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MODERN DATABASE MANAGEMENT SYSTEMS AS A FOUNDATION FOR AI-BASED ANALYTICS IMPLEMENTATION IN SMALL AND MEDIUM-SIZED ENTERPRISES: A LITERATURE REVIEW AND A CONCEPTUAL MODEL

Marcelina Otręba[1*], Danuta Rozpędowska-Matraszek[2]

[1, 2] Stefan Batory Academy of Applied Sciences,
Institute of Information and Technical Sciences, Poland

Abstract: Small and medium-sized enterprises (SMEs) increasingly seek to leverage artificial intelligence (AI) for data-driven decision-making, yet the technical foundation enabling such capabilities – the architecture of the underlying database management system – remains under-explored in the management literature. This article aims to systematise knowledge on the role of database architecture (on-premise, cloud-based, and data warehouse solutions) in enabling AI-based analytics in SMEs, and to propose a conceptual model supporting the architectural choice. A targeted literature review of nine purposively selected sources published between 2019 and 2025, including three PRISMA-based systematic reviews, was conducted across four thematic areas: database and data warehouse impact on performance, cloud computing adoption in SMEs, antecedents of data analytics adoption, and the integration of AI with database architectures, including code-based (Python/SQL) versus low-code approaches. The review reveals that database architecture choice, cloud adoption, and AI analytics implementation are treated as separate research streams, without an integrative decision-support model. A three-layer conceptual model (data architecture, analytical integration, organisational competence) is proposed as a diagnostic tool for SME managers and a starting point for future empirical validation.

Keywords: artificial intelligence, cloud computing, data analytics, database management systems, small and medium-sized enterprises

JEL Classification: L86, M15, O33

[1] Marcelina Otręba, Msc Eng., motreba@ansb.pl, https://orcid.org/0009-0001-6616-2059
[2] Danuta Rozpędowska-Matraszek, PhD, prof. ANSB, dmatraszek@ansb.pl, https://orcid.org/0000-0002-6599-1912
* Corresponding author: Marcelina Otręba, motreba@ansb.pl

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Introduction

The capacity of an organisation to derive value from artificial intelligence (AI) is fundamentally constrained by the quality, structure, and accessibility of the data on which analytical models operate (Maswanganyi et al., 2024). While large enterprises typically dispose of dedicated data engineering teams and mature data governance frameworks, small and medium-sized enterprises (SMEs) face a markedly different reality: limited financial and human resources, fragmented data sources, and, frequently, an absence of formalised database architecture altogether (Salim & Jaffar, 2020). Consequently, before an SME can meaningfully adopt AI-based analytics, it must first resolve a prior, often under-examined question: what database architecture – on-premise, cloud-based, hybrid, relational, or non-relational – will underpin its analytical ambitions.

This architectural decision is far from trivial. It carries direct implications for scalability, cost structure, data security, regulatory compliance, and, critically, for the range of AI and analytics tools that can be subsequently integrated. A recent systematic review has shown that cloud computing adoption alone is associated with measurable improvements in SME operational efficiency and cost structure, yet the same review notes that adoption remains uneven and contingent on organisational readiness (Mkhize et al., 2025). Parallel research on data analytics adoption confirms that technological, organisational, environmental, individual, and data-quality-related factors jointly determine whether an SME successfully progresses from data collection to data-driven decision-making (Husni et al., 2025).

Despite the evident interdependence of these decisions, the literature streams addressing database architecture, cloud adoption, and AI-based analytics in SMEs have developed largely in parallel, with limited cross-referencing. This article addresses that gap by asking: how does database architecture condition the feasibility of AI-based analytics in SMEs, and what factors should guide an SME's choice between code-based (e.g., Python and SQL) and low-code approaches to connecting its data infrastructure with AI analytical tools? The article contributes a conceptual model integrating these previously disconnected decisions into a single, three-layer diagnostic framework, intended to support both future empirical research and practical decision-making by SME managers.

Beyond its technical dimension, the problem addressed here also carries an entrepreneurial and economic-policy relevance. Digital transformation programmes aimed at SMEs frequently promote AI adoption as a generic goal, without addressing the sequential, often invisible infrastructural decisions that determine whether such adoption is feasible at all. A model that makes these decisions explicit may therefore be of interest not only to individual SME managers but also to institutions designing digital-economy support schemes, business incubators, and entrepreneurship education programmes, for which database literacy is rarely treated as a distinct competence area.

The remainder of the article is structured as follows. Section 2 presents the literature review structured around the four thematic areas defined in the search strategy, with database architecture further differentiated into relational and non-relational

database models. Section 3 describes the research methodology applied, including a discussion of the scale of the underlying evidence base. Section 4 presents the results, including the proposed conceptual model, a comparative synthesis table, and a discussion of its implications for SMEs of different sizes. Section 5 concludes with theoretical and practical implications, limitations, and directions for further research.

Literature review

Database and data warehouse architecture and organisational performance

A systematic review dedicated to the impact of database and data warehouse technologies on organisational performance (Maswanganyi et al., 2024) synthesises evidence indicating that the deployment of structured data warehousing capabilities materially enhances the quality and speed of business decision-making. The review cites, among others, evidence on the role of data warehousing in improving decision-making processes in developing economies, as well as on the adoption of hybrid, cloud-based data warehouse solutions as a source of competitive advantage in start-up organisations. Importantly, the review emphasises that the performance benefits of advanced data architecture are conditional: they materialise only where organisational data maturity is sufficient to exploit the technical capability, a finding directly relevant to resource-constrained SMEs.

This conditionality is consistent with a broader body of information systems research suggesting that technology adoption alone is an insufficient predictor of organisational benefit; the interaction between technical capability and organisational absorptive capacity is decisive (Salim & Jaffar, 2020). For SMEs specifically, this implies that decisions about database architecture cannot be evaluated purely on technical merit but must be assessed jointly with the organisation's existing data competences.

Relational and non-relational database models in the SME context

A further architectural dimension relevant to SMEs, though rarely addressed jointly with performance outcomes, is the choice between relational (SQL) and non-relational (NoSQL) database models. Relational databases, structured around normalised tables and enforced schemas, offer strong consistency guarantees and are well suited to transactional business data such as sales records, inventory, or customer relationship data, and they integrate naturally with the SQL-based analytical tooling most widely taught and used in business analytics. Non-relational databases, by contrast, offer schema flexibility and horizontal scalability advantageous for semi-structured or rapidly evolving data sources, such as web log data, sensor streams, or unstructured text, at the cost of weaker consistency guarantees and, typically, a steeper learning curve for teams accustomed to spreadsheet- or SQL-based reasoning (Moniruzzaman & Hossain, 2013).

For most SMEs, whose core operational data remains predominantly transactional and tabular in nature, a relational architecture represents the more accessible default, particularly where existing staff already possess spreadsheet or basic SQL competence (Manning, 2015). Non-relational or hybrid architectures become more relevant where an SME's AI ambitions extend to less structured data sources; however, this generally presupposes a higher baseline of technical competence than a purely relational, SQL-centred approach. This distinction is incorporated into the data architecture layer of the conceptual model presented in Section 4.

Cloud computing and cloud-based databases in SMEs

The most methodologically rigorous evidence available on cloud adoption in SMEs comes from a PRISMA-based systematic review (Mkhize et al., 2025), which screened 18,570 records identified across major databases for the period 2014-2024, narrowing the sample through successive stages of deduplication and abstract screening to a final set of 90 studies meeting the inclusion criteria. This scale of reduction – illustrated in Figure 1 – is itself informative: it demonstrates both the breadth of scholarly interest in the topic and the relative scarcity of methodologically robust, SME-specific empirical studies once rigorous inclusion criteria are applied. The review's substantive findings indicate that cloud adoption improves SME operational processes, reduces fixed infrastructure costs, and increases scalability, with relative advantage of the technology, service quality, and top management support emerging as the most consistently reported success factors.

Complementary evidence from a review of cloud-based Enterprise Resource Planning (ERP) systems in SMEs (Salim & Jaffar, 2020) reinforces these findings, identifying similar determinants of successful adoption and noting that SMEs frequently lack the internal IT capacity to manage on-premise infrastructure, making cloud-based database-as-a-service (DBaaS) offerings a pragmatic default rather than merely a cost-driven preference.

Antecedents of data analytics adoption in organisations

A systematic review of the antecedents of data analytics adoption (Husni et al., 2025), based on the PRISMA protocol and encompassing 43 studies selected from an initial pool of 127 screened publications spanning 2018-2024, identifies five interrelated dimensions shaping adoption: technological, organisational, environmental, individual, and data-quality-related factors. The review notes the continued dominance of the Technology-Organization-Environment (TOE) framework in organisational-level analyses, and highlights that data quality – frequently a direct consequence of underlying database architecture – functions as both a direct adoption antecedent and a moderator of the effectiveness of other factors. Practical methodologies exist to make such data-quality assessment tractable for resource-constrained SMEs, using simplified, generic assessment criteria rather than the complex, resource-intensive approaches typically applied in larger organisations (Günther et al., 2019).

A related systematic review on the impact of big data on SME performance similarly confirms that analytics adoption is associated with improved operational efficiency and revenue growth, while identifying infrastructure quality – encompassing storage, integration, and data governance capacity – as a persistent barrier specific to smaller organisations (Kgakatsi et al., 2024).

Integrating AI with database architecture: Code-based and low-code approaches

A bibliometric and systematic review of AI adoption in SMEs (Yesuf & Fields, 2025), covering the period 2020-2024, identifies three dominant research streams: AI-driven innovation (including machine learning and predictive analytics built upon existing data infrastructure), support for entrepreneurial decision-making, and barriers and enablers of adoption. Relatedly, Ragazou, Passas, Garefalakis, and Zopounidis (2023) propose a business intelligence model explicitly designed to help SMEs make better decisions by integrating existing databases with analytical tools, underscoring the practical importance of database-analytics integration as a distinct design problem rather than a mere implementation detail.

None of the reviewed sources, however, directly addresses the choice between a code-based approach – for instance, Python scripts issuing SQL queries directly against a relational or cloud database – and low-code or no-code tools that connect to databases via pre-built connectors. This omission is notable given that the two approaches carry markedly different implications for flexibility, auditability, and long-term maintainability, and given that many SMEs already possess partial in-house competence (e.g., a single data-literate employee proficient in SQL) that neither purely technical adoption studies nor purely organisational barrier studies adequately account for.

Synthesis and research gap

The reviewed literature converges on four streams that, while individually well-developed, remain largely disconnected: (1) the performance implications of database and data warehouse architecture, including the relational/non-relational distinction, (2) the organisational and technological antecedents of cloud and analytics adoption, (3) the drivers of data analytics adoption more broadly, and (4) the emerging integration of AI with existing data infrastructure, whether through code-based or low-code means. Within the nine-source analytical corpus reviewed here, no reviewed source proposes a model that jointly addresses the sequential decisions an SME must make: which database architecture to adopt, how to connect that architecture to AI analytical capability, and what organisational competences are required to sustain the resulting system. This gap constitutes the point of departure for the conceptual model presented in Section 4.

Research methodology

The purpose of this study is to systematise knowledge on the role of database architecture (on-premise, cloud-based, and data warehouse solutions) in enabling AI-based analytics in small and medium-sized enterprises, and to propose a conceptual

model supporting the architectural choice – consistent with the aim stated in the Introduction and Abstract. This article adopts a targeted literature review methodology, informed by the general logic of the systematic literature review approach (Tranfield et al., 2003), though it does not itself constitute a full, independently executed PRISMA-compliant review. The Scopus and Web of Science databases were searched across four thematic areas corresponding to the subsections of Section 2: (1) database and data warehouse impact on organisational performance, (2) cloud computing and cloud database adoption in SMEs, (3) antecedents of data analytics and big data adoption, and (4) integration of AI with database architecture, including code-based and low-code approaches.

Search terms combined, using Boolean operators, keywords from each thematic area with organisational and SME-related qualifiers. Following an initial pilot search, the SME-related qualifier and the database/data-architecture qualifier were each expanded to their most frequently occurring synonyms and morphological variants, in order to avoid prematurely narrowing recall; the four full search strings applied to both Scopus and Web of Science were: (1) ("database" OR "data warehouse" OR "database architecture" OR "data architecture" OR "relational database" OR "non-relational database" OR "NoSQL" OR "DBaaS" OR "data infrastructure") AND ("performance" OR "organisational" OR "organizational"); (2) ("cloud computing" OR "cloud database" OR "cloud-based database" OR "DBaaS") AND ("SME" OR "SMEs" OR "small and medium enterprise" OR "small and medium-sized enterprise" OR "small and medium enterprises" OR "small and medium-sized enterprises" OR "small business" OR "small businesses" OR "medium-sized enterprise"); (3) ("data analytics" OR "big data") AND ("adoption" OR "antecedents") AND ("SME" OR "SMEs" OR "small and medium-sized enterprises" OR "small business"); and (4) ("artificial intelligence" OR "machine learning") AND ("low-code" OR "no-code" OR "Python" OR "SQL") AND ("database" OR "data architecture" OR "data infrastructure"). Relative to the pilot version, string (4) was additionally constrained with a database/data-infrastructure qualifier, since "Python" and "SQL" alone returned a large proportion of records unrelated to data architecture; this constraint is reported here as it materially affects the composition of the identified evidence base. The searches were restricted to peer-reviewed journal articles and conference proceedings in English, published between 2018 and 2025. The initial searches across both databases were conducted during the first week of July 2026 (1-7 July 2026); a final verification search, to confirm currency of the retrieved records, was carried out during the last week of July 2026 (27-31 July 2026).

The database searches were used to identify broader bodies of literature corresponding to the four thematic areas defined for the review. Because the study was designed as a targeted literature review rather than an exhaustive systematic review, the search process was intended to establish a relevant evidence base for conceptual synthesis rather than to produce a complete census of all publications or an independently documented PRISMA screening flow. From the literature identified within these thematic bodies, nine sources published between 2019 and 2025 were purposively selected for the final analytical corpus. Selection was guided by four criteria: direct relevance to the research question and to at least one of the four thematic

areas; relevance to an organisational or SME context; sufficient methodological transparency to permit critical appraisal; and substantive usefulness for integrating evidence on database architecture, cloud infrastructure, data analytics, and AI adoption. Particular weight was given to systematic reviews capable of representing a broader underlying evidence base. Accordingly, the final set of nine sources should not be interpreted as the total number of publications identified by the database searches, but as a deliberately selected analytical corpus appropriate to the conceptual and synthesis-oriented purpose of the study. Three of the included sources are systematic reviews conducted using PRISMA-based procedures and therefore synthesise substantially larger bodies of primary research. The nine-source analytical corpus was constructed to ensure coverage of all four predefined thematic areas rather than to represent the entire volume of literature retrieved from the databases.

This approach carries an important methodological limitation, made explicit here rather than left implicit: the review is targeted rather than exhaustive and does not constitute an independently executed PRISMA-compliant systematic review. Consequently, the present study does not report a complete PRISMA flow diagram or inter-rater reliability assessment for its own selection process. Instead, it uses transparent thematic search strings and purposive selection criteria to construct an analytical corpus, while drawing on and critically synthesising findings from prior systematic reviews that applied formal PRISMA procedures. This scope is consistent with the conceptual, synthesis-oriented objective of the article, but it also limits claims of exhaustiveness. A fully systematic review with independently documented screening and selection procedures is therefore identified in Section 5 as a direction for future research.

Scale of the underlying evidence base

Before presenting the conceptual model, it is useful to illustrate the scale of literature reduction characteristic of the most rigorous systematic review cited in this article. Figure 1 presents the screening funnel reported by the PRISMA-based review of cloud computing's impact on SME performance (Mkhize et al., 2025): from 18,570 initially identified records to 90 studies meeting full inclusion criteria, a reduction of over 99.5%. This illustrates both the breadth of scholarly attention the topic has received and the comparative scarcity of methodologically robust, SME-specific empirical evidence once rigorous screening is applied – a pattern consistent with the relatively young and fragmented state of the broader research area addressed in this article.

A comparable pattern of reduction is reported by the systematic review of data analytics adoption antecedents, which narrowed an initial pool of 127 screened publications to 43 included studies (Husni et al., 2025). Taken together, the two reviews suggest that although the surrounding topics – cloud computing and data analytics adoption – attract substantial general scholarly interest, the subset of studies applying rigorous empirical methods specifically to SME contexts remains comparatively small, reinforcing the case for the targeted, synthesis-oriented approach adopted in this article rather than an attempt at further primary empirical replication.

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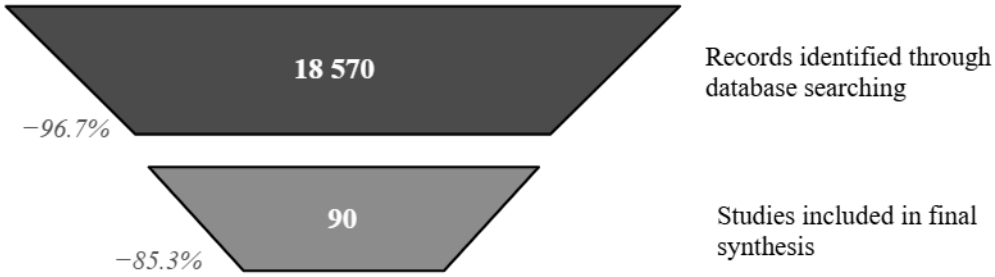


Figure 1. PRISMA screening funnel of the systematic review on cloud computing and SME performance, with stage-to-stage reduction rates

Source: Own elaboration based on (Mkhize et al., 2025)

Results

Synthesis of reviewed sources

Table 1 synthesises the method, sample, and key finding of each reviewed source relevant to the conceptual model, making explicit the evidentiary basis for each element of the model presented in Section 4.

Table 1. Synthesis of reviewed sources

Source	Method	Sample	Thematic area	Model component supported	Key finding relevant to the model
Husni, Madurapperu, & Thilini Sumudu Kumari (2025)	SLR, PRISMA	N = 43 (of 127)	(3) Antecedents of data analytics adoption	Organisational competence layer	Five adoption dimensions identified (TOE framework dominant); data quality is both antecedent and moderator.
Impact of Big Data on SME Performance (2024)	SLR	n/a	(3) Antecedents of data analytics / big data adoption	Organisational competence layer	Infrastructure quality is a persistent barrier specific to smaller organisations.
AI Adoption in SMEs (2025)	Bibliometric + SLR	2020-2024	(4) Integration of AI with database architecture	Analytical integration layer	Three research streams identified; code- vs. low-code integration remains unaddressed.
Ragazou et al. (2023)	Conceptual model	n/a	(4) Integration of AI with database architecture	Analytical integration layer	Proposes BI model integrating existing databases with analytics tools for SME decision-making.

Source	Method	Sample	Thematic area	Model component supported	Key finding relevant to the model
Maswanganyi et al. (2024)	SLR	n/a	(1) Database/ data warehouse impact on performance	Data architecture layer	Structured data warehousing improves decision-making quality and speed; performance benefits are conditional on organisational data maturity.
Mkhize et al. (2025)	SLR, PRISMA	N = 90 (of 18,570)	(2) Cloud computing adoption in SMEs	Data architecture layer	Cloud adoption improves operational efficiency, reduces costs, and increases scalability; relative advantage, service quality, and top management support are key success factors.
Salim & Jaffar (2020)	Review	n/a	(2) Cloud computing adoption in SMEs	Data architecture layer	SMEs frequently lack internal IT capacity for on-premise infrastructure; cloud-based DBaaS is a pragmatic default rather than a purely cost-driven preference.
Ajimati, Carroll, & Maher (2025)	SLR	N = 40	(4) Integration of AI with database architecture	Analytical integration layer	Reviews low-code/ no-code and citizen-development adoption; proposes a framework for LCNC/CD adoption and identifies a future research agenda.

Source: Own elaboration

A conceptual model for database architecture choice supporting AI analytics in SMEs

Building on the synthesis above, this article proposes a three-layer conceptual model supporting SME decisions on database architecture, analytical integration, and organisational competence (Table 2). The model's central premise is sequential dependency: the choice of data architecture precedes and conditions the choice of analytical integration method, and both should be evaluated against actual, rather than aspirational, organisational competence.

Table 2. Three-layer conceptual model for database architecture choice in SMEs

Model layer	Characteristics	Diagnostic question
Data architecture layer	Choice between on-premise vs. cloud (DBaaS) database, relational vs. non-relational model, simple storage vs. data warehouse.	What data volume and structure does the organisation generate, and what scalability does this require?
Analytical integration layer	Method of connecting the database to the AI analytical layer: code-based (Python scripts, SQL queries) vs. low-code tools with pre-built connectors.	What level of flexibility, control, and customisation does the analytical task require?
Organisational competence layer	Team competences in database management and programming (TOE framework); management support for data infrastructure investment.	Can the organisation independently maintain the chosen architecture, or does it require external vendor support?

Source: Own elaboration based on the literature review presented in Section 2

An SME possessing internal SQL and Python competence may rationally opt for a relational database architecture with direct, code-based analytical integration, retaining full control and auditability over its analytical pipeline. Conversely, an organisation with limited internal technical competence may more effectively pursue a cloud-based DBaaS solution paired with a low-code analytical tool offering pre-built AI connectors, trading a degree of customisation for reduced maintenance burden. The model does not privilege either path a priori; rather, it structures the decision as a function of the three layers' mutual consistency.

Implications for SMEs of different sizes and digital maturity levels

The three-layer model is not intended to prescribe a single optimal configuration but rather to be applied differently depending on enterprise size and digital maturity. Micro-enterprises, typically operating with fewer than ten employees and no dedicated IT function, are likely to find the organisational competence layer the binding constraint: for such organisations, cloud-based DBaaS solutions paired with low-code or no-code analytical connectors may generally be expected to dominate as a conceptual proposition requiring empirical validation, since the alternative – maintaining even a modest on-premise, code-based pipeline – is rarely sustainable without external support.

Small enterprises with an emerging, though not fully dedicated, technical function (for example, a single employee with SQL or Python competence, as is common in organisations where such expertise is developed informally rather than through a formal IT department) occupy an intermediate position. For these organisations, the model suggests a hybrid configuration: a relational cloud database administered

with a mix of code-based scripts for recurring analytical tasks and low-code tools for ad hoc exploration by non-technical staff, consistent with the citizen-development pattern documented in the low-code/no-code literature (Ajimati et al., 2025).

Medium-sized enterprises approaching the upper size threshold, and possessing a small but dedicated data or IT team, may be relatively well positioned to benefit from a fully code-based analytical integration layer, as a conceptual proposition requiring empirical validation, provided that the underlying data architecture has reached sufficient maturity (structured schemas, documented data lineage, and consistent data quality controls). For this group, the model's main diagnostic value lies less in determining feasibility and more in avoiding premature or unnecessary adoption of low-code tools that may constrain future customisation once in-house competence exists to justify a fully code-based approach.

This size-contingent reading of the model also offers a preliminary answer to a question left open by the reviewed adoption literature, namely why studies applying the Technology-Organization-Environment framework to SMEs (Husni et al., 2025) report inconsistent effects of organisational readiness across studies: such inconsistency may partly reflect the fact that "SME" is treated as a homogeneous category in much of the existing literature, when in practice micro, small, and medium enterprises face qualitatively different constraints along the three layers proposed here.

Conclusions

This article set out to systematise the literature on the role of database architecture in enabling AI-based analytics in SMEs and to propose a conceptual model addressing an identified gap: the absence of an integrative framework linking database architecture, analytical integration method, and organisational competence. Three main conclusions follow from the review. First, database architecture constitutes a necessary, though not sufficient, condition for effective AI analytics adoption in SMEs; the availability of advanced analytical tools does not compensate for deficiencies in underlying data quality and structure. Second, the literature streams addressing database architecture, cloud adoption, and AI analytics implementation have developed largely independently, despite representing, in practice, an interdependent sequence of decisions facing the same organisation. Third, the proposed three-layer conceptual model offers a diagnostic tool of potential use both to researchers studying SME digital maturity and to practitioners planning data infrastructure investments.

From a practical standpoint, the model suggests that SME managers should address three questions before investing in AI analytics capability: what architecture matches the actual structure and scale of the organisation's data; whether a code-based or low-code integration method better matches the team's existing competences; and whether the organisation can sustain the chosen architecture independently or requires external vendor support. These questions offer a structured starting point that is currently absent from the reviewed literature.

The size-contingent implications discussed in Section 4.4 further suggest that policy instruments supporting SME digitalisation – for example, digital voucher schemes, incubator programmes, or entrepreneurship curricula – could usefully differentiate their guidance by enterprise size rather than treating SMEs as a homogeneous target group. For micro-enterprises, support might most effectively focus on subsidising cloud DBaaS and low-code AI tooling; for medium-sized enterprises with emergent in-house competence, support might instead focus on training in database design and code-based analytical integration, so as to avoid locking growing organisations into tooling that constrains their longer-term analytical flexibility.

This study is subject to limitations that should guide future research. The review is targeted rather than fully systematic in its own right, drawing on previous systematic reviews rather than applying an independently documented PRISMA protocol with a complete flow chart for this study. The proposed conceptual model has not yet been empirically validated. Future research should therefore pursue two directions: conducting a fully systematic literature review employing an independently documented PRISMA protocol, and empirically testing the proposed model through case studies of SMEs with varying database architectures and levels of technical competence, ideally employing a mixed-methods design combining qualitative interviews with quantitative assessment of analytical outcomes.

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NOWOCZESNE SYSTEMY ZARZĄDZANIA BAZAMI DANYCH JAKO FUNDAMENT WDROŻEŃ ANALITYKI OPARTEJ NA SZTUCZNEJ INTELIGENCJI W MAŁYCH I ŚREDNICH PRZEDSIĘBIORSTWACH: PRZEGLĄD LITERATURY I MODEL KONCEPCYJNY

Streszczenie: Małe i średnie przedsiębiorstwa (MŚP) coraz częściej dążą do wykorzystania sztucznej inteligencji (AI) w podejmowaniu decyzji opartych na danych, jednak techniczny fundament tych zdolności – architektura systemu zarządzania bazą danych – pozostaje słabo zbadany w literaturze z zakresu zarządzania. Celem artykułu jest usystematyzowanie wiedzy na temat roli architektury baz danych (lokalnych, chmurowych i hurtowni danych) w budowie zdolności analitycznych opartych na AI w MŚP oraz zaproponowanie modelu koncepcyjnego wspierającego wybór tej architektury. Przeprowadzono ukierunkowany przegląd literatury obejmujący dziewięć źródeł z lat 2019-2025, w tym trzy przeglądy systematyczne oparte na protokole PRISMA. Wyniki wskazują, że wybór architektury bazy danych, adopcja chmury i wdrożenie analityki AI są traktowane jako odrębne nurty badawcze, bez modelu integrującego. Zaproponowano trójwarstwowy model koncepcyjny (architektura danych, integracja analityczna, kompetencje organizacyjne) jako narzędzie diagnostyczne dla menedżerów MŚP i punkt wyjścia do dalszej walidacji empirycznej.

Słowa kluczowe: bazy danych, chmura obliczeniowa, analityka danych, małe i średnie przedsiębiorstwa, sztuczna inteligencja

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