AI Enablement in SMEs: Which Readiness Factors Actually Work

Gvidas Petruzis
Vilnius University Šiauliai Academy, Lithuania

gvidas.petruzis@sa.vu.lt

Abstract: Organisational readiness models for artificial intelligence list strategy, technological resources, data competence, skills and innovation culture as parallel conditions, and maturity models arrange those conditions into cumulative levels. Both traditions were developed in large organisations, where functions are separable and competence is held internally, and both are applied to small and medium-sized enterprises without being tested there. This paper tests them directly. A survey of 380 Lithuanian SME managers and owners was conducted, and the 204 respondents whose firms already use artificial intelligence form the analytical sample, since an enablement mechanism can only be examined where enablement is under way. Eight reflective constructs were measured and seven directional hypotheses were estimated with partial least squares structural equation modelling in SmartPLS, using 5,000 bootstrap subsamples. The measurement model reduced the eight constructs to six, and that reduction is itself a result rather than a technical adjustment: dynamic capabilities could not be discriminated from data management, and human resources could not be discriminated from processes, so two pairs of dimensions that large-firm instruments measure separately are not empirically separable at this scale. Six of seven paths are supported. Strategy produces the strongest effect in the model on technological resources, and significant effects on human resources and processes and on data management, which makes it the root factor through which the remaining dimensions are formed. Artificial intelligence literacy contributes independently to the adaptation of human resources and processes, with an effect larger than that of data management. Innovation orientation, which readiness models treat as a central driver, has no significant effect. The model explains 70.4 per cent of the variance in human resources and processes, 49.0 per cent in technological resources and 45.3 per cent in data management, with positive predictive relevance throughout. Multigroup analysis, preceded by confirmation of partial measurement invariance, finds no significant difference in any path between firms of low and high digital maturity. Digital maturity therefore marks where a firm starts rather than how its enablement mechanism works.

Keywords: AI enablement, Small and medium-sized enterprises, Digital maturity, PLS-SEM, AI literacy, Organisational readiness

1. Introduction

Artificial intelligence is described as a general-purpose technology that reshapes how firms organise work, yet its use in small and medium-sized enterprises (SMEs) remains shallow. Recent reviews report that SMEs adopt narrow, task-level applications and rarely reach the process redesign that produces measurable gains (Oldemeyer, Jede and Teuteberg, 2025; Ayinaddis, 2025), and cross-country evidence points to the same gap between large firms and small ones (OECD, 2025; Schwaeke et al, 2025).

The frameworks used to explain this gap were built in large organisations. Organisational AI readiness models list strategy, resources, data, culture and skills as parallel readiness factors (Jöhnk, Weissert and Wyrtki, 2021), and maturity models arrange them into ordered stages (Kane et al, 2017; Gökalp and Martinez, 2021). Both traditions assume conditions that small firms rarely satisfy: a documented strategy, dedicated units, internal data competence and a separable innovation function. When such models are applied to SMEs, they are usually transferred rather than tested, so it stays unclear which of the listed factors actually drive AI enablement in a firm of twenty employees and which are artefacts of the large-firm setting in which the models were developed.

This paper tests the drivers directly. Using survey data from 380 Lithuanian SME managers and owners and a partial least squares structural equation model estimated on the 204 firms that already use AI, it examines how strategy, technologies, data management, AI literacy and innovation orientation relate to the adaptation of human resources and processes, and whether digital maturity conditions those relationships. Three results run against the expectations built into readiness models. Innovation orientation, treated in most frameworks as a central driver, has no significant effect. AI literacy, usually folded into a broader human resource factor, behaves as a distinct and strong condition. Digital maturity, normally modelled as a contingency, does not moderate any structural relationship, which means the enablement mechanism is the same in low and high maturity firms even though their levels differ.

The contribution is empirical. The paper reports a measured enablement structure for small firms, shows which dimensions the data separate and which they merge, and identifies two factors that carry the mechanism in this context. For practice it reorders priorities: strategic clarity and AI literacy precede innovation programmes.

2. Theoretical Background and Hypotheses

2.1 From Adoption to Enablement

Adoption research asks whether a firm uses a technology. Enablement asks what has to be in place for the firm to use it productively. The distinction matters in the SME setting, where the decision to purchase an AI tool is cheap and reversible while the reorganisation of work around it is neither. Dynamic capability accounts describe this reorganisation as sensing, seizing and transforming activity that depends on managerial attention rather than on formal structures (Teece, 2007; Warner and Wäger, 2019), and studies of AI capability show that value comes from the combination of technical assets with organisational and human resources rather than from the tools alone (Mikalef and Gupta, 2021; Borges et al, 2021). For small firms, where the same person often selects the tool, learns it and redesigns the process, this combination is not an abstraction but a description of daily work (Drydakis, 2022; Arroyabe et al, 2024).

The SME setting adds three constraints that large-firm models do not carry. Competence is scarce and indivisible: there is no analytics unit, so the knowledge needed to judge an AI output sits with one or two people, and reviews of SME adoption identify this knowledge gap, rather than the cost of tools, as the binding barrier (Oldemeyer, Jede and Teuteberg, 2025; Bettoni et al, 2021). Roles are bundled: the person who selects a tool is often the person who redesigns the task and trains colleagues, so dimensions that large-firm instruments measure separately are enacted by the same individual. External dependence is normal: small firms rely on vendors and consultants for capability they cannot hold internally, which shifts part of the enablement work outside the firm boundary (Arroyabe et al, 2024; Ayinaddis, 2025). Together these constraints make it an empirical question, not a matter of transfer, which readiness dimensions are distinct and which drive change in this context.

2.2 Enablement Dimensions and Hypotheses

Readiness inventories converge on a small set of dimensions: strategic direction, technological resources, data management, human resources and processes, competence or literacy, and an innovation-oriented culture (Jöhnk, Weissert and Wyrtki, 2021; Bettoni et al, 2021; Naheed, Pinto and Pirola, 2025). What the inventories do not specify is the order of operation. The hypotheses below state one.

In a small firm, strategic direction is the scarcest coordinating resource: it is the owner's decision about where the firm is going that releases money for tools, time for learning and permission to change a process. Strategy is therefore modelled as the upstream condition for the other resources.

Strategy here does not mean a written plan. Dynamic capability accounts describe strategic activity in smaller firms as continuous managerial sensing and resource commitment rather than documented planning (Teece, 2007; Warner and Wäger, 2019), and the items used in this study capture whether AI use is deliberately directed and aligned with business goals rather than whether a document exists.

H1: Strategy has a positive effect on technologies.

H2: Strategy has a positive effect on human resources and processes.

H3: Strategy has a positive effect on data management.

Technological resources are what make data usable. Cloud services, integrated systems and analytics tools are the precondition for the data quality that AI applications require, which is why technology and data are treated as sequential rather than parallel (Ghobakhloo and Ching, 2019).

H4: Technologies have a positive effect on data management.

Data management, in turn, is what allows a process to be redesigned rather than merely automated, and competence is what allows employees to work with the result. AI literacy is the individual-level capacity to evaluate, use and question AI outputs (Carolus et al, 2023); empowerment research explains why that capacity, rather than access alone, determines whether employees change how they work (Spreitzer, 1995; Faraj, Pachidi and Sayegh, 2018). Innovation orientation, the shared willingness to experiment, is the fourth candidate condition and the one most often assumed rather than measured.

H5: Data management has a positive effect on human resources and processes.

H6: AI literacy has a positive effect on human resources and processes.

H7: Innovation orientation has a positive effect on human resources and processes.

2.3 Digital Maturity as a Contextual Condition

Digital maturity is the accumulated state of a firm's digital practice, from informal activity to measured and optimised management (Kane et al, 2017; Mittal et al, 2018; Borštnar and Pucihar, 2021). Maturity models treat that state as a contingency: the same intervention is expected to work differently at different stages. If this holds, the structural relationships above should differ between low and high maturity firms, which is examined as a group comparison rather than a directional hypothesis.

Maturity was measured by self-assessment against described practice levels, which is the standard approach in SME-oriented maturity instruments (Borštnar and Pucihar, 2021) and carries the known limitation that respondents judge their own practice.

3. Method

3.1 Design and Sample

The study is the quantitative stage of a sequential mixed-method design. A qualitative stage of semi-structured expert interviews, conducted in June 2022 and between February and June 2025, established the dimension set and the wording of the items; the present paper reports the survey stage and uses the qualitative stage only as the source of the instrument. The questionnaire was piloted between July and October 2025 and fielded between February and March 2026. The research ethics compliance committee of Vilnius University Šiauliai Academy approved the study before data collection.

Responses were obtained from 380 managers and owners of Lithuanian SMEs. Because the model concerns the enablement of AI rather than the decision to try it, the analytical sample was restricted to firms that already use AI. The filter combined three criteria: AI used in at least one business process, employees trained or granted access, and alignment of AI use with management and strategic goals. Firms meeting the first criterion form the analytical sample of 204 cases, which satisfies the requirements for the multivariate estimation reported below. Sampling was non-probability, so the sample supports relational inference but not population estimates for Lithuanian SMEs, and no population parameters are reported.

3.2 Measures

All enablement constructs were measured reflectively with multi-item scales on a four-point Likert format, which avoids the neutral midpoint that respondents in pilot testing used as an avoidance option. Digital maturity was measured separately with a five-level scale describing practice, from activity carried out informally through planned and monitored, standardised at organisational level and measurement-based management to continuously optimised. Items were developed from the readiness and maturity literature cited in Section 2 and refined against the qualitative material, then screened in pilot testing.

3.3 Analysis Strategy

Partial least squares structural equation modelling was used because the model is predictive rather than confirmatory, includes a construct measured with two indicators, and is estimated on a sample that does not meet the distributional requirements of covariance-based estimation (Hair et al, 2022). Estimation was carried out in SmartPLS. Firm size was included in the estimated model as a single-indicator control, coded from micro through small to medium. Only its path to technological resources is significant ($\beta = 0.136$, $p = 0.006$); its paths to data management and to human resources and processes are not, so the enablement mechanism itself does not depend on size. The measurement model was assessed through indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted) and discriminant validity using the heterotrait-monotrait ratio with bootstrap confidence intervals (Fornell and Larcker, 1981; Henseler, Ringle and Sarstedt, 2015). The structural model was assessed through path coefficients with 5,000 bootstrap subsamples, explained variance and out-of-sample prediction. The mediation test was computed with the seminr package for R using 5,000 bootstrap samples; all other estimates come from SmartPLS. The maturity comparison used a median split of the maturity scale, measurement invariance testing with the MICOM procedure and bootstrap multigroup analysis (Sarstedt, Henseler and Ringle, 2011; Henseler, Ringle and Sarstedt, 2016).

The maturity comparison was carried out as a group comparison rather than as a continuous interaction term. The maturity instrument describes ordered levels of practice rather than a metric quantity, and the group approach has the additional property that it first tests whether the two groups interpret the constructs in the same way, so that a coefficient difference cannot be an artefact of differing measurement.

4. Results

4.1 Measurement Model: From Eight Constructs to six

The initial measurement model specified eight constructs, following the dimension set of the readiness literature. Two pairs failed discriminant validity. The heterotrait-monotrait ratio between dynamic capabilities and data management was 0.917 with a bootstrap confidence interval whose upper bound of 1.013 included unity, so the two constructs cannot be treated as empirically distinct (Henseler, Ringle and Sarstedt, 2015). The ratio between human resources and processes was 0.919 with an upper bound of 0.987, formally below unity but far above even the liberal 0.90 threshold. Both pairs were merged, giving the six-construct model tested here.

The merges are substantive rather than technical. Respondents in small firms do not distinguish the capability to act on data from the management of data itself, and they do not distinguish the competence of employees from the processes those employees carry out. In a firm where the same employee learns the tool and redesigns the task, the separation that large-firm instruments assume has no referent. This is the first result of the study: dimensions that the literature treats as distinct collapse into single enablement layers in the SME context.

All six constructs of the final model met the reliability and convergent validity criteria. Cronbach's alpha ranged from 0.760 for data management to 0.892 for AI literacy, composite reliability from 0.860 to 0.921, and average variance extracted from 0.591 for human resources and processes to 0.833 for innovation orientation, all above the 0.50 threshold. Discriminant validity was established for every pair in the final model.

4.2 Structural Model

Table 1 reports the structural estimates. Six of the seven hypotheses are supported.

Table 1: Structural model estimates (N = 204)

Hypothesis	Path	β	t	p	Decision
H1	Strategy -> Technologies	0.690	18.106	< 0.001	Supported
H2	Strategy -> Human resources and processes	0.392	5.833	< 0.001	Supported
H3	Strategy -> Data management	0.290	3.502	< 0.001	Supported
H4	Technologies -> Data management	0.440	5.419	< 0.001	Supported
H5	Data management -> Human resources and processes	0.183	2.952	0.003	Supported
H6	AI literacy -> Human resources and processes	0.340	6.096	< 0.001	Supported
H7	Innovation orientation -> Human resources and processes	0.090	1.406	0.160	Not supported

Note. Standardised coefficients, 5,000 bootstrap subsamples, two-tailed.

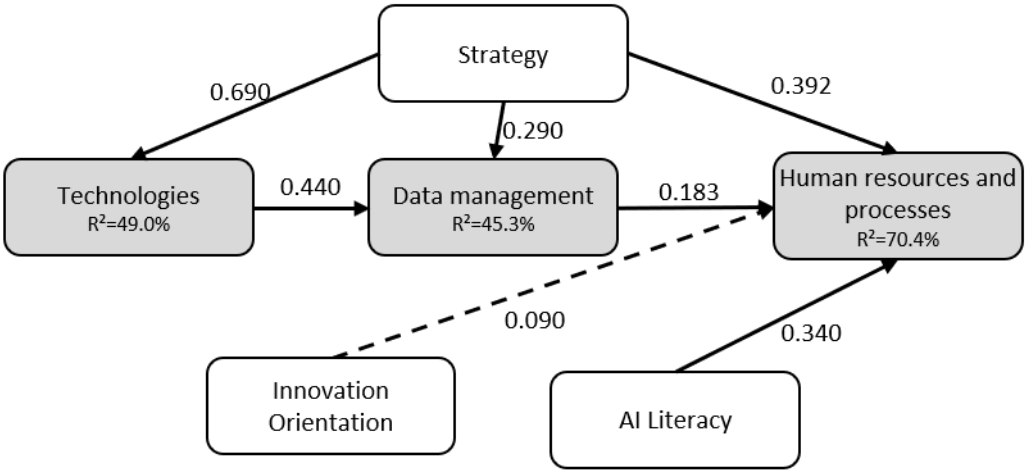
Strategy is the dominant driver. Its effect on technologies is the strongest in the model, and it also reaches human resources and processes and data management directly. The technology path to data management confirms the sequence assumed in Section 2, and data management in turn reaches human resources and processes, though weakly. AI literacy has a considerably larger effect on human resources and processes than data management does, which places individual competence ahead of infrastructure in this part of the model.

Strategy also reaches data management indirectly, through technologies. The specific indirect effect was tested on 5,000 bootstrap samples and is significant: $\beta = 0.304$, $t = 5.096$, $p < 0.001$, with a 95 per cent percentile confidence interval of [0.190, 0.421] that excludes zero. Its magnitude is of the same order as the direct effect of strategy on data management (0.290), and the two combine into a total effect of 0.594 ($t = 11.214$, $p < 0.001$). Because both the direct and the indirect effect are significant and point in the same direction, the pattern is complementary partial mediation: technological resources transmit part of the strategic impulse to data practice without exhausting it.

Innovation orientation is the exception. Its coefficient is small and not significant, so H7 is rejected. This is not a power problem: with the same sample and the same estimation, five paths of smaller or comparable magnitude reach significance at the one per cent level.

The model explains 70.4 per cent of the variance in human resources and processes, 49.0 per cent in technologies and 45.3 per cent in data management. All Q-square predict values are positive, indicating out-of-sample predictive relevance. Figure 1 presents the estimated model.

Strategy mobilises all three enablement resources; innovation orientation does not reach processes



Standardised path coefficients. N=204 AI-using SMEs; PLS-SEM with 5 000 bootstrap subsamples.
Solid arrow = supported at p<0.01
Dashed arrow = not supported.

Figure 1: Estimated structural model of AI enablement in SMEs (N = 204) Firm size is included as a control and omitted from the diagram for clarity

4.3 Digital Maturity as a Grouping Variable

The sample was divided at the median of the maturity scale into a low maturity group and a high maturity group. Before comparing coefficients, the MICOM procedure confirmed partial measurement invariance: compositional invariance held for all six constructs, with original correlations between 0.998 and 1.000 and permutation p values between 0.120 and 0.828, and the equality of variances held for all constructs, with p values between 0.198 and 0.953. Respondents in both groups therefore understand the constructs in the same way, and the coefficient comparison can be interpreted (Henseler, Ringle and Sarstedt, 2016).

The two groups differ in level. Independent-samples t-tests on the six construct means show the high maturity group scoring above the low maturity group, which is expected given that the grouping variable describes digital practice. The question the multigroup analysis answers is different: not whether the groups differ in how much they have, but whether the relationships among the constructs differ.

Bootstrap multigroup analysis with 5,000 subsamples compared ten path coefficients between the groups. None of the differences is statistically significant at the five per cent level. Digital maturity does not moderate the enablement structure: the mechanism operates in the same way in firms at a low and at a high level of digital practice. Maturity separates the groups in level, since the group means differ across constructs, but not in the way the constructs work together.

5. Discussion

5.1 Innovation Orientation is not an Enablement Driver

Prior SME work has mapped the extent of AI use and the barriers to it, reporting shallow adoption and a persistent gap to large firms (Schwaeke et al, 2025; OECD, 2025) and relating adoption to digital capability endowments (Arroyabe et al, 2024). The present results address a different question, namely which conditions

carry the internal mechanism once a small firm has begun to use AI, and they qualify the readiness inventories on three points: one listed factor does not operate, one is more consequential than its usual placement suggests, and two pairs of factors are not empirically separable in this setting.

The rejection of H7 is the finding most at odds with the literature. Innovation culture appears as a readiness factor in the inventories cited above and as a driver in adoption studies. Two readings are consistent with the data. The first is measurement: in a small firm, willingness to experiment is not a property of the organisation separate from its people, and what the innovation items capture may already be carried by the human resource and literacy constructs. The second is substantive: an orientation towards experimentation does not by itself change how work is organised, because changing a process requires the direction and the competence that the other paths represent. The merge of human resources with processes reported in Section 4.1 supports the first reading, and the size of the strategy and literacy coefficients supports the second. Either way, the practical implication is the same: an SME that wants to enable AI cannot expect an innovation programme to substitute for strategic clarity or for competence.

A reviewer of this paper raised a third possibility: that AI literacy has absorbed the effect usually attributed to collective experimentation. The measurement model allows this to be examined rather than assumed. Discriminant validity held for every pair in the final model, including literacy and innovation orientation, and innovation orientation records the highest average variance extracted in the study at 0.833, so the two constructs are not measuring the same thing and the null result is not an artefact of overlap. What the estimates suggest instead is a division of labour between the collective and the individual level: a shared willingness to experiment does not reorganise work, whereas the individual capacity to judge what an AI output is worth does. In small firms, where the person who experiments is also the person who redesigns the task, the two are easily conflated in theory and clearly separable in measurement.

5.2 AI Literacy is a Distinct Condition, not Part of a Human Resource Bundle

AI literacy retains a strong independent effect on human resources and processes, larger than the effect of data management. Readiness models generally treat skills as one element of a personnel factor. The present estimates suggest that in the SME context the capacity to evaluate and question AI output is separable from, and more consequential than, the remaining human resource conditions, which is consistent with the individual-level framing of literacy (Carolus et al, 2023) and with empowerment accounts in which competence precedes changed behaviour (Spreitzer, 1995).

5.3 Maturity Marks the Level, not the Mechanism

Maturity models are built on the premise that stage conditions action. The multigroup results do not support that premise for the relationships tested here. The same paths, with statistically indistinguishable magnitudes, hold in low and high maturity firms. The useful reading is not that maturity is irrelevant, since the groups differ in level on every construct, but that it belongs in enablement models as a state variable describing where a firm starts rather than as a contingency that changes how enablement works. For research this simplifies model specification; for advisory practice it means that the same sequence of measures applies across maturity stages, with the starting point rather than the method differing.

5.4 Practical Implications

Three implications follow for SME managers and for the support organisations that advise them. Strategic clarity about where AI is to be used comes first, because it conditions every other resource in the model. AI literacy is the highest-return investment in people, ahead of infrastructure spending. Innovation programmes, workshops and culture initiatives should not be expected to produce process change on their own.

6. Conclusions, Limitations and Further Research

This study tested an enablement structure for AI in small and medium-sized enterprises on 204 AI-using firms. Strategy mobilises technologies, data management and the human side of enablement; AI literacy contributes independently and strongly; data management contributes weakly; innovation orientation does not contribute at all. The model accounts for 70.4 per cent of the variance in the adaptation of human resources and processes and has positive predictive relevance. Digital maturity does not moderate any of the relationships.

Three limitations bound these conclusions. Sampling was non-probability, so the estimates describe relationships within the sample and are not population estimates for Lithuanian SMEs. The data are cross-sectional, so the sequence argued in Section 2 is a modelled order and not an observed one. The study is confined

to one country, and the strength of the strategy paths may reflect the ownership structure of small Lithuanian firms, in which the owner is usually also the manager.

A fourth limitation concerns the response structure. One informant reported for each firm, which is appropriate when the informant is the owner or manager who makes the decisions described, but it means that construct scores share a single source. Common method variance was not formally assessed in this study.

Three extensions follow. A longitudinal design would test whether strategic clarity precedes competence or the two develop together. Replication in another small-firm economy would show whether the collapse of the human resource and process dimensions is a property of firm size or of this national context. Finally, the null result for innovation orientation deserves a dedicated measurement study, since distinguishing the measurement reading from the substantive one requires instruments designed for small firms rather than adapted from large ones.

Ethics Declaration: the research ethics compliance committee of Vilnius University Šiauliai Academy approved the study before data collection. Participation was voluntary and responses were processed in aggregate form.

Use of AI tools Declaration: the author used a large language model to assist with translation from Lithuanian and with language editing of the manuscript, under direct human oversight. All analysis, interpretation and conclusions are the work and the responsibility of the author.

Funding: this research received no external funding.

References

Arroyabe, M.F., Arranz, C.F., de Arroyabe, I.F. and de Arroyabe, J.C.F. (2024) Analyzing AI adoption in European SMEs: a study of digital capabilities, innovation, and external environment. Technology in Society, 79, 102733. https://doi.org/10.1016/j.techsoc.2024.102733.

Ayinaddis, S.G. (2025) Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: a systematic review and bibliometric analysis. Journal of Innovation & Knowledge, 10(3), 100682. https://doi.org/10.1016/j.jik.2025.100682.

Bettoni, A., Matteri, D., Montini, E., Gladysz, B. and Carpanzano, E. (2021) An AI adoption model for SMEs: a conceptual framework. IFAC-PapersOnLine, 54(1), 702–708. https://doi.org/10.1016/j.ifacol.2021.08.082.

Borges, A.F.S., Laurindo, F.J.B., Spínola, M.M., Gonçalves, R.F. and Mattos, C.A. (2021) The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions. International Journal of Information Management, 57, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225.

Kljajić Borštnar, M. and Pucihar, A. (2021) Multi-attribute assessment of digital maturity of SMEs. Electronics, 10(8), 885. https://doi.org/10.3390/electronics10080885.

Carolus, A., Koch, M.J., Straka, S., Latoschik, M.E. and Wienrich, C. (2023) MAILS – Meta AI Literacy Scale: development and testing of an AI literacy questionnaire. Computers in Human Behavior: Artificial Humans, 1(2), 100014. https://doi.org/10.1016/j.chbah.2023.100014.

Drydakis, N. (2022) Artificial intelligence and reduced SMEs' business risks: a dynamic capabilities analysis during the COVID-19 pandemic. Information Systems Frontiers, 24(4), 1223–1247.

Faraj, S., Pachidi, S. and Sayegh, K. (2018) Working and organizing in the age of the learning algorithm. Information and Organization, 28(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005.

Fornell, C. and Larcker, D.F. (1981) Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104.

Ghobakhloo, M. and Ching, N.T. (2019) Adoption of digital technologies of smart manufacturing in SMEs. Journal of Industrial Information Integration, 16, 100107. https://doi.org/10.1016/j.jii.2019.100107.

Gökalp, E. and Martinez, V. (2021) Digital transformation capability maturity model enabling the assessment of industrial manufacturers. Computers in Industry, 132, 103522. https://doi.org/10.1016/j.compind.2021.103522.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2022) A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). 3rd ed. Thousand Oaks: Sage.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2016) Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405–431. https://doi.org/10.1108/IMR-09-2014-0304.

Jöhnk, J., Weissert, M. and Wyrtki, K. (2021) Ready or not, AI comes: an interview study of organizational AI readiness factors. Business & Information Systems Engineering, 63(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7.

Kane, G.C., Palmer, D., Phillips, A.N., Kiron, D. and Buckley, N. (2017) Achieving digital maturity. MIT Sloan Management Review, 58(2), 1–29.

Mikalef, P. and Gupta, M. (2021) Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434.

Mittal, S., Khan, M.A., Romero, D. and Wuest, T. (2018) A critical review of smart manufacturing & Industry 4.0 maturity models: implications for small and medium-sized enterprises (SMEs). Journal of Manufacturing Systems, 49, 194–214. https://doi.org/10.1016/j.jmsy.2018.10.005.

Naheed, S., Pinto, R. and Pirola, F. (2025) A preliminary multidimensional AI readiness assessment model for SMEs. Procedia Computer Science, 253, 774–783. https://doi.org/10.1016/j.procs.2025.01.139.

OECD (2025) AI adoption by small and medium-sized enterprises. Online. Paris: OECD Publishing. https://doi.org/10.1787/426399c1-en.

Oldemeyer, L., Jede, A. and Teuteberg, F. (2025) Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. Management Review Quarterly, 75, 1185–1227. https://doi.org/10.1007/s11301-024-00405-4.

Sarstedt, M., Henseler, J. and Ringle, C.M. (2011) Multigroup analysis in partial least squares (PLS) path modeling: alternative methods and empirical results. Advances in International Marketing, 22, 195–218. https://doi.org/10.1108/S1474-7979(2011)0000022012.

Schwaeke, J., Peters, A., Kanbach, D.K., Kraus, S. and Jones, P. (2025) The new normal: the status quo of AI adoption in SMEs. Journal of Small Business Management, 63(3), 1297–1331. https://doi.org/10.1080/00472778.2024.2336712.

Spreitzer, G.M. (1995) Psychological empowerment in the workplace: dimensions, measurement, and validation. Academy of Management Journal, 38(5), 1442–1465. https://doi.org/10.2307/256865.

Teece, D.J. (2007) Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640.

Warner, K.S.R. and Wäger, M. (2019) Building dynamic capabilities for digital transformation: an ongoing process of strategic renewal. Long Range Planning, 52(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001.