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DIGITALISING MARKETING PRICING AS A GOVERNED ENTERPRISE BUSINESS PROCESS

ЦИФРОВІЗАЦІЯ МАРКЕТИНГОВОГО ЦІНОУТВОРЕННЯ ЯК КЕРОВАНОГО БІЗНЕС-ПРОЦЕСУ ПІДПРИЄМСТВА

Abstract. *The study develops and externally evaluates an integrated methodology for digitalising marketing pricing as a governed business process. It combines a five-layer architecture, a six-dimensional maturity index that penalises the weakest capability, and an autonomy gate that restricts automatic price publication when key requirements are not met. Anchored scores, fixed weights, evidence rules and sensitivity analysis ensure reproducibility. Validation uses seven Eurostat indicators for European Union enterprises in 2025. The readiness proxy equals 34.57 for the smaller-enterprise group and 72.43 for large enterprises, yielding a 37.86-point gap. All seven gaps are positive; under a descriptive benchmark of independent, equally probable signs, the two-sided probability of seven concordant signs, all positive or all negative, is 0.0156. This value is used only as a directional diagnostic. Leave-one-indicator-out analysis and both alternative weighting schemes preserve the group ordering. The methodology supports bottleneck diagnosis, accountable pricing decisions and a controlled transition to bounded automation. The aggregate evidence supports the known-groups validity of the readiness proxy but does not establish a causal effect on profitability.*

Keywords: *digital pricing; marketing pricing; business process management; pricing maturity; algorithmic governance; empirical validation; data analytics.*

Анотація. Вступ. *Цифровізація маркетингового ціноутворення трансформує формування й контроль цін, проте інформаційні системи підприємств часто залишаються фрагментарними. Неузгодженість даних про попит, витрати, запаси, клієнтів і канали збуту знижує надійність автоматизованих рішень та ускладнює аудит.* ***Метою статті*** *є розроблення й зовнішня перевірка інтегрованої методики маркетингового ціноутворення як керованого бізнес-процесу, що поєднує процесну архітектуру, оцінювання цифрової зрілості та контроль автоматичного оприлюднення цін.* ***Методи.*** *Застосовано дизайн-науковий підхід, декомпозицію бізнес-процесів, багатокритеріальне оцінювання, аналіз чутливості й перевірку валідності за відомими групами. Зовнішню перевірку проведено за сімома відкритими показниками цифровізації підприємств Європейського Союзу за 2025 рік. Стійкість оцінено шляхом почергового вилучення показників, використання альтернативних схем зважування та порівняння зіставного ядра за 2023 і 2025 роки.* ***Результати.*** *Розроблено п'ятирівневу архітектуру, що охоплює основу даних, оцінювання реакції попиту, оптимізацію цінової політики, контрольоване виконання, навчання й аудит. Запропоновано шестикомпонентний індекс зрілості, який поєднує середньозважений показник із показником найслабшої спроможності. Окремо визначено правило допуску до автоматичного оприлюднення цін. Розрив цифрової готовності між підприємствами меншого розміру й великими підприємствами становить 37,86 відсоткового пункту; розриви за всіма сімома компонентами є додатними й перебувають у межах 25–58 пунктів. Після вилучення показників розрив становив 34,50–40,00 пункту,*

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а за двома альтернативними схемами зважування – відповідно 39,55 і 40,34 пункту. Для зіставного ядра він зріс із 46,33 пункту у 2023 році до 48,67 пункту у 2025 році. ***Висновки.*** *Методика забезпечує відтворюване оцінювання цифрової зрілості, виявлення обмежень і поетапний перехід від підтримки ухвалення рішень до обмеженої автоматизації. Результати підтверджують валідність показника цифрової готовності за критерієм відомих груп, але не доводять причинного впливу цифровізації ціноутворення на прибутковість підприємств.*

Ключові слова: *цифрове ціноутворення; маркетингове ціноутворення; управління бізнес-процесами; цифрова зрілість; алгоритмічне управління; емпірична валідація; аналітика даних.*

Statement of the problem. Pricing is simultaneously a marketing signal, a revenue mechanism and a cross-functional business process. A price recommendation becomes economically meaningful only when demand information, product costs, inventory, customer-specific conditions, competitive context and channel rules are synchronised before execution. Digitalisation therefore changes more than the speed of calculation: it changes the decision architecture, the allocation of authority and the evidence available for subsequent audit. This process view corresponds to the broader understanding of digital transformation as a reconfiguration of value-creation paths and organisational structures rather than the adoption of separate technologies [6, pp. 471–475; 15, pp. 120–125].

The practical problem is a persistent implementation gap. Enterprises may use ERP, CRM or analytics software while pricing remains spreadsheet-based, episodic and weakly connected to execution channels. Conversely, an advanced model can generate frequent recommendations without reliable cost and inventory data, approval limits or a record of customer impact.

Analysis of recent research and publications. T. M. Bilousko [1, pp. 1–6] examines the digitalisation of enterprise marketing activity and identifies the integration of digital tools into information, communication and analytical processes as an important condition for improving marketing management. A. M. Bortnik [2, pp. 18–23] interprets digital transformation as a change in the enterprise business model rather than as the isolated automation of individual functions. V. Holovachko, O. Korolovych and O. Havrylets [3, pp. 3–6] consider the interrelated transformation of accounting, management and marketing, emphasising the need to coordinate information flows and managerial decisions. Ye. A. Ivchenko and A.O. Khimchenko [4, pp. 46–49] focus on the digital transformation of business process management systems and substantiate the importance of process integration, monitoring and organisational adaptation.

The broader theoretical literature also treats digitalisation as an organisational and strategic transformation. A. Bharadwaj, O.A. El Sawy, P. A. Pavlou and N. Venkatraman [6, pp. 471–475] link digital business strategy with the reconfiguration of value creation and organisational capabilities. G. Vial [15, pp. 120–125] systematises the mechanisms through which digital technologies influence value-creation paths, structures and organisational responses. From the perspective of business process management, M. Dumas, M. La Rosa, J. Mendling and H.A. Reijers [10, pp. 3–8] demonstrate that sustainable process performance depends on the coordinated design, execution, monitoring and improvement of cross-functional activities. These studies provide a conceptual basis for analysing pricing not merely as a calculation, but as an end-to-end enterprise process.

Research devoted specifically to pricing concentrates mainly on modelling, learning and market effects. I. Ponomarenko and D. Ponomarenko [5, pp. 77–84] analyse the application of dynamic pricing in marketing and the role of digital information in adapting prices to market conditions. A.V. den Boer [8, pp. 3–12] systematises dynamic pricing models under demand uncertainty and shows the importance of combining price optimisation with continuous learning. R. Y. Chenavaz and S. Dimitrov [7, pp. 4–10] review the use of artificial intelligence in dynamic pricing and identify the growing role of predictive analytics and automated decision support. J.-P. Dubé and S. Misra [9, pp. 136–146] examine the welfare consequences of personalised pricing and demonstrate that data-driven differentiation may produce heterogeneous outcomes for consumers. D. Nunan and M. Di Domenico [14, pp. 453–456] draw attention to the ethical risks of algorithmic pricing, including information asymmetry, transparency and accountability.

The reviewed studies therefore substantiate the importance of digital data, integrated processes, demand learning and governance safeguards. However, they generally examine these elements separately. The literature does not provide a single operational methodology that simultaneously links an end-to-end pricing-process architecture, evidence-based maturity assessment, an explicit penalty for the weakest capability, a separate authorisation rule for automatic price publication and an externally reproducible readiness check. This unresolved issue defines the research gap addressed in the present study.

Purpose of the article. The study addresses this gap through three research questions: how digital marketing pricing should be embedded in business process management; how maturity can be measured without allowing strengths elsewhere to conceal a critical weakness; and whether observable digital readiness distinguishes between enterprise groups expected to differ in implementation capacity. The purpose of the study is to develop an integrated methodology, specify its calculation protocol and test the known-groups validity of the construct using official open data. The corresponding tasks are to define the conceptual boundaries of digital pricing, design a five-layer process architecture, construct a hybrid maturity index, demonstrate its calculation, and perform robustness checks using Eurostat data. The contribution is methodological and construct-level: it does not propose a new pricing algorithm or estimate a causal profit effect.

Research methods. The methodology follows design-science logic: explicit requirements are translated into formal rules, from which the artefact is derived and subsequently evaluated against observable evidence. Business process decomposition identifies inputs, decision objects, controls and feedback; multi-criteria analysis operationalises six maturity dimensions; a deterministic illustrative scenario verifies arithmetic reproducibility; and a descriptive equal-sign benchmark, alternative weights, leave-one-indicator-out analysis and a two-

period comparison assess external robustness. The unit of theoretical analysis is an enterprise pricing process. The unit of external validation is an EU enterprise-size category, not an individual firm. This distinction avoids ecological inference from aggregate data. The remainder of the paper is organised into four parts: the conceptual framework, the integrated method, empirical validation and conclusions.

Presentation of the main research material. Business process management treats organisational performance as the result of designed and monitored sequences of activities that extend across functional boundaries [10, pp. 3–8]. Applied to pricing, the relevant process begins before a model is estimated and ends after a market response is measured. It includes data contracts, estimation, commercial constraints, approval, publication, exception handling and learning. Digital marketing pricing is thus defined here as a governed, data-driven control loop that selects and executes price actions by combining customer and market evidence with enterprise objectives and hard safeguards. Dynamic pricing is one possible operating mode; periodic decision support is another. The definition deliberately separates digitalisation from price variability.

Four propositions establish the theoretical logic. P1 (process-coupling proposition): pricing value depends on the continuity of data and responsibility across marketing, sales, finance, operations and information systems; a local analytical optimum may be infeasible for the enterprise as a whole. P2 (bottleneck proposition): the weakest essential capability limits the reliability of the complete pricing loop, so maturity is not fully compensatory. P3 (governance-complementarity proposition): the marginal value of automation rises when decision limits, audit trails, human override and customer safeguards are formalised. P4 (learning-loop proposition): pricing becomes an organisational capability only when outcomes update both models and process rules. These propositions extend the familiar automation perspective by making control architecture part of the construct itself.

The propositions are consistent with research showing that learning under uncertain demand requires controlled experimentation [8, pp. 6–10], while personalised prices can alter both welfare and distributional outcomes [9, pp. 136–144]. Ethical analysis also shows that algorithmic pricing creates value and risk through the same information asymmetry [14, pp. 453–456]. Accordingly, predictive accuracy is necessary but insufficient. A mature process must preserve traceability from input data to the released price, disclose the applicable business rule, detect drift, and provide an accountable route for intervention. Table 1 summarises these distinctions and implications.

The methodological novelty lies in integrating four elements that the reviewed pricing literature treats separately: an end-to-end process architecture, a six-dimensional evidence rubric, a bottleneck-sensitive hybrid index and a binary autonomy gate. The index and the gate answer different questions. The index supports capability prioritisation, whereas the gate determines whether automatic price publication is permissible. This separation prevents strong analytics from compensating for missing data lineage, weak integration or inadequate safeguards.

The theoretical claim is conditional and testable. An admissible index must be bounded and monotonic, and its value must fall as the bottleneck score falls while average capability is held constant whenever $\alpha < 1$. Identical evidence, weights, values of α and rounding rules must yield the same score and gate decision. The external known-groups check requires the expected group ordering to remain unchanged under the pre-specified indicator-deletion and weighting checks. A reversal under these checks or a failure of DMPMI to predict pre-registered process outcomes in a firm-level pilot would weaken the corresponding claim. The claims therefore concern the reproducibility and known-groups validity of the governance construct, not universal optimality or causal effects on profit.

The resulting architecture is shown in Figure 1. The first layer creates a time-stamped analytical record from cost, demand, inventory, customer and channel data. The second estimates demand response and uncertainty. The third translates forecasts into a policy subject to commercial and governance constraints. The fourth releases an approved price consistently across channels. The fifth measures economic and customer outcomes, model drift and exceptions. Feedback returns to both the model and the business rule; this dual loop distinguishes organisational learning from mere model retraining.

Implementation begins with a decision charter that defines the product–channel scope, business objective, decision frequency, decision owner and non-negotiable constraints. For each critical input, a data contract then specifies its system of record, owner, refresh interval,

Table 1

Conceptual distinction and integration logic

Element	Conventional treatment	Integrated treatment	Testable implication
Object	Price or model	End-to-end decision process	A recommendation is evaluated together with execution and feedback
Data	Inputs available to an analyst	Contracted data with an owner, refresh rule and quality threshold	Missing or stale critical data can block release
Optimisation	Single commercial objective	Multi-objective policy under hard constraints	Margin, volatility and fairness limits take precedence
Maturity	Compensatory technology score	Weighted score penalised by the weakest capability	High automation cannot mask a critical bottleneck
Governance	Ex post compliance	Embedded approval, logging, override and monitoring	Each price action is linked to an auditable decision record
Validation	Illustrative case only	Scenario verification plus external known-groups assessment	Calculations are independently reproducible

Source: developed by the authors

permissible missingness and reconciliation test. The analytical stage may use elasticity estimation, causal experiments or forecasting, but must report uncertainty and define its domain of applicability. A policy engine converts the model output into a recommendation subject to price floors, margin requirements, maximum change limits, inventory conditions and customer safeguards. Pricing decisions progress from human decision support to bounded automation only after the monitoring and rollback procedures have been tested.

The enterprise-level Digital Marketing Pricing Maturity Index (DMPMI) contains six dimensions: data quality and observability; system integration and traceability; demand and elasticity analytics; decision orchestration and execution latency; learning and experimentation; and governance and customer safeguards. Scores use five anchored levels: 0.00 (absent), 0.25 (ad hoc), 0.50 (documented but partial), 0.75 (integrated and monitored) and 1.00 (closed-loop, audited and periodically recalibrated). Only these five values are permitted in the baseline protocol. Any interpolation is a sector-specific extension that must be defined and validated before use. This restriction improves inter-rater reproducibility. The dimensions, weights and evidence thresholds are set out in Table 2.

Data quality and integration are assigned weights of 0.20 each because every downstream decision depends on observable and traceable inputs; the four remaining process capabilities are assigned weights of 0.15 each. These are normative design weights fixed ex ante, and any sector-specific change must be documented before outcomes are observed. Let s_{ij} denote the anchored score of enterprise i on dimension j and w_j the fixed weight. The arithmetic component A_i captures average capability. The bottleneck B_i is the minimum dimension score. The hybrid index $DMPMI_i(\alpha)$ combines them with a non-compensation parameter α. The baseline $\alpha = 0.75$ sets the exponent weight on the arithmetic component at 0.75 and that on the bottleneck component at 0.25; this does not imply a linear 75:25 decomposition of the index. The value of α is varied from 0.60 to 0.90 in the sensitivity analysis. It is a declared governance parameter rather than a coefficient estimated from the validation data.

$$A_i = \sum_{j=1}^{6} w_j s_{ij}, B_i = \min_{1 \le j \le 6} s_{ij}, \sum_{j=1}^{6} w_j = 1. \quad (1)$$

where i denotes the enterprise; j denotes the maturity dimension; s_{ij} is the anchored score of enterprise i on dimension j; w_j is the weight of dimension j; A_i is the weighted mean of the six dimension scores; and B_i is the minimum dimension score, representing the critical bottleneck.

$$DMPMI_i(\alpha) = A_i^{\alpha} B_i^{1-\alpha}, 0 < \alpha < 1. \quad (2)$$

The function is bounded on [0, 1] and monotone in every score. Provided $B_i > 0$, it converges to the weighted average as α approaches 1. For $0 < \alpha < 1$, a lower bottleneck strictly reduces the result when A_i is held constant.

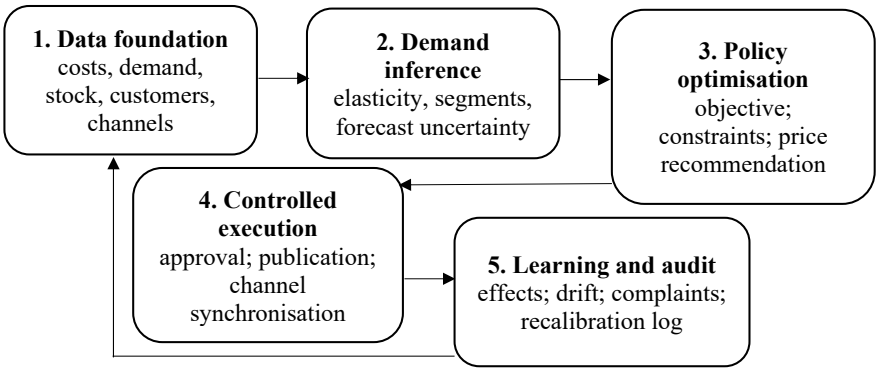


Fig. 1. Integrated digital marketing pricing architecture

Source: developed by the authors

Table 2

DMPMI dimensions and evidence rules

Dimension	Weight	Evidence required for score ≥ 0.75
Data quality and observability	0.20	Named owners; automated validation; freshness and reconciliation thresholds
Integration and traceability	0.20	ERP/CRM/channel linkage; versioned decision record; price propagation test
Demand and elasticity analytics	0.15	Out-of-sample error; uncertainty interval; segment stability check
Decision orchestration and latency	0.15	Workflow, approval limits, exception queue and measured release time
Learning and experimentation	0.15	Test design or quasi-experimental protocol; recalibration trigger; outcome log
Governance and safeguards	0.15	Hard limits, access control, human override, complaint and fairness monitoring

Source: developed by the authors. Weights sum to 1.00

If any essential dimension equals zero, the hybrid score also equals zero, which reflects an interrupted process rather than merely a statistical inconvenience. The index is complemented by an autonomy gate: automatic price publication is prohibited whenever any of the data quality, integration or governance scores is below 0.50, or whenever any hard policy constraint fails. Thus, the continuous score supports prioritisation, while the gate determines whether automated price publication is permitted. Table 3 illustrates the calculation.

The example permits a complete audit. The weighted component rises from 0.4125 to 0.7125, the bottleneck from 0.2500 to 0.5000 and DMPMI from 0.364 to 0.652. At $\alpha = 0.60$ and 0.90, the values before implementation are 0.338 and 0.392, while the values after implementation are 0.618 and 0.688. The direction of change is therefore invariant across the declared interval. The initial integration and governance scores fail the autonomy gate and jointly define the bottleneck. The method would authorise a pilot in decision-support mode, but not unsupervised price publication. This is the type of managerial information that a fully compensatory technology index cannot provide. Table 4 specifies the reproducibility protocol.

The spreadsheet-equivalent expressions reproduce Equations (1)–(2)

Reproduction requires no fitted coefficients or unavailable microdata. Starting from Table 3, an analyst calculates A with SUMPRODUCT, B with MIN, and DMPMI with Equation (2), retaining full precision until the final report. The exact unrounded values are 0.363959 before implementation and 0.652125 after implementation; both round to the reported three-decimal values. The protocol therefore specifies the evidence, formula version, sensitivity range, gate and rounding rule needed to obtain the same decision.

External evaluation uses official Eurostat enterprise digitalisation statistics. The 2025 e-business release reports ERP, CRM and business intelligence adoption for small and large enterprises [13]. The Digitalisation in Europe publication provides indicators of artificial intelligence adoption, the use of paid cloud services, e-sales and basic digital intensity for small and medium-sized enterprises (SMEs) and large enterprises [12]. The underlying surveys cover enterprises with at least ten employees or self-employed persons in the specified non-financial activities. Because the published size bands are not identical, the observations for the smaller-enterprise groups are explicitly treated as a readiness proxy rather than as a single harmonised size category. The analysis tests whether the readiness construct distinguishes between groups known to differ in digital capacity; it does not combine the aggregates with enterprise-level DMPMI scores.

For group q and indicator j, x_{qj} is the reported percentage share of enterprises in group q for indicator j. The equal-weight Digital Marketing Pricing Readiness Proxy (DMP-RP) is the arithmetic mean of the seven shares. The construct is formative: ERP and cloud services support integration, CRM supports customer observability, BI and AI support inference, e-sales represents digital execution, and basic digital intensity captures the broader enabling environment. These technologies are neither sufficient for pricing maturity nor direct observations of it; they are observable preconditions selected before calculation. Two expectations were specified before calculation: (H1) all seven large-minus-proxy gaps would be positive; and (H2) the group ordering would remain unchanged under indicator deletion and the two alternative weighting schemes. Let R_q denote the DMP-RP value for group q.

Table 3

Reproducible illustrative calculation

Dimension	Weight		Before		After	
Data quality and observability	0.20		0.50		0.75	
Integration and traceability	0.20		0.25		0.75	
Demand and elasticity analytics	0.15		0.50		0.75	
Decision orchestration and latency	0.15		0.50		0.50	
Learning and experimentation	0.15		0.50		0.75	
Governance and safeguards	0.15		0.25		0.75	
Weighted component A	–		0.4125		0.7125	
Bottleneck B	–		0.2500		0.5000	
DMPMI, $\alpha = 0.75$	–		0.364		0.652	

Source: authors' calculation. The values provide a deterministic demonstration of the method and are not observations from a real enterprise. Only the five permitted anchor values are used

Table 4

Reproducibility protocol

Step	Operation	Output and audit rule
1	Freeze scope, date and evidence register	One row per dimension with owner, document link and assessment date
2	Assign anchored scores	Use only 0.00, 0.25, 0.50, 0.75 or 1.00; two assessors resolve any disagreement
3	Calculate A and B	SUMPRODUCT (weights, scores); MIN (scores); retain unrounded values
4	Calculate DMPMI	Use Equation (2) with $\alpha = 0.75$; round only the reported result to three decimals
5	Apply autonomy gate	Data quality, integration and governance scores ≥ 0.50; all hard constraints pass
6	Test sensitivity	Recalculate at $\alpha = 0.75$ and 0.90; explain any change in decision category
7	Version and repeat	Store inputs, formula version and reviewer details; reassess after material process change

Source: developed by the authors

$$R_q = \frac{1}{7}\sum_{j=1}^{7} x_{qj}, n = R_{large} - R_{proxy}. \quad (3)$$

where x_{qj} is the percentage share of enterprises in group q for indicator j; R_q is the DMP-RP value for group q; and n is the difference between the large-enterprise and smaller-enterprise proxy means, expressed in percentage points.

The validation data are reported in Table 5.

Percentages are published as rounded values; pp = percentage points

Figure 2 visualises the contrast by enterprise size reported in Table 5.

The ERP, CRM and BI indicators use values for small enterprises; the remaining smaller-enterprise proxy values refer to SMEs

The observed gaps are positive for all seven indicators, from 25 points for e-sales and basic digital intensity to 58 points for business intelligence. Under a descriptive benchmark that assumes independent, equally probable signs, the two-sided probability of seven concordant signs, all positive or all negative, is $2/2^7 = 0.015625$. Because the indicators are systematically related, this quantity is used only as a directional diagnostic and not for population-level inference. Together with the stable group ordering across the robustness checks, this directional evidence supports the expected known-groups ordering: the proxy assigns higher readiness to the group with consistently higher adoption rates of the required digital capabilities. The difference is also substantively large, since the equal-weight group difference is 37.86 points.

Robustness was assessed without treating the seven indicators as independent random observations. Removing one indicator at a time produces gaps of 36.17, 37.50, 34.50, 38.17, 38.67, 40.00 and 40.00 points in the order shown in Table 5. An integration-intensive weighting scheme (0.18, 0.18, 0.18, 0.16, 0.10, 0.10, 0.10 in the order shown in Table 5) gives 40.34 points. An analytics-intensive scheme (0.10, 0.15, 0.20, 0.20, 0.15, 0.10, 0.10) gives 39.55 points. Hence, the group ordering and interpretation remain unchanged under the two pre-specified alternative weighting schemes. The comparable ERP–CRM–BI core also provides a temporal check: its small-enterprise mean rises from 23.67 in 2023 to 25.67 in 2025, while the large-enterprise mean rises from 70.00 to 74.33. The gap therefore changes from 46.33 to 48.67 points [11; 13].

An arithmetic audit provides a direct reproduction path. The seven gaps sum to 265 percentage points, so the equal-weight difference is 265/7 = 37.857 and rounds to 37.86. Removing the 58-point gap gives the leave-one-out minimum, 207/6 = 34.50; removing either 25-point gap gives the maximum, 240/6 = 40.00. The median gap is 36 points, and direct weighted sums reproduce 40.34 and 39.55. Because each published share is rounded to the nearest percentage point, each group mean can deviate by at most 0.5 point, and the difference between the means can deviate by at most 1.0 point. The resulting worst-case rounding interval, 36.86–38.86 points, remains strictly positive. This bound addresses publication rounding, not sampling uncertainty or the mixed small/SME denominator. Table 6 consolidates the validation and robustness results.

Table 5

External validation dataset, EU enterprises, 2025

Indicator	Smaller-enterprise proxy, %	Large, %	Gap, pp	Published band
ERP	41	89	48	Small/large
CRM	25	65	40	Small/large
Business intelligence	11	69	58	Small/large
Artificial intelligence	19	55	36	SME/large
Paid cloud services	52	85	33	SME/large
E-sales	23	48	25	SME/large
Basic digital intensity	71	96	25	SME/large
Equal-weight mean	34.57	72.43	37.86	Proxy result

Note: The CRM gap equals 40 percentage points when calculated from the displayed rounded shares; Eurostat reports 41 percentage points based on unrounded values. All proxy calculations in this study use the displayed integer shares.

Source: calculated by the authors based on [12; 13]

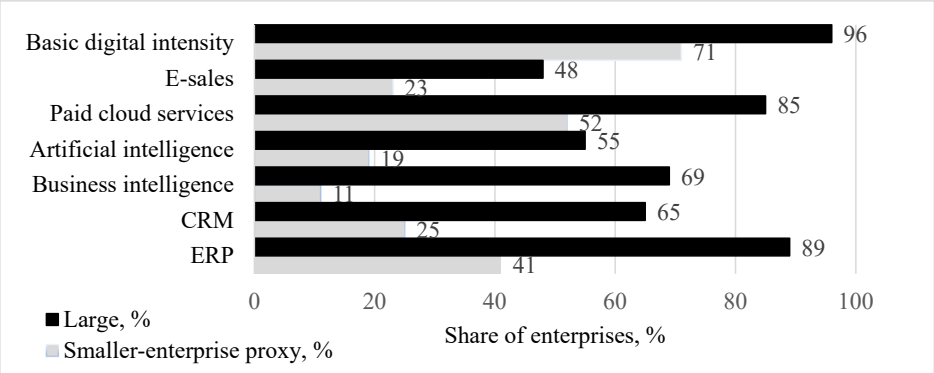


Fig. 2. Observable digital readiness by enterprise size

Source: constructed by the authors based on [12; 13]

Table 6

Validation and robustness results

Test	Result	Interpretation
Equal-weight DMP-RP	34.57 vs 72.43; Δ = 37.86 pp	Large enterprises exhibit higher observable readiness
Directional sign benchmark	7/7 positive; two-sided benchmark probability = 0.0156	Descriptive directional concordance only; no population-level inference
Leave-one-out	Δ range: 34.50–40.00 pp	No single indicator drives the direction or magnitude
Alternative weights	Δ = 39.55 and 40.34 pp	The conclusion remains stable under two pre-specified weighting priorities
Temporal core	46.33 pp (2023); 48.67 pp (2025)	ERP–CRM–BI gap persists and slightly widens
Rounding bound	Δ range: 36.86–38.86 pp	Published rounding cannot reverse the sign or materially alter the magnitude
Inference boundary	Aggregate readiness, not pricing performance	No causal claim about profit or firm-level outcomes is warranted

Source: authors' calculations based on [11–13]

The empirical results support the expected known-groups ordering and the robustness of the readiness construct, not the economic return from a particular pricing algorithm. Aggregate adoption shares cannot reveal data quality, the content of pricing rules, implementation costs or realised margins. They also cannot establish that enterprise size causes maturity. The analysis transparently retains the mixed small/SME denominator rather than attempting statistical harmonisation without microdata. Because the indicators are systematically related and are not independent sampling units, the equal-sign benchmark is interpreted as a compact directional diagnostic, not as a basis for population-level inference. These limitations constrain the scope of the claim but do not undermine the validation objective: a proposed proxy for enabling capabilities should distinguish groups with systematically different digital infrastructures, and it does.

A firm-level validation should therefore proceed prospectively. Enterprises should archive the evidence register, calculate DMPMI before implementation, and compare economic and process outcomes after a staged pilot. At a minimum, the outcomes should include contribution margin, forecast error, price override rate, decision-cycle time, stock-out rate, complaint rate and rollback frequency. A stepped-wedge or matched difference-in-differences design can separate the effect of the new pricing process from common shocks. Pre-registration of the primary outcome, decision rule and exclusion criteria would prevent the maturity score from being tuned retrospectively to a favourable result.

Conclusions. The study's methodological novelty is the integration of a five-layer process architecture, a six-dimensional evidence rubric, a bottleneck-sensitive hybrid index and a binary autonomy gate within one auditable control system. The theoretical contribution is the explicit separation of two decisions: the continuous index supports capability prioritisation, whereas the gate determines whether automated price publication is permissible. This operationalises the weakest-link proposition without allowing strong analytics to conceal poor data quality, weak integration or inadequate safeguards.

The calculation is independently reproducible because the dimensions, weights, score anchors, parameter range, rounding convention and evidence rules are fixed ex ante. In the illustrative scenario based solely on anchored scores, DMPMI increases from 0.364 to 0.652 at $\alpha = 0.75$ and remains directionally stable across $\alpha = 0.60$–0.90. External known-groups validation on official 2025 Eurostat data yields a 37.86-point readiness gap, seven positive component gaps and a descriptive equal-sign benchmark value of 0.0156. Leave-one-out and alternative-weight checks preserve the conclusion; the worst-case interval attributable to publication rounding remains positive at 36.86–38.86 points, and the comparable 2023–2025 core shows a persistent difference by enterprise size.

For managers, the method provides a sequence for investment and control: repair the weakest capability, establish decision ownership and data contracts, begin with supervised recommendations, and expand automation only after monitoring and rollback are operational. For researchers, the method provides a testable link between digital transformation, business process management and pricing analytics. The evidence does not yet support a causal claim about profitability. Future research should examine the inter-rater reliability of the rubric, assess its predictive validity against firm-level outcomes, compare sectors and countries, and evaluate whether the bottleneck parameter should vary by regulatory and market context. A longitudinal multi-enterprise pilot with a pre-registered design is the next stage of validation.

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