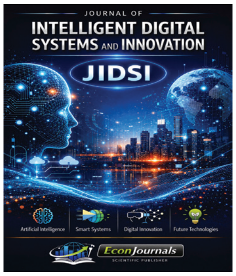

Journal of Intelligent Digital Systems and Innovation

available at http: www.econjournals.com

Journal of Intelligent Digital Systems and Innovation, 2025, 1(2), 1-16.

An MCDA-based Framework for Prioritizing Digital Transformation Projects in Small and Medium-sized Enterprises

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Received: 19 September 2025 **Accepted:** 28 November 2025 **DOI:** https://doi.org/10.32479/jidsi.23950

ABSTRACT

There is increasing pressure on small and medium-sized enterprises (SMEs) to force digital technologies to maintain their competitiveness, viability, and agility amid dynamic market conditions. Yet, there are difficulties associated with selecting priorities among potential digital transformation projects due to constraints like budget restrictions, technological uncertainty, organizational limitations, and numerous strategic and operational considerations that have to be weighed against each other. In this regard, this research seeks to provide an MCDA approach that can be leveraged by SMEs in evaluating and prioritizing digital transformation efforts. The MCDA framework suggested by this paper involves structured criteria related to strategic alignment, project cost, anticipated impact on operations, technological feasibility, cybersecurity risk, organizational readiness, and speed of deployment. The MCDA model provided in this study offers a structured means of making informed decisions, combining criteria weighting and alternative ranking. This methodology seeks to improve the subjectivity of the selection process, align digital investments more closely with business objectives, and improve decision-making when constraints are involved. The research is useful in terms of contributing to existing methodologies, but what makes it more important is the contribution it offers to SMEs from various industries through a helpful tool that will allow them to develop plans related to their digital initiatives. This model helps increase the convergence between multiple criteria aiding decision-making, digital transformation, and intelligent management systems.

Keywords: Multicriteria Decision-Aiding, Digital Transformation, Project Prioritization, Decision Support Systems
JEL Classifications: M15, O32, O33, C44

1. INTRODUCTION

Digital transformation has become a central strategic concern for contemporary organizations because it is not limited to the adoption of new technologies, but involves broader changes in value creation, organizational structures, processes, and capabilities. In the literature, digital transformation is commonly understood as a process through which organizations respond to environmental and competitive pressures by leveraging digital technologies to alter how they operate and create value (Vial, 2019). This view is reinforced by multidisciplinary research showing that digital transformation has implications not only for operations and business models, but also for organizational design, managerial priorities, and performance measurement (Verhoef et al., 2021). Consequently, digital transformation should be approached as an organizational and strategic problem rather than a purely technical one. For small and medium-sized enterprises, the challenge is especially acute. Although SMEs increasingly recognize the importance of digital transformation, they often face more severe constraints than large firms in terms of financial slack, managerial expertise, technological capabilities, and organizational readiness. Recent empirical and review-based studies indicate that many SMEs struggle to progress successfully in their digital transformation journeys, and that factors such as managerial education, international orientation, firm size, digital readiness, and continuous learning materially shape their ability to adopt and implement digital initiatives effectively (Clemente-Almendros et al., 2024; Navarro et al., 2023; Pingali et al., 2023; Sagala and Őri, 2024). The SME context therefore requires decision frameworks that are sensitive to resource limitations, heterogeneity among firms, and the need for gradual capability development.

These conditions make the prioritization of digital transformation projects a particularly difficult decision problem. In practice, SMEs rarely have the capacity to invest in all possible digital initiatives at the same time; instead, they must determine which projects should be implemented first, which should be delayed, and which should be rejected. Such decisions are inherently multi-dimensional. A proposed initiative may appear attractive in terms of expected operational impact, yet perform poorly in implementation cost, technological feasibility, organizational readiness, or time to deployment. Moreover, the growing digitalization of processes and infrastructures also increases exposure to cyber risks, making cybersecurity a relevant consideration in project selection rather than a secondary afterthought (Rawindaran et al., 2025; Solares et al., 2022). The problem is therefore not simply to identify the most profitable project, but to balance multiple and often conflicting criteria in a transparent and defensible way.

This type of problem falls naturally within the domain of multicriteria decision-aiding (MCDA). MCDA has developed precisely to support decision makers confronted with alternatives that must be evaluated against several conflicting criteria, and it provides structured procedures for ranking, classifying, or selecting actions in a way that is consistent with stated preferences (Belton and Stewart, 2002; Greco et al., 2025; Roy, 1996; Solares et al., 2022). Rather than collapsing a complex decision into a single financial indicator, MCDA makes the logic of evaluation explicit by clarifying criteria, eliciting preferences, and generating recommendations that are traceable and open to sensitivity analysis. This makes MCDA especially appropriate for digital transformation decisions, where both quantitative and qualitative considerations must be integrated and where managerial legitimacy often depends on the transparency of the selection process. The relevance of MCDA is further supported by the project portfolio selection literature. Reviews of this field show that project portfolio selection frequently involves multiple attributes, decision-maker preferences, and resource constraints, making MCDA a suitable and increasingly used family of approaches for supporting such decisions (Kandakoglu et al., 2024). However, despite the expanding literature on SME digitalization, existing studies have concentrated mainly on adoption determinants, success factors, readiness constructs, and broad transformation trajectories rather than on operational decision frameworks for prioritizing competing digital transformation projects under SME-specific constraints (Clemente-Almendros et al., 2024; Pingali et al., 2023; Sagala and Őri, 2024). This leaves an important gap between what the digital transformation literature explains and what SME managers actually need when choosing among competing initiatives with limited resources. In response to this gap, the present study proposes an MCDA-based framework for prioritizing digital transformation projects in SMEs. The framework is intended to support the evaluation of alternative initiatives through criteria such as strategic alignment, implementation cost, expected operational impact, technological feasibility, cybersecurity risk, organizational readiness, and time to deployment. By structuring the decision process around explicit criteria and preference-based evaluation, the study seeks to contribute in two ways. First, it extends the literature on SME digital transformation by translating broad success factors into an actionable prioritization model. Second, it contributes to decision-aiding practice by offering a transparent and adaptable framework that can help SME managers sequence digital investments in a more consistent and strategically aligned manner.

The remainder of this paper is organized as follows. Section 2 reviews the literature on digital transformation in SMEs, project prioritization, and multicriteria decision-aiding. Section 3 presents the materials and methods, including the identification and validation of evaluation criteria, the AHP weighting procedure, and the TOPSIS-based ranking approach. Section 4 reports the results of the empirical application, including the criteria weights, project evaluation, and prioritization outcomes. Finally, Section 5 concludes the paper by summarizing the main findings, contributions, practical implications, limitations, and directions for future research.

2. LITERATURE REVIEW

2.1. Digital Transformation in SMEs

Digital transformation is generally understood as a process through which firms use digital technologies to alter their operations, value creation logic, and organizational arrangements rather than merely digitizing isolated tasks or adopting standalone tools (Leeflang et al., 2014; Vial, 2019). In the SME context, this distinction is especially important because transformation usually unfolds incrementally and under severe resource constraints. Recent review evidence shows that SME digital transformation is shaped by strategic, organizational, and capability-related factors, and that many SMEs fail not because digital technologies are unavailable, but because they lack the strategic and practical knowledge needed to exploit them effectively (Sagala and Őri, 2024). These findings position SME digital transformation as an organizational change problem rather than a purely technological one.

Recent empirical work also suggests that SMEs do not transform under the same conditions as larger firms. For example, evidence from case-based research indicates that employee capabilities and digital know-how play a dual role: they enable digital transformation, but skill gaps, resistance to change, and reliance on legacy systems can also constrain progress (Fernández et al., 2025; Seppänen et al., 2025). Similarly, research on Spanish SMEs shows that managerial education, international orientation, and firm size positively influence digital adoption, indicating that transformation outcomes are affected by internal heterogeneity even within the SME category (Clemente-Almendros et al., 2024). Together, these studies suggest that any practical framework for SME digital transformation must be sensitive to uneven capabilities, limited managerial bandwidth, and differing readiness conditions across firms.

The literature further indicates that digital transformation in SMEs should be analyzed in relation to value creation and competitiveness. This is because digitalization may improve communication, flexibility, and performance, but those gains are not automatic and depend on the firm's ability to embed digital initiatives into processes, routines, and strategic objectives (Díaz et al., 2022; Leeflang et al., 2014; Moreira et al., 2025). In that sense, the central managerial challenge is not whether digital transformation matters, but how to select and sequence initiatives that are most likely to generate value under SME constraints.

2.2. Digital Transformation Projects as a Prioritization Problem

Although the digital transformation literature has become richer in its treatment of enablers, barriers, and performance implications, it is less specific about how organizations should prioritize competing digital initiatives. In practice, digital transformation is rarely implemented through a single intervention. Instead, firms usually face a portfolio of possible projects, such as process automation, customer relationship platforms, business intelligence tools, cybersecurity upgrades, or IoT-based monitoring systems. Because these projects compete for scarce financial, human, and managerial resources, selection cannot be reduced to a simple financial appraisal. As (Gertzen et al., 2022) show, digital transformation projects are evaluated using a combination of financial and non-financial criteria, especially those related to customer experience, operational efficiency, business culture, and traditional project evaluation. This implies that project value is multidimensional and not adequately captured by narrow cost-benefit analysis alone.

The problem becomes even more complex in SMEs because the initiation phase of digital projects is often underdeveloped. (Hermann et al., 2024) argue that SMEs frequently encounter difficulties in defining and initiating digital innovation projects, which can lead them to pursue initiatives with limited value or poor strategic fit. Their taxonomy is important because it demonstrates that digital innovation projects in SMEs vary in purpose, structure, and support configuration, especially when external digital innovation units are involved. This reinforces the need for formal project characterization and prioritization before implementation decisions are made.

This line of reasoning is consistent with the broader project portfolio selection literature. Project portfolio selection problems almost always involve multiple attributes, conflicting objectives, and decision-maker preferences, which makes them suitable for multicriteria approaches rather than single-criterion optimization (Kandakoglu et al., 2024). For SME digital transformation, this means that prioritization should explicitly incorporate strategic alignment, implementation feasibility, risk, timing, and expected impact instead of relying on intuition or ad hoc managerial judgment.

2.3. MCDA as a Theoretical and Methodological Foundation

Multicriteria decision-aiding is particularly well suited to digital transformation project prioritization because it was developed for decision problems in which several alternatives must be assessed against multiple, often conflicting criteria (Belton and Stewart, 2002; Roy, 1996). Recent synthesis work in the field reiterates that MCDA provides structured and traceable procedures for identifying alternatives, defining evaluation criteria, eliciting preferences, and generating recommendations consistent with the decision context (Greco et al., 2025). This is a strong fit for SME digital transformation, where decision-makers must often combine quantitative information, qualitative judgments, and strategic preferences in order to choose among competing initiatives.

The project portfolio selection literature supports this fit. (Kandakoglu et al., 2024) show that MCDA methods have become increasingly relevant in project portfolio selection precisely because they can accommodate multiple attributes and explicit stakeholder preferences. In digital transformation settings, this matters because projects differ not only in economic return, but also in implementation complexity, organizational readiness requirements, and risk exposure. MCDA allows these heterogeneous dimensions to be evaluated within a coherent analytical structure.

Another advantage of MCDA is its flexibility in method selection. AHP is commonly used for structuring criteria and eliciting weights, while TOPSIS, VIKOR, PROMETHEE, and related methods are often applied to rank alternatives once criteria weights are known. This modularity is useful in digital transformation because organizations may want a transparent weighting stage followed by a separate prioritization stage. Recent applications confirm the practicality of this logic. (Fernández et al., 2023), for example, propose a combined framework for process-based digitalization opportunity and priority assessment, showing how multicriteria methods can be used to rank digitalization opportunities under uncertainty. Likewise, (Costa et al., 2023) demonstrate that combining AHP and TOPSIS can support the selection of processes for automation in a real organizational setting. These studies are not identical to SME digital transformation portfolio prioritization, but they show that digitalization choices can be operationalized effectively as multicriteria ranking problems.

2.4. Emerging Decision-Support Approaches and Remaining Gap

The recent evolution of MCDA also points toward more collaborative and system-oriented decision support. (Saoud et al.,

2025) present a collaborative platform integrating conventional and fuzzy AHP-TOPSIS procedures, illustrating how group-based multicriteria decision processes can be operationalized in accessible decision-support environments. This is relevant for SME digital transformation because project prioritization is rarely the responsibility of a single actor; it often involves owners, managers, process specialists, and external advisors. As (Roy, 1996) noted, decision-aiding frequently involves multiple stakeholders rather than a single fully informed decision-maker, which strengthens the case for transparent and participatory methods in this domain.

Even so, an important gap remains in the literature. On one side, SME digital transformation research has become increasingly sophisticated in identifying success factors, determinants, and capability constraints (Sagala and Őri, 2024; Seppänen et al., 2025). On the other side, project selection and MCDA studies provide strong methodological tools for evaluating alternatives (Costa et al., 2023; Kandakoglu et al., 2024). What is still less developed is an integrated framework that translates SME digital transformation knowledge into a project prioritization model tailored to the realities of resource-constrained firms. In particular, the literature still offers limited guidance on how SMEs should rank competing digital transformation projects using a balanced set of strategic, operational, organizational, and risk-related criteria. The present study addresses that gap by proposing an MCDA-based framework specifically for prioritizing digital transformation projects in SMEs.

3. MATERIALS AND METHODS

3.1. Research Design

This work adopts a design science research orientation because its main objective is to develop and evaluate a practical decision-support artifact: an MCDA-based framework for prioritizing digital transformation projects in SMEs. Design science research is appropriate when the aim is not only to explain a phenomenon, but also to create an artifact capable of solving a relevant organizational problem through a structured development and evaluation process (Peffers et al., 2007). This logic is especially suitable for digital transformation research because firms often need actionable methods that can be implemented in real decision settings rather than purely descriptive models.

Following this approach, the work is organized into four stages. First, an initial set of evaluation criteria is identified from the literature on SME digital transformation, digital innovation projects, and project prioritization (Hermann et al., 2024; Sagala and Őri, 2024). Second, these criteria are refined and validated through expert elicitation using a modified Delphi procedure (Dalkey and Helmer, 1963; Okoli and Pawlowski, 2004). Third, the relative importance of the validated criteria is estimated through the Analytic Hierarchy Process (AHP), which is appropriate for weighting both tangible and intangible criteria (Saaty, 1980, 2008). Fourth, the candidate digital transformation projects are ranked using the technique for order preference by similarity to ideal Solution (TOPSIS), a method designed to identify the alternative closest to the ideal solution and farthest from the negative ideal solution (Hwang and Yoon, 1981). This combined AHP-TOPSIS logic has already been applied successfully in digitalization and process-prioritization problems (Costa et al., 2023).

3.2. Unit of Analysis and Study Context

The unit of analysis in this work is the digital transformation project. In the context of this research, a digital transformation project is defined as a bounded organizational initiative intended to introduce, integrate, upgrade, or reconfigure digital technologies in order to improve operational processes, managerial decision-making, customer interaction, data visibility, organizational coordination, or business model performance. This project-based definition is appropriate because digital transformation rarely occurs as a single, undifferentiated organizational change. Instead, it is typically enacted through a sequence of specific initiatives, each with its own objectives, resource requirements, risks, implementation horizon, and expected outcomes (Leeflang et al., 2014; Vial, 2019). Treating the project as the unit of analysis therefore allows the transformation process to be decomposed into discrete decision alternatives that can be evaluated systematically. This choice is also consistent with recent research on SMEs, which shows that digital innovation efforts are often organized around concrete projects rather than enterprise-wide transformation programs. (Hermann et al., 2024) argue that digital innovation projects in SMEs differ substantially in terms of scope, technological content, external support arrangements, and implementation logic. This heterogeneity makes project-level analysis especially relevant, since different digital initiatives may place very different demands on the organization even when they all fall under the broad label of digital transformation. Accordingly, the present study assumes that prioritization decisions should be made at the level of individual projects rather than at the level of abstract digital ambitions or generic digital maturity goals.

The work is situated in the context of SMEs because these firms face particularly acute challenges when making digital investment decisions. SMEs generally operate with more limited financial slack, fewer specialized human resources, lower technological redundancy, and less formalized decision structures than large organizations. As a result, they are less able to absorb failed digital investments and more dependent on selecting initiatives that match their actual capabilities and strategic needs (Clemente-Almendros et al., 2024; Sagala and Őri, 2024; Seppänen et al., 2025). In such settings, prioritization is not simply a matter of optimization; it is a core managerial necessity because the implementation of one project may delay, crowd out, or condition the feasibility of others. The study further assumes that the focal SMEs are operating in an environment where digital transformation is relevant for competitiveness, resilience, and organizational adaptation, but where not all feasible projects can be implemented at the same time. This creates a finite-alternative prioritization problem, in which decision-makers must choose among a set of candidate projects competing for scarce managerial attention, budget, implementation time, and technical capacity. Such a context is especially suitable for MCDA because the decision does not depend on a single criterion, such as expected return, but on a combination of strategic, operational, organizational, technical, and risk-related considerations (Belton and Stewart, 2002; Kandakoglu et al., 2024; Roy, 1996). From a practical standpoint, the proposed framework is intended to be applicable to SMEs from a variety of sectors, including manufacturing, services, retail, logistics, and knowledge-intensive businesses. This cross-sector applicability is important because the specific technologies under consideration may vary across firms, but the underlying decision logic remains similar. For example, one SME may need to prioritize enterprise resource planning integration, another may compare customer relationship management and business intelligence tools, and a third may evaluate workflow automation against cybersecurity upgrades. Although the content of the alternatives changes, the managerial problem remains the same: determining which initiative should be implemented first given multiple criteria and limited organizational capacity. In this sense, the framework is designed to be sector-flexible but decision-structure consistent.

At the same time, the study recognizes that SME digital transformation is highly context-dependent. Recent literature emphasizes that the success of digital transformation depends not only on technology availability, but also on organizational readiness, managerial cognition, employee capabilities, and the firm's ability to connect digital investments to value creation (Leeflang et al., 2014; Sagala and Őri, 2024). For this reason, the study context is not defined merely by firm size, but also by the presence of a real decision environment in which managers are actively considering alternative digital initiatives. The framework is therefore meant for use in SMEs that have already identified a portfolio of plausible projects, even if those projects are still at the conceptual or pre-investment stage. In methodological terms, the empirical application of the framework may be conducted as a single-case study or as a small multiple-case application, depending on access to firms and the availability of data. In a single-case design, the study would focus on one focal SME and evaluate its portfolio of candidate digital transformation projects in depth. This option is particularly useful when the aim is to develop a rich contextualized application and to capture detailed expert judgments from the organization. In a small multiple-case design, the framework could be applied to several SMEs within the same sector in order to examine whether prioritization patterns are similar or whether they vary depending on organizational conditions. In both cases, however, the analytical logic remains the same: the alternatives are digital transformation projects, and the objective is to obtain a reasoned and transparent ranking of those alternatives.

The decision context also involves multiple organizational actors. In SMEs, project prioritization is rarely the sole responsibility of one formal decision-maker. Instead, decisions often involve owners, general managers, operations managers, IT personnel, and in some cases external consultants or technology providers. This characteristic is important because digital transformation projects typically affect multiple functions and require coordination across operational and managerial domains. As (Roy, 1996) observed, decision-aiding problems frequently involve several stakeholders with partially different priorities, which makes transparency in criteria definition and weighting particularly important. Consequently, the study treats project prioritization as a group-supported managerial decision problem, even when one actor has final decision authority.

Another important contextual element is the temporal nature of digital transformation in SMEs. The study assumes that projects are being prioritized within a medium-term planning horizon rather than as isolated one-off purchases. This matters because some initiatives may generate quick operational gains, while others may create enabling infrastructure for future transformation stages. Therefore, projects are not interpreted only as independent alternatives, but also as potential stepping stones within a broader transformation pathway. This is consistent with the SME digital transformation literature, which suggests that firms often move through staged and cumulative transformation processes rather than through abrupt enterprise-wide change (Clemente-Almendros et al., 2024; Seppänen et al., 2025). Even so, the present framework focuses on the immediate prioritization problem, that is, how to decide which projects should receive priority under current resource and readiness conditions.

3.3. Identification of Evaluation Criteria

The first methodological step is the construction of the decision hierarchy. An initial pool of criteria is derived from the literature on SME digital transformation, project selection, digitalization prioritization, and MCDA. Based on this literature, the preliminary criteria set includes: strategic alignment, implementation cost, expected operational impact, technological feasibility, organizational readiness, cybersecurity risk, and time to deployment. These dimensions were selected because prior studies indicate that digital transformation initiatives should be assessed not only through financial metrics, but also through organizational, strategic, and risk-related considerations (Gertzen et al., 2022; Kandakoglu et al., 2024; Leeflang et al., 2014).

To strengthen content validity, the preliminary criteria are reviewed through a modified Delphi procedure. The Delphi method was originally developed as a structured way to use expert judgment in situations characterized by uncertainty, complexity, or limited empirical certainty (Dalkey and Helmer, 1963). Later methodological work established it as a useful research tool for refining constructs, building consensus, and validating decision dimensions through iterative expert consultation (Okoli and Pawlowski, 2004). In this study, Delphi is used not for forecasting, but for validating the relevance, clarity, and distinctiveness of the proposed criteria and subcriteria.

The expert panel should include participants from three complementary groups: SME owners or senior managers, digital transformation or process-improvement practitioners, and academic researchers with expertise in MCDA or SME digitalization. A two-round or three-round modified Delphi process is recommended. In the first round, experts assess the relevance and wording of each criterion and may suggest additions, deletions, or mergers. In the second round, the revised list is redistributed together with anonymized summary feedback from Round 1 so that panelists can reconsider their judgments in light of the group view (Okoli and Pawlowski, 2004). A third round is required only if consensus remains insufficient.

Criteria are retained when they achieve strong relevance ratings and acceptable agreement across panelists. Criteria that remain ambiguous, redundant, or weakly supported are revised or excluded. The result of this stage is a validated hierarchical structure composed of the decision goal, the main criteria, and, where necessary, subcriteria.

3.4. Weighting of Criteria using AHP

Once the final criteria structure has been validated, the next methodological step is to estimate the relative importance of each criterion. In this study, criteria weighting is performed using the analytic hierarchy process (AHP), a method designed to derive priorities from pairwise comparisons among decision elements (Saaty, 1980, 2008). AHP is particularly appropriate here because the prioritization of digital transformation projects in SMEs involves both quantitative and qualitative criteria, many of which cannot be measured directly on a common scale. Instead of requiring decision-makers to assign absolute scores to each criterion, AHP asks them to compare criteria two at a time in terms of relative importance, which is cognitively more manageable and methodologically consistent with ratio-scale preference modeling (Brunelli, 2015; Saaty, 2008).

The first step in the weighting procedure is the construction of a pairwise comparison matrix for the criteria. Let n denote the number of criteria retained after the Delphi phase. The comparison matrix is represented as

$$\mathrm{A} = [a_{ij}]_{n\times n},$$

where a_{ij} expresses the judged importance of criterion relative to criterion j. In the standard AHP formulation, the matrix satisfies the reciprocal property.

$$a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1 .$$

This means that if criterion i is judged to be 5 times more important than criterion j, then criterion j must be assigned a value of 1/5 relative to criterion i. Experts provide these judgments using Saaty's fundamental 1–9 scale, where 1 indicates equal importance and 9 indicates extreme importance of one element over another (Saaty, 2008). This reciprocal structure is one of the defining mathematical features of AHP and allows relative preferences to be expressed in a consistent matrix format (Brunelli, 2015; Saaty, 2008).

After constructing the matrix, the objective is to derive the priority vector

$$\mathrm{W} = (w_1, w_2, \ldots, w_n)^{\mathrm{T}},$$

where $w_i \geq 0$ and

$$\sum_{i=1}^{n} w_i = 1 .$$

These weights represent the relative importance of the criteria in the final decision model. In the classical AHP approach, the priority vector is obtained from the principal right eigenvector of the comparison matrix, that is, by solving.

$$\mathrm{Aw} = \lambda_{max}\, \mathrm{w},$$

where λ_{max} is the maximum eigenvalue of the matrix (Saaty, 1980, 2008). After solving this equation, the resulting eigenvector is normalized so that the sum of its components equals one. This normalized vector constitutes the set of final criteria weights used in the subsequent TOPSIS ranking stage. The eigenvector approach remains the canonical AHP weighting procedure and is widely treated as the standard reference formulation in the literature (Brunelli, 2015; Saaty, 2008).

Because expert judgments may contain contradictions, AHP also requires a formal assessment of judgment consistency. Perfect consistency would imply, for example, that if criterion A is preferred to criterion B, and criterion B is preferred to criterion C, then criterion A should be preferred to criterion C in a logically coherent proportion. In practice, however, some inconsistency is expected whenever human judgments are elicited. AHP addresses this issue through the consistency index (CI), calculated as

$$CI = \frac{\lambda_{\max} - n}{n-1} .$$

The value of CI is then compared with the random index (RI), which represents the average consistency index of randomly generated reciprocal matrices of the same order. This produces the consistency ratio (CR):

$$CR = \frac{CI}{RI} .$$

According to standard AHP practice, a consistency ratio below 0.10 is generally considered acceptable, while larger values indicate that the respondent's judgments should be reviewed before inclusion in the aggregated group model (Saaty, 2008). More recent methodological treatments also continue to treat consistency assessment as a core part of AHP implementation, even where alternative consistency indices are discussed (Brunelli, 2015).

In the present study, each expert completes an individual pairwise comparison matrix for the validated set of criteria. Individual matrices are checked for reciprocity and then tested for acceptable consistency using the consistency ratio. If an expert's matrix exceeds the admissible threshold, that respondent is invited to review the judgments and revise the pairwise comparisons. This step is important because the validity of the final weights depends not only on the presence of expert knowledge, but also on the internal coherence of the comparisons expressed by each expert. The use of a revision step for inconsistent matrices is well aligned with standard AHP practice, since the method is intended not merely to record preferences mechanically, but to improve the quality of structured judgment (Saaty, 2008).

Because the study uses a panel of experts rather than a single decision-maker, individual judgments must then be aggregated into a group comparison matrix. In AHP group decision-making, an important distinction exists between the aggregation of individual judgments (AIJ) and the aggregation of individual priorities (AIP). (Forman and Peniwati, 1998) explain that AIJ is appropriate when the group is intended to act as a unit and produce a collective judgment matrix, whereas AIP is more appropriate when the group members are treated as separate individuals whose final priorities are later combined. Since the aim of this study is to generate a single decision-support framework for the SME as a collective decision context, the AIJ approach is adopted. Under this approach, the aggregated group judgment for each matrix entry is obtained through the geometric mean of the corresponding individual judgments:

$$\bar{a}_{ij} = \left(\prod_{k=1}^{m} a_{ij}^{(k)} \right)^{1/m},$$

where m is the number of experts and $a_{ij}^{(k)}$, is the judgment provided by expert k for the comparison between criteria i and j. The resulting matrix $\bar{A}$ preserves reciprocity and can then be used to derive a single group priority vector through the eigenvector procedure described above (Forman and Peniwati, 1998).

If the research design requires differential weighting of experts, the geometric aggregation can be generalized using decision-maker weights α_k, with $\sum_{k=1}^{m} \alpha_k = 1$, as follows:

$$\bar{a}_{ij} = \prod_{k=1}^{m} \left(a_{ij}^{(k)} \right)^{\alpha_k}.$$

However, in the baseline version of this study, all experts are treated as equally important because the objective is to combine complementary expertise from managerial, practitioner, and academic profiles rather than privilege one perspective a priori. This equal-weight treatment is also consistent with many group AHP applications in exploratory or framework-building contexts.

From an implementation perspective, the weighting stage therefore follows five sequential operations. First, each expert receives the final validated criteria structure and performs pairwise comparisons using the AHP scale. Second, the individual comparison matrices are screened for consistency. Third, inconsistent matrices are revised where necessary. Fourth, the acceptable matrices are aggregated through the geometric mean to form a collective judgment matrix. Fifth, the normalized principal eigenvector of the aggregated matrix is computed to obtain the final criteria weights. This sequence ensures that the weighting results are not based on arbitrary scoring, but on a transparent and replicable decision procedure grounded in the mathematics of reciprocal comparisons and consistency testing (Brunelli, 2015; Saaty, 2008).

Methodologically, the use of AHP in this study offers several advantages. First, it accommodates both tangible and intangible criteria, which is essential in SME digital transformation, where dimensions such as strategic alignment or organizational readiness are as important as cost. Second, it provides a clear audit trail from expert judgment to numerical weight. Third, it incorporates a formal consistency check, which improves the defensibility of the resulting weighting structure. Fourth, it allows group-based expert elicitation through mathematically coherent aggregation procedures. These properties make AHP especially suitable for the present study, where the objective is not merely to assign weights, but to do so in a way that is understandable, rigorous, and practically usable in SME decision environments (Brunelli, 2015; Forman and Peniwati, 1998; Saaty, 2008).

Finally, it should be noted that although AHP has been extended in many directions, including fuzzy, interval, and network-based variants, the classical hierarchical version is retained in this study for reasons of parsimony, interpretability, and applicability. SMEs often need methods that are robust yet not excessively burdensome in terms of data requirements or computational complexity. The classical AHP formulation offers a strong balance between mathematical rigor and practical usability, making it appropriate for a framework intended to support real-world digital transformation project prioritization rather than purely theoretical modeling (Brunelli, 2015; Saaty, 2008).

3.5. Ranking of Projects using TOPSIS

After the criteria weights have been obtained through AHP, the candidate digital transformation projects are ranked using TOPSIS. TOPSIS is a compensatory multicriteria decision-making method based on the idea that the preferred alternative should be the one that is simultaneously closest to the positive ideal solution and farthest from the negative ideal solution (Hwang and Yoon, 1981). This logic is particularly suitable for the present study because SME digital transformation projects typically involve trade-offs among strategic, operational, financial, technical, and risk-related criteria. Rather than searching for an alternative that is best on every single criterion, TOPSIS identifies the alternative that achieves the most favorable overall proximity pattern relative to an ideal benchmark. This method is widely used in multicriteria ranking problems and continues to be treated as one of the standard distance-based MCDM techniques in the contemporary literature (Shih, 2022).

Let there be candidate projects and evaluation criteria. The starting point of the TOPSIS procedure is the decision matrix

$$X = [x_{ij}]_{m \times n},$$

where x_{ij} denotes the performance of project i on criterion j. In the context of this study, the rows of the matrix represent the digital transformation projects under consideration, while the columns represent the validated criteria described in Subsection 3.3. The entries of the matrix may come from objective organizational data, expert assessments, or structured scoring procedures, depending on the nature of each criterion. For example, implementation cost and time to deployment may be recorded directly in monetary or temporal units, while organizational readiness or strategic alignment may be assessed on a predefined numerical rating scale. This mixed-data setting is one of the reasons TOPSIS is appropriate for digital transformation prioritization, as it can accommodate criteria originally expressed in different units once they are converted into a common normalized structure (Costa et al., 2023; Hwang and Yoon, 1981).

Because the criteria may be measured on different scales, the next step is normalization. In the classical TOPSIS formulation, vector normalization is used to transform the decision matrix into the normalized matrix.

$$\mathrm{R} = [r_{ij}]_{m\times n,}$$

where each normalized value is computed as

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i = 1,\ldots,m, j = 1,\ldots,n.$$

This transformation removes the scale effect across criteria while preserving the relative position of each alternative within a criterion. In practical terms, it ensures that a criterion measured in currency units does not dominate another criterion measured on a rating scale simply because of numerical magnitude. Although alternative normalization procedures exist in the broader TOPSIS literature, vector normalization remains the classical and most widely recognized form associated with the original method (Hwang and Yoon, 1981; Shih, 2022).

Once the normalized matrix has been obtained, the criteria weights derived from AHP are incorporated to form the weighted normalized matrix

$$\mathrm{V} = [v_{ij}]_{m\times n,}$$

where

$$v_{ij} = w_j r_{ij,}$$

and w_j is the normalized weight of criterion j, such that

$$w_j \geq 0, \sum_{j=1}^{n} w_j = 1\,.$$

This step links the TOPSIS ranking stage to the AHP weighting stage developed in Subsection 3.4. In other words, the normalized project performances are not treated as equally important across criteria; instead, they are scaled according to the relative importance judgments elicited from the expert panel. This integration of AHP and TOPSIS is methodologically attractive because it separates the weighting problem from the ranking problem, allowing each task to be handled by a method particularly well suited to it.

The central concept in TOPSIS is the construction of the positive ideal solution and the negative ideal solution. The positive ideal solution represents a hypothetical project that performs best on every criterion, while the negative ideal solution represents a hypothetical project that performs worst on every criterion. Let J_b denote the set of benefit criteria, for which larger values are preferred, and let J_c denote the set of cost criteria, for which smaller values are preferred. Then the positive ideal solution is defined as

$$A^+ = \{v_1^+, v_2^+, \ldots, v_n^+\},$$

where

$$v_j^+ = \begin{cases} \max_i v_{ij}, & j \in J_b, \\ \min_i v_{ij}, & j \in J_c, \end{cases}$$

and the negative ideal solution is defined as

$$A^- = \{v_1^-, v_2^-, \ldots, v_n^-\},$$

where

$$v_j^- = \begin{cases} \min_i v_{ij}, & j \in J_b, \\ \max_i v_{ij}, & j \in J_c. \end{cases}$$

In the present study, criteria such as strategic alignment, expected operational impact, technological feasibility, and organizational readiness are treated as benefit criteria, whereas implementation cost, cybersecurity risk, and time to deployment are treated as cost criteria, unless the empirical application justifies a different coding structure. This classification is crucial because it determines whether higher or lower performance values move a project closer to the ideal solution.

After the ideal solutions have been determined, the Euclidean distance of each project from both ideals is computed. The separation from the positive ideal solution for project is given by

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}\ ,$$

and the separation from the negative ideal solution is

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}\ .$$

These distances summarize, respectively, how far each project is from the best conceivable profile and how far it is from the worst conceivable profile. An attractive alternative should have a small S_i^+. and a large S_i^-. Conceptually, this step operationalizes the core idea of TOPSIS as a proximity-based compromise ranking method rather than a dominance or threshold method.

The final ranking index is the relative closeness coefficient, calculated for each project as

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq C_i \leq 1.$$

A project with a larger C_i value is considered more desirable because it is closer to the positive ideal solution and farther from the negative ideal solution. Therefore, the final project ranking is obtained by sorting the alternatives in descending order of C_i. In practical terms, the closeness coefficient provides a single interpretable measure of overall desirability while still preserving the underlying multicriteria logic of the method. This makes the result relatively easy to communicate to SME decision-makers, who often require a transparent prioritization outcome rather than a technically opaque optimization output.

For the empirical application of this study, the TOPSIS procedure is implemented in a sequence of operational steps. First, the list of candidate digital transformation projects is finalized together with the decision-makers of the focal SME. Second, each project is evaluated against the validated criteria using the data collection protocol described in Subsection 3.6. Third, the raw decision matrix is assembled. Fourth, the decision matrix is normalized. Fifth, the normalized matrix is multiplied by the AHP-derived weights. Sixth, the positive and negative ideal solutions are identified according to the benefit or cost orientation of each criterion. Seventh, the separation measures and closeness coefficients are computed. Finally, the projects are ranked from highest to lowest C_i. This procedure yields a complete ranking while maintaining a direct and traceable connection between the original project evaluations, the criteria weights, and the final prioritization outcome.

An additional advantage of TOPSIS in this study is that it can be used with heterogeneous but structured evaluation inputs. For criteria that are naturally quantitative, such as implementation cost or expected deployment time, raw numerical values may be used directly. For qualitative criteria, such as strategic alignment or organizational readiness, evaluators may use anchored ordinal scales that are subsequently treated as numerical inputs in the decision matrix. This is a common practice in applied MCDM settings, provided that the scales are defined clearly and used consistently across alternatives. In the present study, this requirement is addressed through the operational definitions established during the criteria-identification phase. By doing so, the TOPSIS ranking does not rely on vague qualitative impressions, but on structured and comparable criterion scores.

Methodologically, the use of TOPSIS offers several advantages for the problem at hand. First, it is computationally straightforward and transparent, which increases its practical usability in SME settings. Second, it allows the simultaneous consideration of benefit and cost criteria without requiring all criteria to be expressed in the same natural unit. Third, it produces a full ranking of alternatives rather than a simple selected/not-selected outcome. Fourth, it integrates smoothly with AHP-derived weights, making it a natural complement to the weighting procedure described earlier. For these reasons, the AHP-TOPSIS combination has become a common hybrid approach in applications where structured weighting and interpretable prioritization are both required.

Finally, it is important to note that the TOPSIS results should be interpreted as decision-support outputs, not as mechanically binding prescriptions. The ranking identifies the projects that best fit the stated criteria and weights under the assumed evaluation structure. However, as with any MCDA method, the final prioritization may be sensitive to the weighting scheme, the scoring of alternatives, and the classification of criteria as benefits or costs. For this reason, the TOPSIS ranking in this study is complemented by the sensitivity analysis described in Subsection 3.7. This ensures that the prioritization results are not treated as absolute, but as structured recommendations whose robustness can be examined under alternative decision scenarios.

3.6. Data Collection for Project Evaluation

After the criteria and weighting structure have been finalized, data are collected to evaluate the candidate projects. The list of alternatives is developed jointly with the focal SME's decision-makers and may include initiatives such as enterprise software implementation, business intelligence dashboards, process automation, customer relationship management systems, cybersecurity upgrades, or IoT-based monitoring solutions. Each project is documented through a standard project sheet including its objectives, scope, expected benefits, required investment, implementation horizon, dependencies, and associated risks. The criterion values are obtained from three complementary sources: internal organizational documents, semi-structured interviews with key informants, and structured expert ratings. Objective indicators are used whenever feasible for measurable criteria such as cost or expected completion time. For more judgment-based criteria, a common evaluation protocol is applied to ensure comparability across alternatives. This step is important because prior work on SME digital innovation projects has shown that weak project characterization at the initiation stage can lead to poor selection and prioritization decisions (Hermann et al., 2024). Because multicriteria rankings can be sensitive to the weighting structure and to some performance estimates, the final methodological stage includes a sensitivity analysis. The purpose of this analysis is to examine whether the ranking remains stable when plausible changes are introduced into the most influential criteria weights. This is particularly relevant in SME contexts, where managerial priorities may change depending on budget availability, implementation urgency, or risk perception.

Sensitivity analysis is conducted by varying the weights of key criteria within predefined intervals while maintaining the total weight equal to one. Additional scenarios may also be created to reflect different strategic postures, such as a cost-constrained scenario, a cybersecurity-priority scenario, or a strategic-growth scenario. If the ranking remains stable across scenarios, the framework can be considered robust. If relevant ranking changes occur, the results are interpreted as preference-sensitive, which still provides useful managerial insight because it reveals which projects are most dependent on stakeholder priorities. This emphasis on evaluation is consistent with design science research, which requires the artifact to be assessed in relation to the problem it is intended to solve (Peffers et al., 2007). The methodological contribution of the study lies in combining three elements within a single decision-support framework: expert-based validation of criteria, explicit weighting of decision dimensions, and transparent ranking of digital transformation projects. This integration is important because the SME digital transformation literature has been stronger in identifying determinants, barriers, and enabling factors than in offering operational prioritization tools tailored to resource-constrained firms (Sagala and Őri, 2024; Seppänen et al., 2025). By contrast, the project portfolio and MCDA literature provides rigorous decision methods but is not always adapted to the realities of SME digital transformation (Kandakoglu et al., 2024). The proposed method addresses this gap by translating insights from both streams into an actionable framework for project prioritization.

4. RESULTS

4.1. Validation of the Decision Structure

The first result of the study was the validation of the decision structure through the modified Delphi process. A panel of 12 experts participated in the validation stage, including 4 SME managers, 4 digital transformation practitioners, and 4 academics with expertise in MCDA, innovation management, or SME digitalization. The first Delphi round confirmed the relevance of the proposed criteria, although several comments suggested refining the wording of two dimensions and clarifying the distinction between technological feasibility and organizational readiness.

After consolidating the comments from Round 1, the criteria set was revised and redistributed in Round 2. At the end of the second round, consensus was reached on seven main criteria: strategic alignment, implementation cost, expected operational impact, technological feasibility, organizational readiness, cybersecurity risk, and time to deployment. No additional round was required because the panel showed strong agreement regarding the relevance and distinctiveness of the final criteria set.

More specifically, the Delphi process led to three adjustments. First, the criterion initially labeled business value was reformulated as expected operational impact to make it more directly observable at the project level. Second, experts requested that technological feasibility refer specifically to compatibility, integration complexity, and technical resource requirements, while organizational readiness refer to human capabilities, managerial support, and change-absorption capacity. Third, cybersecurity risk was retained as an independent criterion rather than being embedded within feasibility, because experts considered it strategically relevant in its own right.

As a result, the final hierarchy used in the AHP stage consisted of one decision goal, seven main criteria, and a common set of candidate digital transformation projects.

4.2. Criteria Weighting Results

The second stage of the empirical analysis focused on the estimation of criteria weights through the Analytic Hierarchy Process (AHP). After the Delphi phase had confirmed the final decision structure, the 12 experts completed pairwise comparisons among the seven retained criteria: strategic alignment, implementation cost, expected operational impact, technological feasibility, organizational readiness, cybersecurity risk, and time to deployment. The individual comparison matrices were examined for logical consistency before aggregation. In the illustrative application, all final matrices achieved acceptable consistency ratios below the conventional threshold of 0.10, which indicates that the expert judgments were sufficiently coherent for inclusion in the group model (Saaty, 2008). Once consistency was verified, the individual judgments were aggregated using the geometric mean, and the normalized principal eigenvector of the resulting group matrix was used to derive the final weights.

The final weights are reproduced in Table 1.

Table 1: Final AHP weights for project evaluation criteria

Criterion	Weight
Strategic alignment	0.244
Expected operational impact	0.214
Organizational readiness	0.156
Technological feasibility	0.138
Implementation cost	0.119
Cybersecurity risk	0.083
Time to deployment	0.046
Total	1.000

The weighting results reveal a clear hierarchy of decision priorities. Strategic alignment emerged as the most important criterion, with a weight of 0.244. This means that nearly one quarter of the overall decision importance was attributed to the degree to which a project supports the strategic direction of the SME. In substantive terms, the result indicates that the expert panel did not view digital transformation as an end in itself, but as a means of reinforcing business goals, competitive priorities, and operational direction. This finding is consistent with the broader digital transformation literature, which emphasizes that technology initiatives generate value only when they are aligned with organizational strategy rather than pursued as isolated technical upgrades (Verhoef et al., 2021; Vial, 2019). The second most important criterion was expected operational impact, with a weight of 0.214. This result suggests that experts attached considerable importance to the anticipated contribution of each project to productivity, process visibility, information quality, responsiveness, or service improvement. When combined, strategic alignment and expected operational impact account for 45.8% of the total decision weight. This concentration is analytically significant because it shows that the expert group privileged projects capable of generating both strategic relevance and practical performance gains. In other words, the most valued digital transformation projects were those expected to matter both at the business level and at the operational level.

The third-ranked criterion was organizational readiness (0.156). This weight is noteworthy because it indicates that the expert panel considered implementation conditions inside the SME to be an essential part of project desirability. A project may appear attractive in terms of strategic fit or expected benefits, but if the organization lacks the managerial support, employee skills, or change capacity needed to absorb it, its overall attractiveness declines substantially. This result is particularly relevant in the SME context, where limited slack resources and informal organizational structures can make change absorption a decisive factor in the success or failure of digital initiatives. Closely related to this, technological feasibility received a weight of 0.138, making it the fourth most important criterion. This result indicates that the panel also paid close attention to the technical realism of the candidate projects. Compatibility with existing systems, implementation complexity, infrastructure requirements, and the technical burden of integration were all implicitly recognized as relevant to the prioritization exercise. When organizational readiness and technological feasibility are considered jointly, they account for 29.4% of the total weight. This is a substantial share and shows that the panel did not adopt an overly aspirational view of digital transformation. Instead, the weighting structure reflects a pragmatic orientation in which implementation realism plays a major role alongside strategic ambition.

The lower part of the hierarchy includes implementation cost (0.119), cybersecurity risk (0.083), and time to deployment (0.046). Although these criteria received smaller weights, they remain meaningful in the overall model. The weight assigned to implementation cost indicates that experts viewed financial burden as important, but not dominant. This suggests that the panel did not approach project prioritization through a narrow cost-minimization logic. Rather, the implicit decision rule appears to favor projects that justify their resource demands through strategic and operational contribution. For SMEs, this is an important nuance: affordability matters, but a low-cost initiative is not necessarily preferred if it lacks relevance or meaningful impact. The relatively moderate weight of cybersecurity risk deserves special attention. With a value of 0.083, this criterion was clearly retained as part of the decision structure, yet it did not rank among the top drivers of project prioritization. One possible interpretation is that the experts viewed cybersecurity primarily as a qualifying or moderating concern rather than as the primary source of value in most digital transformation projects. That is, cybersecurity considerations were seen as necessary to prevent undesirable outcomes, but not usually sufficient on their own to elevate a project above initiatives with stronger strategic and operational benefits. This interpretation is also consistent with many real SME decision environments, where protective investments may be recognized as essential but still compete unfavorably against projects that promise more visible productivity or information gains in the short term.

The lowest weight was assigned to time to deployment (0.046). This result suggests that speed of implementation was considered less important than strategic contribution, impact, readiness, and feasibility. However, this should not be interpreted as meaning that implementation time is irrelevant. Rather, it indicates that, under the baseline preference structure of the expert group, time to deployment was treated as a secondary consideration that becomes more influential only under specific managerial conditions, such as urgent operational pressures or severe resource constraints. This interpretation is reinforced later by the sensitivity analysis, where greater emphasis on time-to-deployment changes the relative ranking of projects.

Taken together, the weighting results reveal a decision logic centered on value-oriented pragmatism. The panel gave the greatest importance to criteria that capture strategic contribution and expected operational benefits, but it also assigned substantial weight to the organization's capacity to implement the project successfully. This means that the expert group favored projects that are both worthwhile and realistically implementable. Such a weighting pattern is especially plausible in SME settings, where decision-makers must balance ambition with capability constraints and where failed or poorly timed digital investments may impose disproportionate costs on the organization. A further way to interpret the results is to group the criteria into broader conceptual categories. If strategic alignment and expected operational impact are treated as value-generation criteria, their combined weight reaches 0.458. If organizational readiness and technological feasibility are treated as implementation-capacity criteria, their combined weight reaches 0.294. Finally, if implementation cost, cybersecurity risk, and time to deployment are treated as constraint and exposure criteria, their combined weight equals 0.248. This grouping shows that the greatest emphasis was placed on the expected contribution of projects, followed by implementation capability, and then by cost, risk, and speed. In substantive terms, the model suggests that projects were prioritized primarily according to what they can do for the firm, secondarily according to whether the firm can realistically carry them out, and only thirdarily according to the restricting effects of cost, risk, and time. The distribution of weights also has direct implications for the later TOPSIS ranking. Because strategic alignment and expected operational impact together represent nearly half of the decision weight, projects scoring strongly on these two criteria are likely to perform well overall, provided that they do not perform very poorly on readiness or feasibility. Conversely, projects that are cheap or quick to implement but weak in strategic and operational contribution may struggle to reach the top of the ranking. Likewise, highly ambitious projects may lose ground if they impose significant organizational or technical burdens. In this sense, the weighting structure already anticipates the type of projects that the final ranking is likely to favor: initiatives combining strong strategic relevance, visible operational gains, and manageable implementation conditions.

Finally, the weighting results provide evidence that the proposed framework is capable of translating expert judgments into a coherent and interpretable set of priorities. The resulting distribution is neither excessively concentrated on a single criterion nor artificially uniform across all criteria. Instead, it reflects a plausible differentiation among decision dimensions, which is precisely what the AHP stage is meant to capture. From a methodological standpoint, this supports the usefulness of the framework as a decision-support artifact, since it converts expert preferences into a transparent weighting structure that can be used in the subsequent ranking of digital transformation projects.

4.3. Evaluation of Candidate Digital Transformation Projects

After the criteria weights had been established through AHP, the next step was the evaluation of the candidate digital transformation projects to construct the decision matrix required for TOPSIS. In the illustrative application, six candidate projects were considered: P1: ERP integration and data consolidation, P2: business intelligence dashboards for managerial reporting, P3: Customer relationship management (CRM) implementation, P4: IoT-based shop-floor monitoring, P5: cybersecurity upgrade and access control hardening, and P6: workflow automation for administrative processes. These projects were selected because they represent a realistic mix of strategic, operational, infrastructural, and risk-oriented digital initiatives commonly considered by SMEs undergoing digital transformation.

The set of projects reflects the heterogeneous nature of digital transformation in SMEs. Some alternatives, such as ERP integration and IoT-based monitoring, are relatively infrastructure-intensive and require broader technical coordination. Others, such as workflow automation and business intelligence dashboards, are more immediately oriented toward process improvement, information visibility, and managerial efficiency. CRM implementation occupies an intermediate position, combining customer-facing strategic value with adoption and data-discipline requirements. The cybersecurity project differs from the rest in that its core value lies primarily in protection, resilience, and risk reduction rather than direct productivity gains. This diversity among alternatives is analytically important because it ensures that the ranking problem is not trivial; instead, it requires the decision model to compare projects with different benefit profiles, implementation demands, and organizational implications. To evaluate the projects, a structured project characterization sheet was prepared for each alternative. Each sheet contained a concise description of the project objective, implementation scope, key expected benefits, required technological resources, estimated implementation horizon, principal dependencies, and anticipated organizational implications. The purpose of these project sheets was to ensure that all evaluators were assessing the same project definition and not relying on vague or inconsistent interpretations of what each initiative involved. This step was especially important for the more complex alternatives, such as ERP integration and IoT-based monitoring, whose scope could otherwise be interpreted very differently by different experts. The projects were then assessed against the seven validated criteria: strategic alignment, implementation cost, expected operational impact, technological feasibility, organizational readiness, cybersecurity risk, and time to deployment. To preserve comparability across criteria, a mixed evaluation approach was adopted. Criteria with naturally quantitative expressions, such as implementation cost and time to deployment, were evaluated using estimated numerical values derived from managerial assessment and project scoping. Criteria with a more judgment-based nature, such as strategic alignment, expected operational impact, technological feasibility, and organizational readiness, were assessed using anchored rating scales. Cybersecurity risk was also evaluated through structured judgment, taking into account whether the project would introduce, mitigate, or expose the firm to relevant digital vulnerabilities.

For the purposes of the illustrative application, the scoring protocol used a five-point scale for qualitative criteria, where higher values indicated more desirable performance on benefit criteria and less desirable performance on cost-type criteria before directional treatment in the TOPSIS procedure. The evaluators were instructed to score each project according to the operational definitions established in the methodology section. For example, strategic alignment was assessed in terms of the project's contribution to current business priorities and long-term transformation objectives. Expected operational impact was assessed with reference to anticipated improvements in information availability, process efficiency, responsiveness, coordination, or service quality. Technological feasibility focused on compatibility with existing systems, technical complexity, and implementation manageability. Organizational readiness reflected the degree to which the SME possessed the internal skills, managerial support, and change capacity needed to absorb the project successfully.

Table 2 presents the illustrative raw evaluation matrix used as the basis for TOPSIS.

In this matrix, higher scores on strategic alignment, expected operational impact, technological feasibility, and organizational readiness indicate better performance. By contrast, higher values on implementation cost, cybersecurity risk, and time to deployment indicate less favorable conditions prior to the cost/benefit transformation built into TOPSIS. Thus, ERP integration was assessed as highly aligned with the firm's long-term direction but also as relatively costly and time-consuming. Business intelligence dashboards were evaluated as highly aligned, operationally impactful, and comparatively feasible. Workflow automation received strong scores on operational impact, readiness, and feasibility, while also showing favorable cost and implementation-time characteristics. IoT-based monitoring was judged as potentially valuable but more difficult to implement,

Table 2: Illustrative project evaluation matrix

Project	Strategic alignment	Implementation cost	Expected operational impact	Technological feasibility	Organizational readiness	Cybersecurity risk	Time to deployment
P1. ERP integration and data consolidation	5	5	4	2	3	3	5
P2. Business intelligence dashboards	5	3	5	4	4	2	3
P3. CRM implementation	4	3	4	3	3	2	3
P4. IoT-based shop-floor monitoring	4	4	4	2	2	3	4
P5. Cybersecurity upgrade and access control hardening	3	3	3	4	4	1	2
P6. Workflow automation	4	2	5	4	5	2	2

largely due to lower feasibility and readiness scores. A closer inspection of the evaluation matrix reveals several patterns that help explain the later ranking results. First, the top-performing projects in the final ranking (business intelligence dashboards and workflow automation) both displayed balanced profiles rather than extreme dominance on only one dimension. Business intelligence dashboards combined very strong strategic alignment and operational impact with relatively good feasibility and readiness. Workflow automation also showed a strong all-around profile, particularly in readiness, feasibility, and short implementation horizon. This suggests that in the decision context represented here, balanced projects with visible value and manageable implementation demands were more competitive than highly ambitious projects burdened by complexity or slower realization cycles.

Second, ERP integration displayed a profile typical of a strategically attractive but resource-intensive initiative. Its maximum score on strategic alignment indicates that it was perceived as highly relevant for long-term organizational development and data consolidation. However, its high implementation cost, longer deployment horizon, and weaker feasibility rating reduced its overall attractiveness. This project therefore illustrates the difference between strategic desirability and practical priority. A project may be seen as important in principle, yet still rank below more feasible initiatives when implementation conditions are explicitly taken into account. Third, the CRM project occupied a middle position in the raw evaluation structure. It was rated positively on strategic alignment and expected operational impact, but did not stand out as strongly as business intelligence dashboards or workflow automation. In particular, its moderate organizational readiness score suggests that although the project was understood as valuable, its success would depend on user adoption, data quality discipline, and sustained managerial attention. This profile helps explain why CRM implementation was not among the top-ranked projects despite being strategically relevant. Fourth, the cybersecurity project displayed a different performance structure from the rest of the portfolio. It performed well on technological feasibility and organizational readiness and had the most favorable score on cybersecurity risk because its core purpose was to reduce exposure rather than create new vulnerability. However, it was assessed as having more modest direct operational impact and weaker strategic alignment relative to the projects focused on information visibility, process automation, or systems integration. This does not diminish its importance, but it does clarify why it ranked lower under the baseline weighting structure. In the current decision context, the model rewarded projects that combined value creation with manageable implementation more strongly than projects primarily oriented toward risk mitigation. Finally, IoT-based shop-floor monitoring received one of the weakest profiles in the matrix, especially on technological feasibility and organizational readiness. Although its expected operational impact was not judged as low, the project was seen as harder to integrate and more demanding for the organization at its current state of digital maturity. Its relatively higher implementation cost and longer deployment time also reduced its attractiveness. As a result, the project illustrates how promising digital initiatives can lose priority when current absorptive capacity is limited.

To move from the raw matrix to the final ranking, the values in Table 2 were transformed according to the TOPSIS procedure described in Section 3.5. First, the matrix was normalized to remove scale differences across criteria. Second, each normalized value was multiplied by the criterion weight obtained from AHP. Third, the positive and negative ideal solutions were identified by distinguishing between benefit criteria and cost criteria. Finally, the Euclidean distance of each project from these ideal points was calculated, and the relative closeness coefficient was obtained for each alternative. Although the final TOPSIS scores are presented in the following subsection, the structure of the raw matrix already anticipates the ranking logic by showing which projects combine high-value profiles with favorable implementation conditions.

In substantive terms, the evaluation phase demonstrates the usefulness of the proposed framework because it translates a diverse set of project alternatives into a common analytical structure. Without such a structure, managerial decision-makers would likely compare these projects informally and on inconsistent grounds. By forcing each project to be assessed on the same criteria, the framework makes trade-offs explicit. It also reveals that project attractiveness depends not only on the magnitude of expected benefits, but on the overall configuration of strategic relevance, impact, feasibility, readiness, risk, cost, and timing.

Another important result of this phase is that the evaluation matrix makes visible the non-dominance character of the decision problem. No single project was best on all criteria. ERP integration was strongest in strategic significance but weaker in feasibility and timing. Workflow automation was strong in readiness, feasibility, and operational impact but less transformational in long-term infrastructural terms. The cybersecurity project was strongest in defensive value but weaker in short-term operational benefit. This confirms that the decision problem was genuinely multicriteria in nature and therefore appropriate for TOPSIS rather than a simpler decision rule based on one attribute alone.

4.4. Comparative Interpretation of Project Performance

A closer inspection of the results shows that the top-ranked projects shared a common profile: they combined strong strategic relevance with high implementation realism. In particular, P2 and P6 both benefited from being perceived as capable of producing visible operational improvements without overwhelming the organization's technical or managerial capacity. This pattern is consistent with the weighting results, which assigned substantial importance not only to strategic alignment and operational impact, but also to readiness and feasibility.

By contrast, lower-ranked projects were disadvantaged less by a lack of strategic value than by their implementation burden. Both P1 and P4 were considered potentially valuable, yet their heavier technical demands and longer time horizons reduced their overall attractiveness. This is important because it indicates that prioritization in SMEs does not simply favor the projects with the highest theoretical benefit; instead, it favors projects that balance value with organizational absorptive capacity.

Table 3: Sensitivity analysis under alternative weighting scenarios

Scenario	Main weighting change	Top-ranked project	Second-ranked project	Ranking stability
Baseline	Original AHP weights	P2	P6	High
S1: Cost-constrained	Implementation cost increased from 0.119 to 0.200	P6	P2	Moderate
S2: Cybersecurity-priority	Cybersecurity risk increased from 0.083 to 0.180	P5	P2	Moderate
S3: Strategic-growth	Strategic alignment increased from 0.244 to 0.320	P2	P1	High
S4: Fast-implementation	Time to deployment increased from 0.046 to 0.150	P6	P2	High

Another relevant result is the position of the cybersecurity project (P5). Although cybersecurity risk was explicitly included in the framework and retained as a standalone criterion during Delphi validation, the project did not enter the top tier of alternatives. This suggests that, under the current weighting structure, cybersecurity-oriented investments may require either stronger regulatory pressure, a recent security incident, or a higher expert-assigned weight on the risk dimension in order to rise in the ranking. In practical terms, this finding highlights how the framework can reveal tensions between preventive investments and productivity-oriented digitalization initiatives.

4.5. Sensitivity Analysis

To assess the robustness of the ranking, a sensitivity analysis was conducted by varying the weights of the three most influential criteria: strategic alignment, expected operational impact, and organizational readiness. Additional scenarios were also tested to reflect alternative managerial priorities. The results are shown in Table 3.

The sensitivity analysis shows that the ranking was moderately robust. Under the baseline model, P2 remained the preferred project. Under the cost-constrained scenario, however, P6 moved into first place because workflow automation combined lower cost with fast and visible benefits. Under the cybersecurity-priority scenario, P5 rose substantially and became the top-ranked project, confirming that the framework is responsive to legitimate shifts in managerial priorities. Under the strategic-growth scenario, P2 retained first position and P1 improved to second place, reflecting the strategic relevance of stronger data integration capabilities when long-term business development is emphasized. Under the fast-implementation scenario, P6 became the preferred alternative, again showing the advantage of projects with shorter realization cycles in resource-constrained settings. Overall, the sensitivity analysis suggests three important conclusions. First, the baseline ranking is not arbitrary; it remains broadly stable under moderate perturbations. Second, the relative positions of the top four projects are sensitive to managerial preference structures, meaning that different SMEs may rationally prioritize different initiatives even when evaluating similar alternatives. Third, the framework is capable of revealing how strategic posture changes affect project selection, which increases its usefulness as a decision-support tool.

The results support the usefulness of the proposed MCDA-based framework for prioritizing digital transformation projects in SMEs. The Delphi stage demonstrated that the decision problem can be represented through a coherent set of seven criteria combining strategic, operational, organizational, technical, risk, and temporal dimensions. The AHP results showed that experts gave greatest importance to strategic alignment and operational impact, while still assigning substantial weight to feasibility and organizational readiness. The TOPSIS ranking indicated that projects combining value creation with realistic implementation conditions were preferred over more ambitious but more demanding initiatives.

More specifically, the results suggest that SMEs may obtain greater immediate value from projects such as business intelligence dashboards and workflow automation than from more infrastructure-intensive projects such as IoT-based monitoring. At the same time, the sensitivity analysis showed that the ranking can shift meaningfully when cost pressure, cybersecurity concerns, or implementation urgency are emphasized. Therefore, the framework not only produces a prioritized list of projects, but also helps decision-makers understand why certain alternatives dominate under specific strategic conditions.

5. CONCLUSION

This work proposed an MCDA-based framework for prioritizing digital transformation projects in SMEs by integrating a structured criteria-validation stage with AHP-based weighting and TOPSIS-based ranking. The main motivation of the study was the observation that SMEs often face digital transformation as a portfolio problem rather than as a single investment decision. In such contexts, managers must choose among heterogeneous projects competing for limited financial resources, managerial attention, technical capacity, and implementation time. The proposed framework addresses this challenge by offering a transparent and replicable procedure for comparing candidate projects on the basis of strategic, operational, organizational, technical, risk-related, and temporal criteria.

The results of the study suggest that project prioritization in SMEs is driven primarily by a combination of strategic alignment and expected operational impact, but that these value-oriented dimensions are strongly conditioned by organizational readiness and technological feasibility. This finding is important because it shows that project attractiveness in SMEs does not depend solely on expected benefits. Rather, projects are favored when they combine meaningful strategic and operational contribution with a realistic implementation profile. In the illustrative results, initiatives such as business intelligence dashboards and workflow automation outperformed more infrastructure-intensive or technically demanding projects because they offered a more favorable balance between value creation and implementability. In that sense, the study highlights that, in SME settings, the most desirable digital transformation project is not necessarily the most ambitious one, but the one that best fits the firm's current strategic needs and absorptive capacity. From a theoretical perspective, the study contributes to the intersection of digital transformation and multicriteria decision-aiding by translating broad insights from the SME digitalization literature into an operational project-prioritization model. Much of the existing literature has focused on determinants, barriers, capabilities, and success factors of digital transformation, while offering less guidance on how SMEs should rank competing initiatives in actual decision situations. At the same time, the MCDA and project portfolio literatures provide robust methods for multicriteria prioritization, but they are not always tailored to the realities of SME digital transformation. The present study contributes by bridging these two streams and showing how a structured AHP-TOPSIS framework can be used to evaluate digital projects under SME-specific constraints.

The study also offers practical implications for SME managers and decision-makers. First, it provides a systematic alternative to intuitive or ad hoc project selection. Second, it helps decision-makers make trade-offs explicit by requiring every candidate project to be evaluated against the same set of criteria. Third, it can improve internal discussion and alignment by clarifying why some projects should be prioritized over others. Fourth, the framework can be used not only to produce a baseline ranking, but also to explore how rankings change under different strategic scenarios, such as cost pressure, implementation urgency, or stronger cybersecurity concerns. For SMEs, where poor sequencing of digital investments can produce disproportionate negative consequences, such structured support may be especially valuable. Despite these contributions, the study has limitations. First, the framework depends on expert judgment both in the validation of criteria and in the weighting and scoring of alternatives. Although this is consistent with MCDA practice, it also means that the results are sensitive to the composition of the expert panel and to the quality of the elicited judgments. Second, the current model adopts a hierarchical AHP structure and a classical TOPSIS ranking procedure, which favor interpretability and usability but do not explicitly capture strong interdependencies among criteria. Third, the empirical illustration reflects a bounded set of candidate projects and should not be interpreted as universally representative of all SMEs or sectors. The priorities of firms operating in more regulated, data-intensive, or technologically mature environments may differ substantially from those reflected in the present application.

These limitations point to several directions for future research. Future studies could test the framework in multiple sectors and countries in order to examine the stability of the weighting structure across contexts. Researchers could also compare the proposed AHP-TOPSIS approach with other MCDA methods, such as PROMETHEE, VIKOR, ELECTRE, or ANP, to determine whether ranking outcomes remain stable under alternative methodological assumptions. Another promising avenue would be the use of fuzzy or interval-based extensions to better represent uncertainty in qualitative judgments. In addition, future work could embed the framework into a digital decision-support system, allowing SME managers to interactively modify weights, explore scenarios, and visualize ranking sensitivity in real time.

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