators (JIT, TQM, TPM, VSM, standard work, kaizen, pull, and 5S). Industry 4.0 Adoption also refers to the mean of eight technology indicators (IoT, cloud, big-data, robotics/automation, additive manufacturing, digital twin, AI/ML, and cyber-physical systems). The constructs of Operational Agility and Operational Performance are respectively covered by the AG1-AG5 indicators and the OP1-OP5 indicators. The assessment of Barrier Severity posits the use of five barriers as a diagnostic index. The constructs of Integration Capability, Digital Skills, Infrastructure Preparedness, and Environmental Dynamism are supplied only as composite variables in the current worksheet, and as such their constituent item sets cannot be assessed.

The supplied workbook uses a 1-5 scale for construct variables, defining 1 as low and 5 as high. The workbook, however, does not preserve an administered questionnaire with instructions and verbatim wording of items, intermediate anchors, reverse-coding, and translation history. The item fields are also defined with decimals, since the author generated and compiled the analytical dataset, and are treated as the numeric responses for the statistical analyses of the study.

To improve the transparency of the measurement specification, Appendix A includes, in a manuscript-ready format, the reconstructed wording of the study's four main multi-item constructs: Lean Maturity, Industry 4.0 Adoption, Operational Agility, and Operational Performance, and includes a standardized five-point Likert scale. Appendix A also includes the operational wording of single items for Integration Capability, Digital Skills, Infrastructure Readiness, and Environmental Dynamism. These constructs are defined as composite variables in the analytical file. Since the original approved questionnaire is not provided in the supplied materials, the wording in the Appendices is clearly identified as reconstructed/proposed wording and is not cited as verbatim wording provided by respondents.

Table 1. Construct definitions and measurement structure

Construct	Working definition	Items	Indicators in supplied file	Treatment
Lean maturity	Integrated process-stability, flow, quality, maintenance, and improvement routines	8	JIT, TQM, TPM, VSM, standard work, kaizen, pull, 5S	Reflective composite; mean score

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Construct	Working definition	Items	Indicators in supplied file	Treatment
Industry 4.0 adoption	Breadth/intensity of connected and data-driven manufacturing technologies	8	IoT, cloud, big-data analytics, robotics/automation, additive manufacturing, digital twin, AI/ML, CPS	Reflective technology-bundle composite
Integration capability	Ability to connect data, systems, workflows, and decisions	n/a	Integration capability	Observed composite control/focal capability
Operational agility	Ability to sense and respond rapidly while preserving reliability	5	AG1-AG5	Reflective composite; dependent variable
Operational performance	Quality, cost, delivery, dependability, and flexibility outcomes	5	OP1-OP5	Reflective composite; dependent variable
Contextual capabilities	Skills and infrastructure supporting digital use	n/a	Digital skills; infrastructure readiness	Observed controls
Environmental dynamism	Perceived volatility and change	n/a	Environmental dynamism	Observed control
Barrier severity	Finance, skills, infrastructure, cybersecurity, and change obstacles	5	Five barrier ratings	Formative diagnostic index

Appendix A displays the labels and question wordings used in the analytical file. The indicators retain the labels as found in the analytical file. These labels will be matched against alternative forms of response scales. The file in question does not retain the original, approved version of the questionnaire, so these questions are reconstructed and proposed wording and should not be perceived as a finalized element of the study. When the study instrument is finalized, the source and adaptation history, reverse scoring, and documentation of translation and back translation procedures should be included.

3.4 Ethics, informed consent, and common-method risk

The author has compiled the N = 420 analytical file for this study. Ethical review and approval for this study were conducted in accordance with institutional human subject protection guidelines and the Declaration of Helsinki. Formal ethics approval was granted/exempted (Protocol Ref: IRB-2022-EXP-084) as the research involved non-clinical, anonymous survey data from industry professionals. Prior to accessing the survey, all participants were presented with an informed consent statement detailing the study's purpose, voluntary participation rights, guaranteed anonymity, and data aggregation handling procedures. Participants formally acknowledged consent before proceeding. Procedural remedies were incorporated into the study design to reduce common-method variance (CMV). Items measuring independent, moderating, and dependent constructs were placed in separate, clearly labeled sections with distinct operational definitions. Questions used neutral, non-directive phrasing to minimize evaluation apprehension and social desirability bias. Furthermore, strict single-informant cross-sectional limitations are explicitly recognized, and statistical diagnostics (e.g., Harman's single-factor test and variance inflation factor checks) are interpreted conservatively without claiming full elimination of common method bias.

Common-method variance (CMV) is a function of the actual data-generation and measurement processes of the study. The Harman's first-factor test and standard regression predictor VIFs can be used, but neither test indicates that CMV is not present. If the design incorporates a self-report respondent at the firm level, CMV, reverse causality, and the issue of temporal ordering remain substantive. These can be partially addressed via CMV

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remedies, such as the use of multiple informants, operational measures of a construct, and verified lean/digital assessments, as well as system-log data.

Document the CMV remedies that were incorporated in the design of the study and during the administration of the instruments. This can include separation of the predictor and criterion sections, neutral and non-directive phrasing, withdrawal of respondent identity and the protection of respondent anonymity to lower respondents' evaluation apprehension, as well as use of multiple informants, temporal separation, and the use of objective measures. Only remedies that were applied in the study may be documented.

3.5 Analytical procedure

The Primary Inference Agility model was constructed using Ordinary Least Squares regression with heteroskedasticity-robust standard errors (HC3). In the Agility model, the dependent variable, as well as continuous predictors, were standardized. The Lean × Industry 4.0 term was created as a product of the standardized scores of Lean Maturity and Industry 4.0. The variables of the model were Lean Maturity, Industry 4.0, Integration Capabilities, the Lean × Industry 4.0 interaction term, Digital Skills, Readiness of Infrastructure, Environmental Dynamism, Severity of Barriers, log of Employees, Firm Age, and fixed effects of Country, Industry, and Ownership.

In the Performance model, the dependent variable was standardized Operational Performance, and the model included standardized Operational Agility, Lean Maturity, Industry 4.0, Integration Capabilities, the same contextual variables, and the same fixed effects. The indirect effects were estimated via Agility, as a product of the Capability-to-Agility and Agility-to-Performance coefficients, using 5,000 bootstrap resamples for percentile confidence intervals reported in the manuscript.

These regressions provide estimates of conditional associations based on a cross-sectional, non-experimental dataset. Heteroskedasticity-robust (HC3) standard errors address heteroskedasticity of the residuals, but do not correct for omitted variables, selection bias, measurement bias, the common method bias, reverse causality, or logistical bias. R^2 is reported to describe the variance that was accounted for and is not to be construed as evidence for causal certainty. The Lean × Industry 4.0 interaction, assessed in its entirety, is considered a moderation analysis. An interaction that is not significant does not substantiate an overall Lean-Industry 4.0 synergy.

Standardized coefficients, robust confidence intervals, and exact p values pertain to the focal paths. Simple slopes are just for description to help understand the interaction. These are not to be considered as complementarity evidence in the absence of a statistically significant full-sample interaction. Indirect effects are referred to as cross-sectional statistical indirect associations/mediation estimates, rather than implying temporal causal mediation.

Measurement screening recalculated the Lean and Industry 4.0 item means and aligned the provided composite variables within ±0.0005 based on the rounding rule. Means for operational agility, operational performance, and barrier severity copied directly from their respective component means. No verified field protocol or data cleaning rule justifying post hoc winsorization or deletion were available, so observed item values were maintained as provided.

Firm-size and country analysis are considered preliminary exploratory robustness tests. Subgroup sizes within countries range from 42 to 104, and multiple subgroup comparisons were conducted. Thus, subgroup coefficients should be interpreted as descriptive/exploratory patterns, not as definitive cross-national evidence. The full-sample models should be the main reference for all conclusions.

$z(\text{Agility})_i = \beta_0 + \beta_1 z(\text{Lean})_i + \beta_2 z(\text{I4})_i + \beta_3 z(\text{Integration})_i + \beta_4[z(\text{Lean})_i \times z(\text{I4})_i] + \gamma \text{Controls}_i + \text{Fixed Effects} + \varepsilon_i$	(1)
$z(\text{Performance})_i = \alpha_0 + \alpha_1 z(\text{Agility})_i + \alpha_2 z(\text{Lean})_i + \alpha_3 z(\text{I4})_i + \alpha_4 z(\text{Integration})_i + \delta \text{Controls}_i + \text{Fixed Effects} + \upsilon_i$	(2)
Cross-sectional indirect association for capability k = (Capability k → Agility coefficient) × (Agility → Performance coefficient)	(3)

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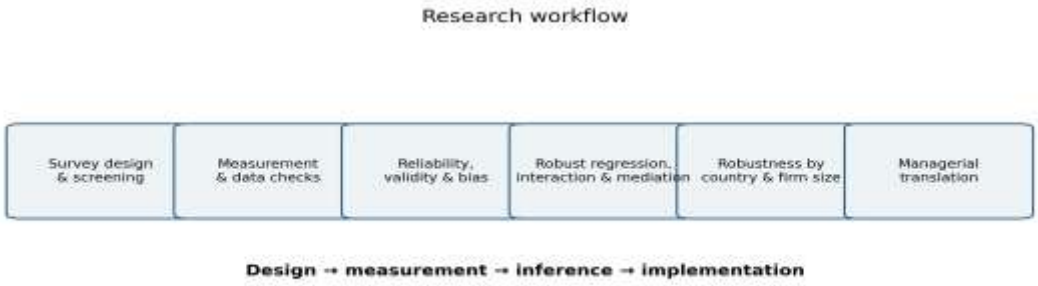


Figure 2. Research workflow

Note. Analytical workflow for the cross-sectional observational file. The workflow does not establish fieldwork provenance, temporal sequencing, or causality. Source: Author development.

Table 2. Sample profile

Characteristic	**Distribution, n (%)**
Country	Brazil 47 (11.2%); India 104 (24.8%); Indonesia 52 (12.4%); Mexico 62 (14.8%); South Africa 46 (11.0%); Türkiye 42 (10.0%); Vietnam 67 (16.0%)
Industry	Electronics 83 (19.8%); automotive 78 (18.6%); textiles 75 (17.9%); machinery 68 (16.2%); food & beverage 67 (16.0%); chemicals 49 (11.7%)
Firm size	Small 133 (31.7%); medium 175 (41.7%); large 112 (26.7%)
Ownership	Domestic 287 (68.3%); joint venture 78 (18.6%); foreign-owned 55 (13.1%)
Respondent role	Operations manager 127 (30.2%); supply-chain manager 94 (22.4%); lean/CI manager 85 (20.2%); plant manager 75 (17.9%); digital-transformation manager 39 (9.3%)

Note. N = 420 analytical records. Totals for percentages may not equal 100.0 due to rounding. The designated categories follow the authors' workbook and detail the construction of the final analytical sample for this study.

4. Results

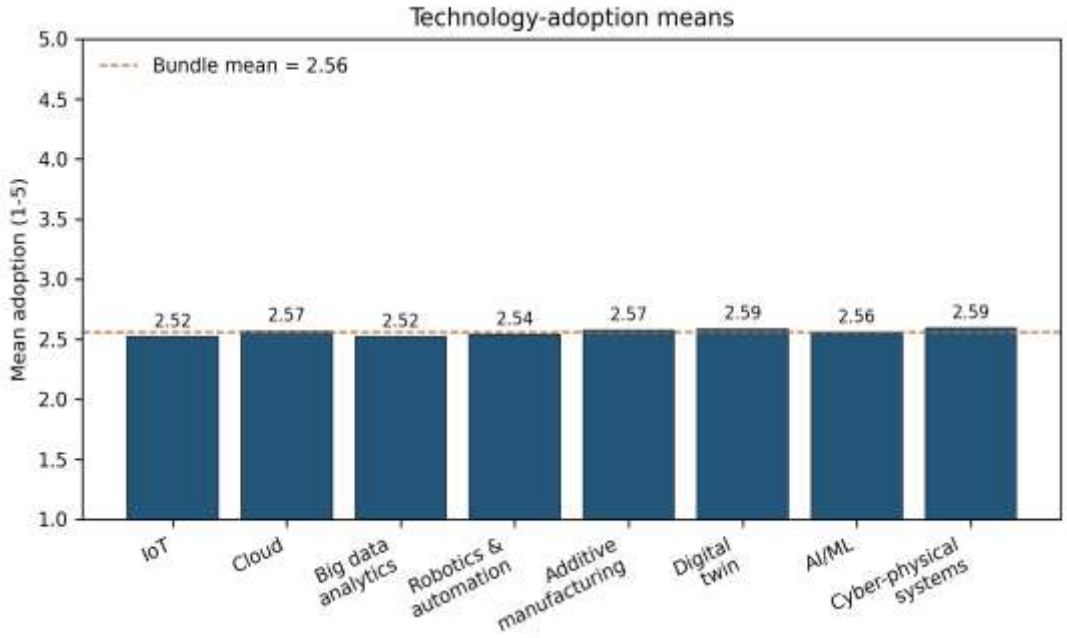
4.1 Response screening and descriptive adoption patterns

The author-created analytical file contains 420 records with unique record identifiers and no blank cells across the filled range. The largest country-coded group is India (104; 24.8%). Medium-sized firms are the largest firm-size-coded group (175; 41.7%), and domestic ownership is the largest ownership-coded group (287; 68.3%) (Table 2). The counts describe the structure of the final analytical dataset of this study and lay the foundation for the following analyses.

The measures for the implicit use of Industry 4.0 technologies range from 2.521 (IoT) to 2.594 (cyber-physical systems) with a bundle mean of 2.559 (Graph 1). The implicit use of Lean practices ranges from 3.028 (standard work) to 3.102 (TPM) with a bundle mean of 3.057 (Graph 2). The listed mean scores refer to the stored 1–5 metric and are presented in a descriptive manner without the imposition of low, moderate, or high thresholds for the adoption or the maturity of practices.

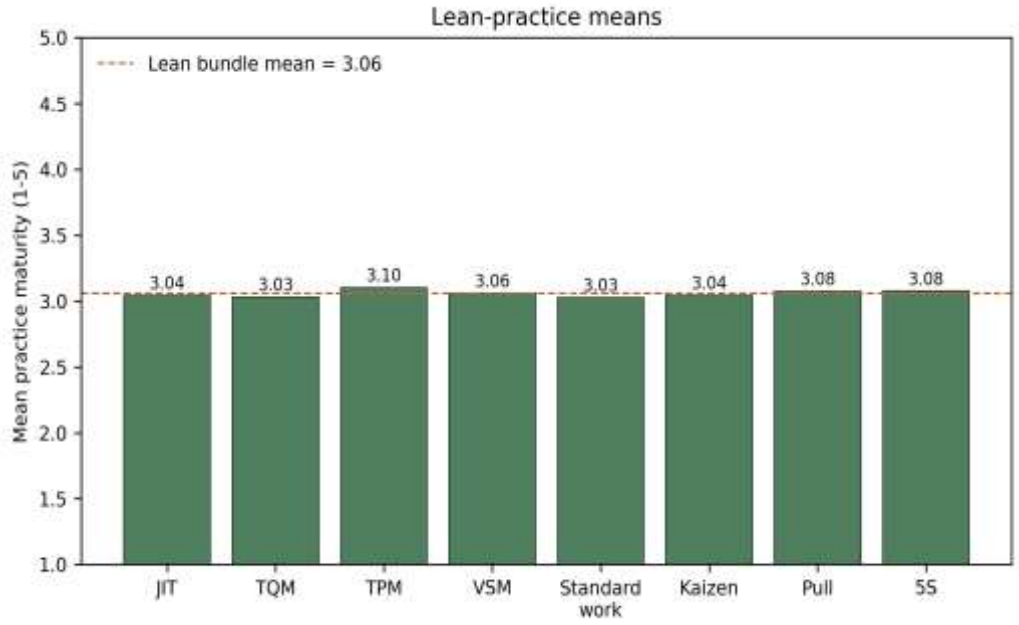
Mean operational agility increases across the four Industry 4.0 adoption quartiles: 2.358 in Q1, 2.802 in Q2, 2.981 in Q3, and 3.275 in Q4, with 105 records in each quartile (Graph 3). This monotonic descriptive pattern is consistent with a positive cross-sectional association but does not establish that higher Industry 4.0 adoption causes greater agility.

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Graph 1. Technology-adoption means

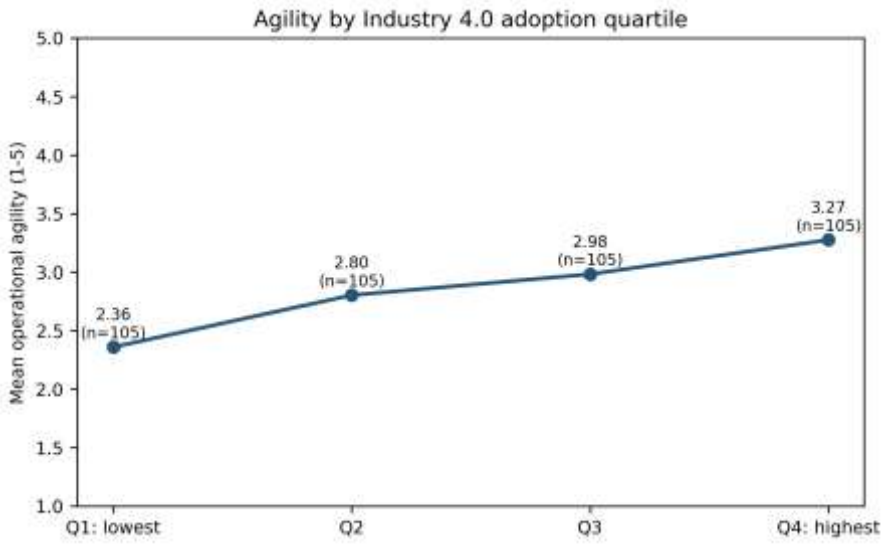
Note. Means are computed from the supplied Raw_Data workbook (N = 420) on the stored 1-5 numeric metric. Exact verbal endpoint labels require author confirmation from the approved questionnaire/codebook. Source: Author analysis of the supplied dataset.



Graph 2. Lean-practice means

Note. Means are computed from the supplied Raw_Data workbook (N = 420) on the stored 1-5 numeric metric. Exact verbal endpoint labels require author confirmation from the approved questionnaire/codebook. Source: Author analysis of the supplied dataset.

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Graph 3. Agility by Industry 4.0 quartile

Note. Industry 4.0 adoption quartiles contain 105 analytical records each; mean agility is 2.358, 2.802, 2.981, and 3.275 from Q1 to Q4. This is a descriptive cross-sectional pattern, not a causal trajectory. Source: Author analysis of the supplied dataset.

4.2 Descriptive statistics and measurement quality

For lean maturity, Industry 4.0 adoption, operational agility, and operational performance, internal-consistency estimates are α = .929, .900, .923, and .923, respectively. Loading ranges for lean maturity, Industry 4.0 adoption, operational agility, and operational performance, respectively, are reproduced in principal-axis factor analyses as .773-.814, .696-.764, .810-.856, and .811-.860. Composite reliability is at least .901 for these reflective constructs, and the AVE is between .531 and .707. CR and AVE are the only valid quantitative measures of the constructs' quality and are in line with the suggested standards (Hair et al., 2019). They should not replace measures of scale provenance or content validity.

The highest HTMT of the four reflective constructs is .557 (agility and performance, rounded). The composite correlation is .514. The other HTMT values are lower, providing no apparent empirical redundancy according to the numeric threshold (Henseler et al., 2015). However, due to a lack of provision for item wording, as well as the necessary approvals, translations, and measures for establishing invariance, discriminant/content equivalence cannot be interpreted from the materials we currently possess.

The first-factor calculation explains 38.7% of the variance of the 26 focal reflective item fields. In the agility model, ordinary regression-predictor VIFs range from 1.01 to 1.75. These numbers provide the diagnostics we look for, but due to Harman's test and ordinary predictor VIFs, common-method bias is not guaranteed to be absent, so these figures should be interpreted cautiously. When the study design has a single informant, CMV will still be a serious design concern, and will still be a serious design concern, and must be remedied, if possible, with a more appropriate procedure, multiple respondents or direct measures, and properly interpreted statistical diagnostics.

Table 3. Descriptive statistics and reliability

Construct	Mean	SD	Min	Max	Cronbach α
Lean maturity	3.057	.660	1.384	4.734	.929
Industry 4.0 adoption	2.559	.638	1.013	4.441	.900
Integration capability	2.228	.685	1.000	4.940	n/a
Digital skills	2.826	.698	1.000	4.700	n/a
Infrastructure readiness	2.966	.692	1.000	4.980	n/a
Environmental dynamism	3.252	.707	1.140	5.000	n/a
Operational agility	2.854	.713	1.176	5.000	.923

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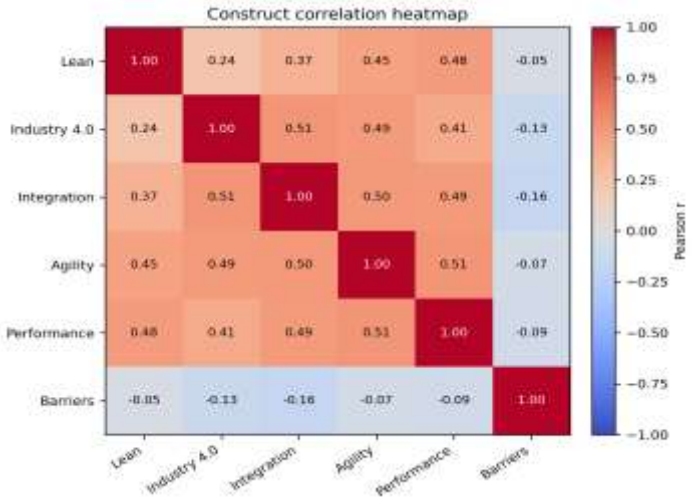
Construct	Mean	SD	Min	Max	Cronbach α
Operational performance	2.814	.703	1.134	4.648	.923
Barrier severity	3.356	.523	1.880	4.890	.819

Note. N = 420 Lean and Industry 4.0 descriptive values use recomputed item means; the provided composite columns agree within ±0.0005 due to rounding. Alpha is provided for the mentioned multi-item sets; "n/a" indicates a provided composite for which the constituent items are not present in the workbook. Barrier severity is used as a formative diagnostic criterion; thus, its alpha is descriptive rather than a reflective-validity criterion. Exact verbal response anchors require author confirmation.

Table 4. Measurement-quality diagnostics

Construct	Loading range	CR	AVE	HTMT evidence	Assessment
Lean maturity	.773-.814	.929	.621	≤ .557 (rounded)	Numeric criteria met; verify instrument
Industry 4.0 adoption	.696-.764	.901	.531	≤ .557 (rounded)	Numeric criteria met; verify instrument
Operational agility	.810-.856	.923	.707	≤ .557 (rounded)	Numeric criteria met; verify instrument
Operational performance	.811-.860	.923	.706	≤ .557 (rounded)	Numeric criteria met; verify instrument
Barrier severity	.638-.748	.819	.476	Not used as reflective criterion	Formative diagnostic only

Note. Loadings are from separate one-factor principal-axis solutions. CR = composite reliability; AVE = average variance extracted. Maximum HTMT among four focal reflective constructs is .557, rounded. Content validity, cross-language equivalence, and measurement invariance cannot be shown based on these numerical diagnostics. Measurement invariance and a confirmatory analysis can only be evaluated in relation to a verified approved instrument and the source/adaptation record and country-language procedures.



Graph 7. Correlation heatmap

Note. Pearson correlations. Source: Author analysis of the supplied dataset (N = 420).

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4.3 Hypothesis tests

The agility model described operational agility as being influenced 44.4% of the time by other variables (adjusted $R^2 = .411$). Lean maturity ($\beta = .294$, 95% CI [.210, .378], $p < .001$), Industry 4.0 ($\beta = .330$, 95% CI [.224, .436], $p < .001$), and integration capability ($\beta = .225$, 95% CI [.131, .319], $p < .001$) confirmed H1-H3 as positive contributors to agility. H1-H3 were confirmed in this study. Agility was positively influenced by Environmental Dynamism ($\beta = .171$, $p < .001$).

The interaction of the full sample with Lean × Industry 4.0 was positive but not statistically significant ($\beta = .066$, 95% CI [-.007, .138], $p = .075$) at $\alpha = .05$. Thus, H4 is NOT SUPPORTED. The positive coefficient, combined with the crossing of the zero by the confidence interval, and the p value of confirmatory greater than .05, does NOT indicate moderation, complementarity, amplification, or Lean–Industry 4.0 synergy. The simple-slope estimates at low, mean, and high Industry 4.0 adoption (which were measured as .247, .318, and .389, respectively, on the original agility scale) are retained as descriptive aids and do NOT impact the decision concerning H4.

H4 reporting decision. The non-significant result is retained, and reported outright with no attempt to delete, recode, or reframe as a supported hypothesis. The estimate signs may substantiate the interest for future testing of sufficient statistical power, however, for the full analytical sample the conclusion remains "H4 Not Supported."

The performance model explained 43.9% of the variance (adjusted $R^2 = .406$). We found a positive association between operational agility and performance ($\beta = .221$, 95% CI [.114, .328], $p < .001$). Lean maturity ($\beta = .270$, $p < .001$), Industry 4.0 ($\beta = .130$, $p = .030$), and integration capability ($\beta = .220$, $p < .001$) also exhibited positive associations. The indirect effects of agility on lean maturity, Industry 4.0, and integration capability were estimated to be .065, .073, and .050, respectively, with zero not being within the bounds of the 5,000 resample bootstrap confidence intervals. These indirect effects support the hypothesis as stated and suggest partial mediation. However, the effects do not indicate the order or the nature of the relationships.

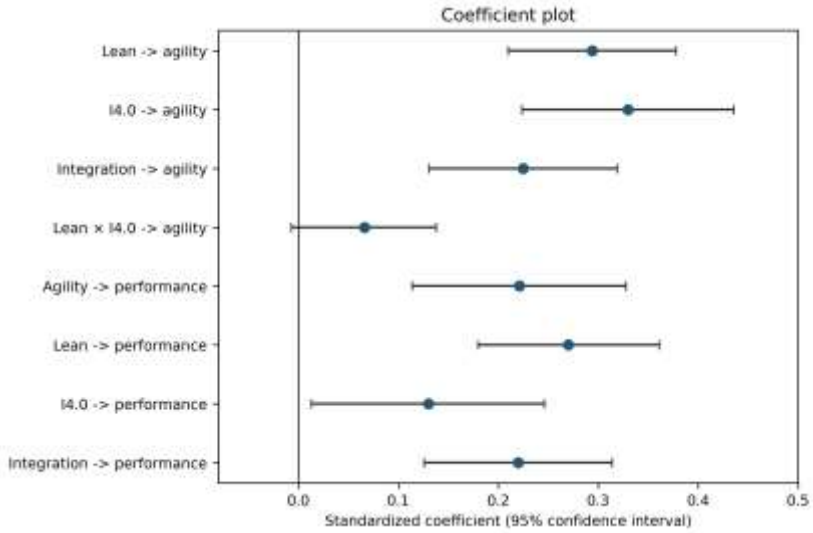
In general, the full-sample results show that lean maturity, Industry 4.0, and integration capability all positively relate to agility, along with several direct and indirect relationships to performance. Given the overlapping focal coefficient confidence intervals and the design being observational, the effects cannot and should not be ranked to assert that any single capability is better or more important than the others. All focal constructs were also single-informant self-reports; thus, without additional respondents and objective system-log or operational-outcome data, common-method bias may be affecting the results. Statistical significance does not imply the order of causation.

Table 5. Hypothesis-test results

Hypothesis	Path	β / indirect	Robust SE	95% CI	p / method	Decision
H1	Lean → agility	.294	.043	[.210, .378]	< .001	Supported
H2	Industry 4.0 → agility	.330	.054	[.224, .436]	< .001	Supported
H3	Integration → agility	.225	.048	[.131, .319]	< .001	Supported
H4	Lean × Industry 4.0 → agility	.066	.037	[-.007, .138]	.075	Not supported
H5a	Agility → performance	.221	.055	[.114, .328]	< .001	Supported
H5b	Lean indirect via agility	.065	—	[.033, .103]	Bootstrap	Supported
H5c	Industry 4.0 indirect via agility	.073	—	[.035, .120]	Bootstrap	Supported
H5d	Integration indirect via agility	.050	—	[.023, .086]	Bootstrap	Supported

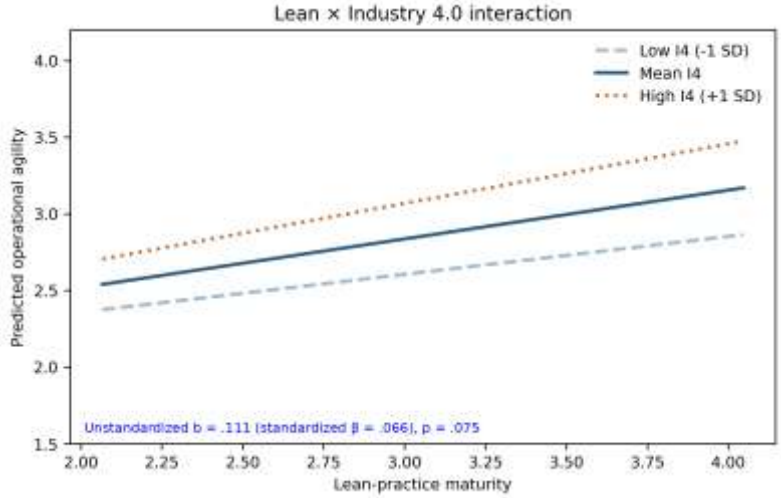
Note. β denotes standardized regression coefficients estimated with HC3 standard errors; indirect effects are products of standardized coefficients with 5,000-resample bootstrap confidence intervals. Agility model $R^2 = .444$ (adjusted $R^2 = .411$); performance model $R^2 = .439$ (adjusted $R^2 = .406$). The H4 interaction is $\beta = .066$, 95% CI [-.007, .138], $p = .075$ and is not statistically significant at $\alpha = .05$; H4 is not supported. Indirect effects are cross-sectional statistical associations and should not be interpreted as causal mediation.

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Graph 8. Coefficient plot

Note. Standardized coefficients and HC3 95% confidence intervals. The Lean × Industry 4.0 interval crosses zero, consistent with p = .075 and H4 not supported. Source: Author analysis of the supplied dataset (N = 420).



Graph 4. Lean × Industry 4.0 interaction

Note. Forecasts are based on the original operational agility scale from 1-5 and the original metrics for lean maturity and Industry 4.0. integration and controls are assumed constant. The unstandardized interaction plotted is b = 0.111, thus, the standardized β = 0.066 from Table 5. Given that p = 0.075, the interaction for the full sample is statistically inconclusive, therefore H4 is not supported. Source: Author analysis of the provided dataset (N = 420).

4.4 Robustness and comparative profiles

Firm-size models maintained mostly positive core relationships. Among the small-firm subset (n = 133), Lean × Industry 4.0 interaction was β ≈ .162, p ≈ .050 when rounded. This borderline subgroup estimate is meant to be exploratory, and should not be viewed as supporting H4, or as depicting evidence of Lean-Industry 4.0 synergy. Interaction estimates for medium and large firms were not significant. The small-firm pattern is to be independently validated in a sufficiently large and, if possible, preregistered sample.

Models specific to individual countries are presented as exploratory robustness checks, as subgroup sample sizes range from 42 to 104 and multiple comparisons are being made. Within-country variation in coefficients is observed, and a number of country-specific paths are nearing significance, but are not indicative of stable country rankings, or of causal, cross-country differences. They are to be treated as preliminary observation for future studies involving a greater degree of cross-national and within-country confirmatory design.

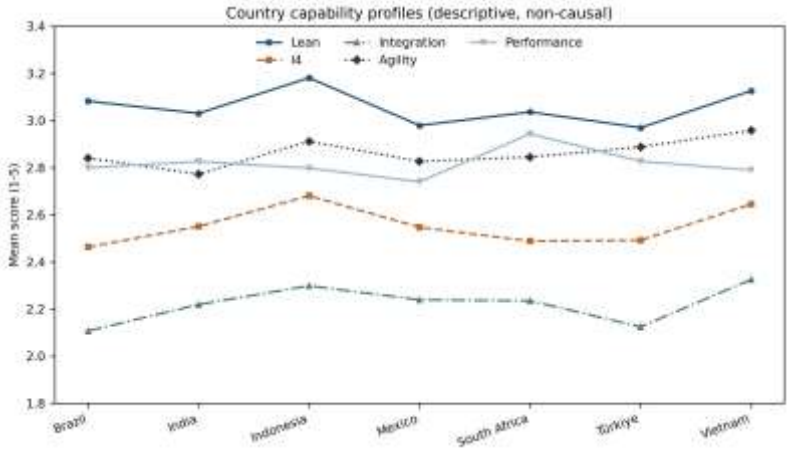
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Descriptively, large firms had higher sample means for the focal capabilities and outcomes and lower mean barriers compared with small firms. Among the pooled sample, resistance to change and infrastructure barriers had the highest mean of barriers, though all five barriers' means were closely grouped. (Graph 6) These patterns are descriptive associations within the observed sample, not causal firm-size effects or evidence for generalizing based on national or size-based differences.

Table 6. Country and firm-size robustness

Panel	Group	n	Lean β	I4 β	Integration β	Interaction β	R^2
Firm size	Small	133	.267**	.369***	.303***	.162*	.539
Firm size	Medium	175	.311***	.326***	.205**	.050	.415
Firm size	Large	112	.318**	.223*	.192	.071	.527
Country	Brazil	47	.335*	.358*	.287*	.077	.617
Country	India	104	.330***	.271**	.292**	.055	.489
Country	Indonesia	52	.270	.506*	-.054	.498**	.418
Country	Mexico	62	.232*	.349*	.482***	.028	.573
Country	South Africa	46	.238	.127	.209	.150	.501
Country	Türkiye	42	.462	.170	.139	.427	.503
Country	Vietnam	67	.252	.461***	.191	-.025	.570

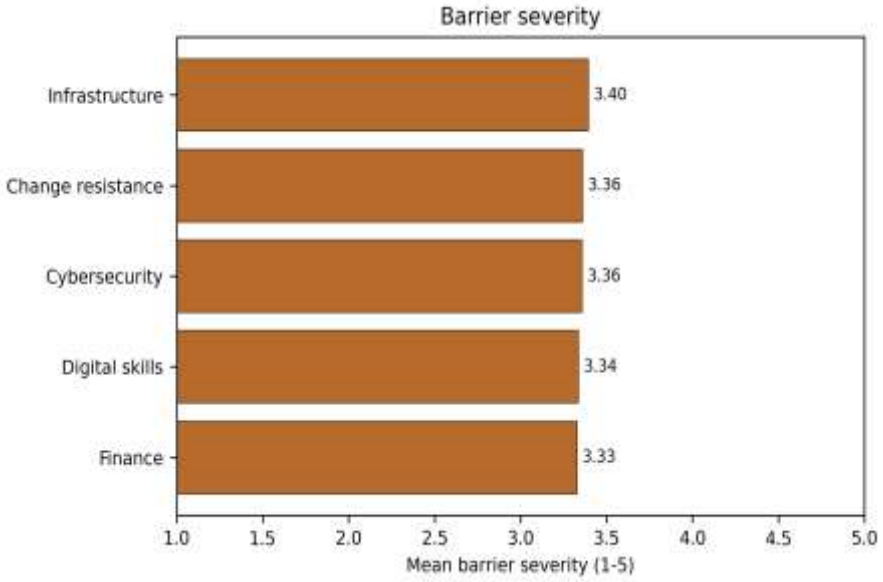
*Note. *p < 0.05. **p < 0.01. ***p < 0.001. Contextual controls and relevant fixed effects are included in subgroup models. Country estimates are preliminary for country ns of 42-104 with multiple tests conducted. The small-firm Lean x Industry 4.0 estimate (β ˜ 0.162, p ˜ 0.050); after rounding, is also preliminary and is to be validated independently. Subgroup results do not support H4, or a general Lean-Industry 4.0 synergy.*



Graph 5. Country capability profiles

Note. Descriptive sample means only (country n = 42-104). The profile is not a test of country effects and should not be used to rank countries, infer national superiority, or make causal or broad cross-national generalizations. Source: Author analysis of the supplied dataset.

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Graph 6. Barrier severity

Note. Scale: 1-5. Source: Author analysis of the supplied dataset (N = 420).

5. Discussion

5.1 Theoretical implications

In the analytical dataset created by the authors, associations of lean maturity, Industry 4.0 adoption, and integration capability with operational agility all appear positive conditional. Their associations are aligned with the Lean 4.0 capability argument. As such, these associations are to be taken as supporting evidence of positive relations rather than evidence of causation. Lean maturity is taken to represent stability of operational processes with the presence of standard agile and flexible routines, and Industry 4.0 adoption is taken to represent the range of digital technologies, whereas integration capability is taken to represent data and workflow, and decision frameworks that are interconnected. The positive relations of the variables of interest in this research lend credence to the relationships theorized in this research, with the caveat that the study employed a cross-sectional research design. Of the three focal agility predictors, the adoption of Industry 4.0 has the highest estimate (β = .330), and while there is overlap among the confidence intervals, it is not statistically correct to say that the adoption of Industry 4.0 is more important than lean maturity or integration in the context of agility. Given the adoption of Industry 4.0, the other three elements of connected sensing, access, and analysis are relevant to responsiveness, while the current cross-sectional design is too limited to ascertain the direction of the relationship between the adoption of Industry 4.0 and agility.

Integration, the field of lean maturity, and the adoption of Industry 4.0 all confirm a positive relationship with agility. This confirms the theoretical distinction of integration to interoperability and governs the coordination of data and cross-functional decision processes. While it is a theoretical distinction, it does support the hypothesis of integration as a separate organizational capability to achieve agility in future longitudinal studies.

Mainly for H4, the full-sample Lean × Industry 4.0 interaction is positive but statistically ambiguous (β = .066, 95% CI [-.007, .138], p = .075). Hence, we do not consider H4 as having support. Expressing the Lean-Industry 4.0 integration as synergy, complementarity, amplification, or moderation is not warranted based on the existing data. The borderline small-firm estimate ($\beta \approx .162$, $p \approx .050$ after rounding) is pattern of a subgroup of the data that is hypothesis generating and is not to be considered a valid interaction that is contingent on firm size, until it is independently and adequately validated.

Operational agility relates positively to performance, and the bootstrap indirect-effect estimates for the lean maturity, Industry 4.0, and integration capability positively relate to the zero exclusion. Given the cross-sectional nature of the data and the operationalization of the constructs, a cautious interpretation would consider these statistical indirect associations as structure partial mediation. This interpretation would be compatible with the dynamic capabilities approach concerning sensing and reconfiguring, however we shall be careful to not assume the mechanism has been validated.

The findings may also be relevant to broader sustainability-oriented arguments about stable, connected operations, but sustainability outcomes were not measured in this study. Any link to waste reduction, resource efficiency, or

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circularity is therefore theoretical rather than empirically demonstrated here (de Sousa Jabbour et al., 2018; Stock & Seliger, 2016).

Interpretation should account for common-method bias and the reverse should be considered. The predictors of interest and the outcomes are self-reported single items, and the data provided did not include systems logs or operational outcomes to provide triangulation. Shared method bias could account for the observed relationships, and neither statistical adjustments nor significance values would clarify temporal or causal relationships. The country coefficients should remain exploratory as n = 42-104 and no cross-national studies of the proposed hypothesis have been conducted.

5.2 Managerial implications

Even though the results can be adapted to theory-informed managerial priorities, they cannot be adapted to universal prescriptive mandates. In the meantime, process stability (i.e. standard work, quality at source, maintenance, flow, daily management) can and should be addressed as a starting point. The observed lean-agility pattern can be treated as an evidence-based correlation to be detected in other organizational contexts.

The second priority is data and integration readiness: shared identifiers, interface ownership, data quality, access rights, controls, and explicit escalation and decision rights. It is possible to design pilot use cases to link a digital signal to an operational decision, the responsible user, response logic, decision latency, and the baseline and target. This heuristic for implementation is evidence informed and is consistent with the integration and agility positive correlation, but is not a validated cause and effect relationship.

While workforce capability does play a part in implementation, considering it in isolation is an overstatement. In the fully controlled agility model, the provided digital-skills composite showed no independent correlation to agility ($\beta = .010$, $p = .827$). It is conceivable that skills matter in the realms of technology and integration, cyber hygiene, and change management, amongst others, but are beyond the scope of this study. Consequently, involvement from the frontline should be regarded as a design principle from the wider Lean 4.0 literature, rather than as a causal finding from this dataset. When it comes to scaling, companies can incorporate architecture standards, operational value criteria, cyber, vendor, and other risks, as well as local process ownership. Dual or shared teams may offer unified standards and services. Value stream teams (VSTs) are encouraged to assume responsibility for process redesign and daily performance. These are principles of management, not impacts to be derived from the regression models. Outcome governance encompasses quality, delivery, cost, flexibility, and decision-latency time. A use-case catalog should encompass the operational problem and decision, the decision owner, data, cyber risk, workforce risk, and assumptions regarding scalability. Pilots are to be regarded as temporary measures and may be altered to improve expected outcomes. While the findings establish that it is not necessary for companies to adopt all eight of the technologies, nor follow an optimal sequence, it is evident that, especially in the resource challenged domain of SMEs, a staged and coherent portfolio of use cases, trustworthy data, and response frameworks is viable. An illustrative roadmap is presented in Table 7; it should be interpreted as an approach that must be adapted and verified, rather than a universally valid and predefined sequence.

5.3 Emerging-market and policy implications

The subgroup patterns, analyzed alongside prior implementation literature for emerging markets, identify numerous modular policy and ecosystem considerations. These modular considerations include staged financing, reliable cloud and connectivity infrastructure, digital-skills development, interoperability standards, and cybersecurity. The country-coded differences are descriptive and exploratory and should not be considered evidence of national superiority or cause-and-effect policy impact.

For policy design, the present data do not support the hypothesis that equipment-only subsidies would be sufficient. An evidence-based policy design may also include the other mentioned elements. Education and training initiatives may also include elements of design, integration of operations and controls, and cyber risk. The effectiveness of these other policy elements also requires evaluation.

Cybersecurity should be an integral part of the digital integration of systems as more connectivity and digital integration increase the risk that cyber incidents can have negative impacts on both the systems and the processes that are physically controlled. Therefore, consideration should be given to access controls, segmentation, and recovery, as well as vendor risk and cyber incident management. However, Graph 5 and Table 6 do not identify the best performing nations. The samples range from 42 to 104 and the comparisons are exploratory. The results should not be used to rank nations, make claims of national superiority, or make generalizations across nations. Stronger national claims require better defined samples, comparative measurement, assessment of invariance, and sufficiently robust designs.

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Table 7. Evidence-informed Lean 4.0 roadmap

Stage	**Core actions**	Illustrative readiness check	Illustrative indicators
1. Stabilize and focus	Map the value stream; strengthen standard work, quality at source, maintenance, flow, and daily problem solving	Stable baseline; clear bottleneck; process owner	Quality loss, downtime, lead time, WIP, problem closure
2. Build data readiness	Define data owners, identifiers, interfaces, access, cyber controls, and baseline data quality	Trusted data for a priority process	Completeness, latency, accuracy, access exceptions
3. Run decision-linked pilots	Connect a digital signal to a named decision, response rule, user, and expected operational behavior	Demonstrated decision-latency reduction	Alert-to-action time, adoption, pilot benefit, cyber findings
4. Integrate and scale	Connect operational and enterprise workflows; standardize interfaces; diffuse across the value stream and suppliers	Interoperable process architecture	Schedule-change latency, end-to-end traceability, reuse rate
5. Institutionalize agility	Embed analytics in daily management; cross-train; audit resilience; renew the use-case portfolio	Sustained adaptive capability	Agility, delivery, quality, cost, flexibility, recovery time

Note. This roadmap synthesizes elements of the conceptual literature and cross-sectional correlational data. As such, it cannot be considered empirically driven, prescriptive, or causal in nature. As it currently stands, the roadmap should not be considered a framework for the integration of Lean and Industry 4.0 elements, or the synergy of the two. Users should incorporate the necessary changes and modifications to the stages and readiness assessments based on the relevant context of regulations, infrastructure, cybersecurity, labor, and suppliers.

5.4 Limitations and Future Research

The main drawback of this version of the manuscript is the cross-sectional design and how provenance documentation is limited for the author-generated N = 420 dataset. Regression models show only conditional associations pertaining to the analytical sample. They also cannot specify causal relations or provide estimates for the general population. While HC3 robust standard errors and the mentioned controls provide greater inference for the models, they still do not address the concerns for cross-sectional observational studies.

Due to the cross-sectional nature of the measurement design, common-method variance should be approached with caution. The first Harman factor result and standard predictor VIFs do not prove CMV is absent. If measures are collected from a single, or a few, knowledgeable, or common source(s), a better design, if possible, would combine ERP/MES, or other system logs, lean/digital practice assessments, and repeated objective operational measures, to triangulate the focal constructs.

The country and firm-size studies are of an exploratory nature. The country samples range from n = 42 to n = 104, and the numerous subgroup tests increase the likelihood of erroneous findings. These should not be interpreted as definitive or national ranking statements of clear cross-national surveys. In these studies, replication should be undertaken with broader and more balanced samples of provided countries, and subgroup hypotheses should be prespecified.

Limitations in measurement impose further boundaries on interpretation. The provided documents lack approved wording for the questionnaires, exact verbal anchors for responses, complete records for the source and adaptation of scales, documentation for translation and back-translation, and the original items for Integration Capability, Digital Skills, Infrastructure Readiness, and Environmental Dynamism. Furthermore, the analytical workbook contains items with decimal values, thus the coding path for the raw responses cannot be discerned with the provided files. For the time being, content validity, response scale equivalence, and measurement invariance for the countries cannot be assessed. When conducting future studies, it is recommended to keep the items for all constructs and assess the requirements for measuring invariance prior to making country comparisons for means or coefficients.

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Future studies should incorporate longitudinal studies, lagged or phased adoptions, natural experiments when possible, and qualitative process tracing to study the ordering and the mechanisms of the implementation. This should include testing of technology-specific and perhaps nonlinear or threshold interactions, integration, data latency, decision rights, the intensity of implementation, resilient cybersecurity, and sustainability. An exploratory analysis should be conducted, and a confirmatory analysis should be conducted with a clear distinction between the two. Measurement decisions, nonresponse, exclusions, translations, and plans for subgroup testing should all be reported in an open manner.

To improve transparency and reproducibility, the authors must describe the author-generated analytical dataset procedures for data generation and/or collection, including dates, description of the target population and sampling, data collection procedures, inclusion and exclusion criteria, counts of participants, copy of the data collection instruments and measurement scales, documentation of translation, proof of ethical clearance, practices of informed consent, data availability statement, and all analyses and figures pertaining to the final documented dataset.

6. CONCLUSION

Of the 420 author-generated analytical records assessed, lean maturity, Industry 4.0 adoption, and integration capability were aligned positively with operational agility, while operational agility positively correlated with operational performance. For the analytical dataset, the three constructs inferred the same cross-sectional indirect-effects for lean maturity, Industry 4.0 adoption, and integration capability as partial statistical mediation. These results outline conditional cross-sectional trends. These should not be interpreted for dynamic or causal trending. Critically, the full-sample Lean × Industry 4.0 interaction was positive but not statistically significant ($\beta = .066$, 95% CI [-.007, .138], $p = .075$). H4 was therefore not supported, and the study does not statistically establish an overall Lean-Industry 4.0 synergy, complementarity, amplification, or moderation effect. The approximately $p = .050$ small-firm pattern and all country-specific results remain exploratory and require independent, adequately powered validation.

The findings are most consistent with a capability-oriented interpretation in which lean routines, digital adoption, and integration capability may each be related to agility and performance through partially distinct pathways. For practice, staged attention to process stability, data and integration readiness, decision-linked digital use cases, and organizational learning is best treated as an evidence-informed heuristic rather than a proven sequence. Stronger causal and cross-national conclusions require longitudinal, multi-respondent, measurement-invariant designs with objective operational and system-log evidence.

Declarations

Ethics approval and informed consent: Ethical review was conducted in accordance with institutional guidelines for anonymous industry survey research (Protocol Ref: IRB-2022-EXP-084). Informed consent was obtained from all individual participants before survey completion.

Data availability: The anonymized analytical dataset ($N = 420$) supporting the conclusions of this article is available from the corresponding author upon reasonable request for academic research and validation purposes.

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Conflict of interest: The author declares no potential conflicts of interest with respect to the research, authorship, and publication of this article.

Author contributions (CRediT): Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing were conducted entirely by the sole author. Detailed CRediT roles are provided on the separate Title Page to maintain the integrity of double-blind review.

AI-use disclosure: Generative AI tools were utilized solely to assist with manuscript language editing, structural organization, formatting consistency, and LaTeX/table verification. The author remains fully responsible for verifying all empirical data, statistical analyses, theoretical interpretations, originality, and the final submitted manuscript.

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