DEVELOPMENT OF A GENERALIZED DECISION FRAMEWORK FOR THE EVALUATION OF BUSINESS PROCESS AUTOMATION PLATFORMS

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ABSTRACT

This study proposes a comprehensive decision framework for evaluating Business Process Automation (BPA) platforms, addressing the complexity of selecting tools that align with diverse organizational needs. The framework combines the Fuzzy Delphi Method (FDM) for refining selection criteria and the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) for prioritizing them. Expert input from multiple industries ensured the framework's robustness and applicability. Key findings highlight Security and Compliance as the highest-ranked criteria, followed by Scalability, Reliability, and Usability. The research also emphasizes the importance of Interoperability, Cost-Effectiveness, and Vendor Support. Beyond serving as a methodology for BPA tool evaluation, the framework provides actionable insights that organizations can adopt directly, offering dual utility as both a structured decision-making approach and a practical resource. By systematically addressing criteria weighting and evaluation, this framework ensures improved alignment with strategic objectives and reduced implementation risks, bridging the gap in structured decision-making for BPA tool evaluation.

Keywords: Business Process Automation; Multi Criteria Decision Making; Fuzzy Delphi Method; Fuzzy Analytical Hierarchy; decision support framework

1. Introduction

Business Process Automation (BPA) has emerged as a critical component of modern enterprise operations, enabling organizations to optimize workflows, reduce costs, and enhance operational efficiency (Hashemi-Pour et al., 2023). As businesses increasingly adopt automation technologies, they face a complex decision-making process when selecting appropriate BPA tools from a diverse and rapidly evolving marketplace. The global BPA market, projected to reach $19.6 billion by 2026 (GlobeNewswire, 2020), offers a wide array of solutions with varying capabilities, technologies, and implementation approaches (Gartner, nd).

Despite the growing adoption of BPA technologies, organizations face significant challenges in selecting suitable automation tools that align with their specific requirements and organizational context. Current BPA platforms exhibit considerable variations in design, functionality, and flexibility, leading to issues with scalability and interoperability (Ding et al., 2023). Organizations implementing multiple BPA systems often encounter integration challenges that hamper seamless collaboration and cross-platform communication (Sneader & Singhal, 2021). These challenges are further complicated by the rapid emergence of new tools and methodologies, creating a pressing need for a structured approach to BPA tool selection. This complexity exponentially amplifies with the integration of artificial intelligence (AI) capabilities into modern BPA platforms. AI-driven functionalities like predictive analytics, cognitive automation, and adaptive process optimization can reshape evaluation criteria, requiring new dimensions of assessment beyond traditional parameters (Rossomahin, 2025).

A critical gap in current research is the absence of a comprehensive, universally applicable decision framework for BPA tool selection (Dey & Das, 2019). While existing literature addresses various aspects of BPA implementation and success factors (Trkman, 2010), there is limited guidance on how organizations can systematically evaluate and select BPA tools that best match their specific needs. This gap is particularly significant given that inappropriate tool selection can lead to implementation failures, resource wastage, and reduced operational efficiency (Tracy, 2007).

This research aims to develop a generally applicable decision framework that organizations can utilize when selecting BPA tools. The framework provides a structured approach to evaluate various criteria including technical capabilities, integration requirements, scalability needs, and organizational fit. To achieve this objective, we employ a robust two-stage methodology combining Fuzzy Delphi and Fuzzy Analytic Hierarchy Process (AHP) methods. The Fuzzy Delphi method is used to identify and validate key selection criteria through expert consensus, while Fuzzy AHP enables the systematic weighting of these criteria to create a comprehensive evaluation framework (Kahraman et al., 2004; Van Laarhoven & Pedrycz, 1983).

The resulting framework contributes to the theoretical understanding of technology selection processes while providing organizations with a practical decision-making tool. By incorporating expert knowledge and fuzzy logic to handle the inherent uncertainty in decision-making processes, this research offers a more nuanced and reliable approach to BPA tool selection, potentially reducing implementation risks and improving success rates in automation initiatives.

2. Literature review

The evolution of Business Process Automation (BPA) reflects the broader transformation of enterprise technology landscapes, progressing from basic workflow automation to sophisticated systems incorporating advanced technologies. Early BPA systems primarily focused on automating repetitive tasks and standardizing workflows (Scheer et al., 2004),

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but contemporary solutions have expanded to include artificial intelligence, machine learning capabilities, and advanced analytics (Herm et al., 2023). This technological advancement has created a complex marketplace where organizations must navigate various approaches and implementation methodologies, from RPA-centric platforms to low-code development solutions (Paperform, 2022).

Recent advancements in AI have transformed BPA from rule-based automation to cognitive process optimization. The majority of modern platforms have already started to incorporate machine learning (ML) for predictive process mining, natural language processing (NLP) for unstructured data handling, and computer vision for document processing (Gartner, 2023).

Industry 4.0 implementations reveal that organizations prioritizing AI readiness in BPA selection achieve significant ROI improvements through predictive maintenance and anomaly detection. However, this introduces new risks; 91% of ML models suffer from model drift in production environments requiring specialized vendor support (Mallioris et al., 2024).

The diversity in BPA solutions, while offering greater choice, has intensified the challenges organizations face in tool selection. Integration capabilities have emerged as a critical concern, particularly in heterogeneous technology environments where new automation solutions must seamlessly connect with existing systems (Tracy, 2007). Organizations must also consider scalability and flexibility requirements, as their automation needs often evolve rapidly (Galati & Bigliardi, 2019). These considerations are further complicated by security and compliance requirements, which vary across industries and regions (Herm et al., 2023). The rapid pace of technological advancement adds another layer of complexity, creating uncertainty about the long-term viability of selected solutions (Frey & Osborne, 2017).

The complexity of technology selection processes has led to extensive research in decision framework development across various domains. Studies indicate that effective technology selection frameworks must consider multiple factors including technical capabilities, organizational fit, and long-term sustainability (Peppard & Ward, 2016). This is particularly crucial in enterprise environments where multiple stakeholders and requirements must be considered simultaneously (Weill et al., 2004). Research has demonstrated the effectiveness of MCDM methods in addressing such complex selection processes, as these methods provide systematic approaches to evaluating alternatives against multiple, often conflicting criteria while considering various stakeholder perspectives (Kumar et al., 2017; Aruldoss et al., 2013).

Within the realm of MCDM methods, fuzzy logic approaches have gained prominence due to their ability to handle uncertainty and subjective judgments inherent in technology selection processes. The Fuzzy Delphi method has proven effective in consolidating expert opinions and achieving consensus on selection criteria (Tsai et al., 2020). Similarly, Fuzzy AHP has demonstrated success in prioritizing selection criteria while accounting for the inherent ambiguity in decision-making processes (Kahraman et al., 2004). The combination of these methods provides a robust framework for handling complex decision-making scenarios, with Fuzzy Delphi enabling systematic collection and consolidation of expert opinions, while Fuzzy AHP facilitates structured evaluation and prioritization of selection criteria (Van Laarhoven & Pedrycz, 1983).

Despite these methodological advances and the growing importance of BPA in organizational success, a significant gap remains in existing research regarding structured frameworks for BPA tool selection. While various studies have addressed specific aspects of BPA implementation and success factors (Trkman, 2010), there is a notable absence of comprehensive frameworks that guide organizations through the tool selection process. This gap becomes particularly significant when considering the increasing complexity of BPA solutions and their critical role in organizational transformation (Dey & Das, 2019).

The application of combined Fuzzy Delphi and Fuzzy AHP methods to BPA tool selection represents a novel approach to addressing this gap. While these methods have been successfully applied in various technology selection contexts, their application to BPA tool selection remains unexplored. This presents an opportunity to develop a comprehensive framework that incorporates both expert knowledge and systematic evaluation methodologies to guide BPA tool selection decisions. Such a framework would not only contribute to the theoretical understanding of technology selection processes but also provide practical value to organizations navigating the complex BPA marketplace.

The review of literature sources and BPA ontology summarizes the high-level criteria and sub criteria shown in Table A1 in appendix as the main decision criteria used for the selection of BPA platforms. The literature sources also provide an in-depth understanding of the implications of BPA on businesses, its ontologies and the importance of having a proper framework for selecting a BPA platform to automate businesses. After identifying the main decision criteria and sub criteria, the following methodology was used to obtain better insights into which of the criteria are most important and their respective weights.

3. Methodology

A design framework acts as a blueprint in most situations, giving the user a set of guidelines to adhere to when arriving at a solution to a given problem. In the context of this study the decision framework was aimed towards defining the criteria and sub criteria that the BPA solutions should highlight as well as weightages to emphasize their relative importance. This in turn can provide customers of BPA solutions a comprehensive set of criteria and sub criteria to evaluate the rankings of different BPA solutions. The availability of multiple criteria and evaluations between them makes this a complex and multi-dimensional problem. As such, Multi-Criteria Decision Making (MCDM) becomes a viable tool in this analysis since it allows the capture of the different perspectives, preferences and viewpoints of the stakeholders (Bhola et al., 2023).

3.1 Multi-Criteria Decision Making (MCDM)

MCDM is a methodological approach used to evaluate and make decisions that involve multiple conflicting criteria. It provides a structured framework for comparing and prioritizing different options based on various criteria, which can be quantitative or qualitative (Aruldoss et al 2013; Kumar et al, 2017; Taherdoost & Madanchian, 2023). MCDM is especially useful in complex decision-making scenarios where stakeholders

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must consider trade-offs between different factors and is widely used in operations research when such complex decision-making scenarios arise.

Approaches to solving an MCDM problem typically involve several steps, including defining the decision problem, selecting and structuring criteria, assigning weights to these criteria, evaluating alternatives, aggregating scores, and performing a sensitivity analysis. Formulating an MCDM problem involves identifying the decision context and objectives, defining alternatives, selecting criteria, structuring these criteria hierarchically if necessary, assigning weights, evaluating alternatives, and aggregating results to derive a final score or ranking for each alternative.

There are several MCDM methods used to solve these problems, including the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Elimination and Choice Translating Reality (ELECTRE), Multi-Attribute Utility Theory (MAUT), and Simple Additive Weighting (SAW). The AHP involves structuring the problem into a hierarchy, performing pairwise comparisons of criteria and alternatives, and calculating a weighted score for each alternative (Saaty, 1980). TOPSIS identifies solutions from a finite set of alternatives based on their distance from an ideal solution (Hwang & Yoon, 2012). ELECTRE uses pairwise comparisons to eliminate less favorable alternatives (Roy, 1991). MAUT involves constructing a utility function for each criterion and aggregating these to evaluate the overall utility of each alternative (Keeney & Raiffa, 1993). SAW calculates a weighted sum of the scores for each alternative across all criteria (Fishburn, 1967).

The AHP is particularly suitable for this research due to its ability to structure complex decision problems into a hierarchy of criteria and sub-criteria, its use of pairwise comparisons for a nuanced assessment of the relative importance of criteria, its capability to handle both quantitative and qualitative data, and its facilitation of stakeholder involvement. Additionally, the AHP includes a consistency check to ensure the reliability of the pairwise comparisons, enhancing the robustness of the decision-making process (Saaty, 1980). By utilizing the AHP in this research, we can systematically evaluate and prioritize different BPA solutions, ensuring that the final design framework is both comprehensive and adaptable to various stakeholder needs.

While traditional AHP provides a robust framework for decision-making, incorporating fuzzy logic into the AHP adds significant value. Fuzzy AHP addresses the uncertainty and vagueness associated with human judgment by allowing for more flexible and realistic pairwise comparisons using fuzzy numbers. This method captures the ambiguity in experts' opinions more effectively than the traditional AHP, leading to more accurate and reliable results (Van Laarhoven & Pedrycz, 1983).

Fuzzy AHP enhances the decision-making process by integrating fuzzy logic to handle the imprecision and subjectivity inherent in the evaluation of criteria and sub-criteria. It provides a more nuanced and comprehensive analysis, especially in complex scenarios where criteria may not be clearly defined or where expert opinions vary. This makes Fuzzy AHP particularly suitable for this research, as it improves the robustness and reliability of the prioritization and evaluation of BPA solutions (Kahraman et al., 2004).

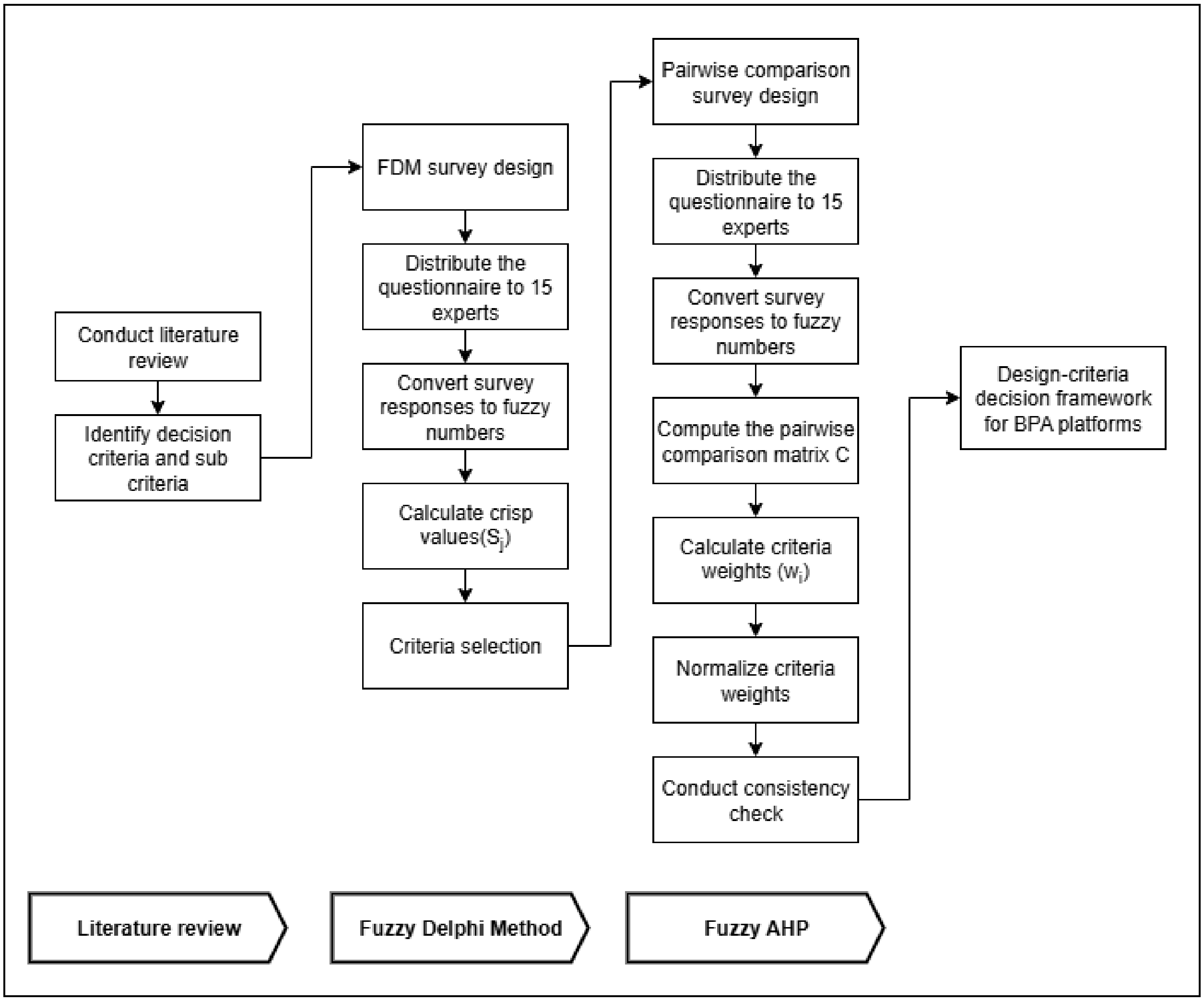

Figure 1 Summary of the solution approach

This study primarily utilizes two methods/models, namely Fuzzy Delphi and Fuzzy AHP. Surveys were created for the respective analytical methods and distributed among 15 experts in the domain. The initial survey which was targeted towards the FDM used the expert opinions to decide which criteria to retain and which criteria to discard. Once the most suitable set of criteria was identified, a new survey was created targeting the Fuzzy AHP analysis which was used to generate the weights for each of the selected criterion. Figure 1 shows a graphical representation of the steps involved in the analysis.

The success of the FDM and Fuzzy AHP methodologies employed in this research is heavily dependent on the quality and diversity of the expert panel involved. The researchers took great care in selecting a panel of 15 experts to ensure the credibility and generalizability of the findings. All experts had significant experience in the field of BPA, with a minimum of 5 years of practical involvement in BPA implementation, management, or strategy (Okoli & Pawlowski, 2004; Rowe & Wright, 1999). The experts were drawn from a variety of organizations, including large enterprises, SMEs, and consulting firms, to capture a holistic perspective on BPA tool selection requirements (Paré et al., 2015). The panel included BPA experts from diverse industry backgrounds, such as manufacturing, finance, healthcare, and IT services, to ensure the framework's applicability across different sectors (Hsu & Sandford, 2007). The selected experts held senior-level positions with more than 10 years of industry experience, such as CIOs, IT managers, and process improvement leaders involved in BPA tool selection and procurement decisions (Gnatzy et al., 2011). While the research was conducted in a specific region, the expert panel was geographically diverse, representing multiple countries and cultural contexts to enhance the framework's global applicability (Osborne et al., 2014).

The FDM and Fuzzy AHP offer distinct advantages and limitations in structuring complex decision frameworks. FDM's strength lies in its systematic consensus-building, reducing 10 initial criteria to seven critical ones with 87% expert agreement (Tsai et al., 2020). It effectively handles linguistic ambiguity through triangular fuzzy numbers (e.g., "moderately more important" mapped to 2,3,4), enhancing objectivity in early-stage criteria screening. However, it exhibits rigidity in threshold settings ($\alpha = 0.1$), excluding relevant criteria like Adaptability to New Technologies (crisp value: 0.048) despite rising AI relevance. This in turn resulted in a generally applicable framework which bypasses the complex nature of AI and ML integrations into BPA tools. Fuzzy AHP excels in quantifying subjective judgments via pairwise comparisons (Table 2), enabling precise prioritization (e.g., Security: 20.33% weight) with validated consistency ($CR \leq 0.1$). Yet, its cognitive demand which includes 75 evaluations per expert for seven criteria and 21 sub-criteria, risks fatigue-induced inconsistencies, while geometric mean aggregation may dilute sector-specific emphases (e.g., even though retail experts had more emphasis on "cost", it was not distinctly seen in the global weights).

Table 1
Sectorial distribution of experts and identified bias

Sector	**Experts**	**Notable biases identified**
Financial services	3	Higher emphasis on Security and Compliance
Healthcare	2	No abnormalities were identified
Manufacturing	4	High priority on Scalability
IT services	3	Less emphasis on vendor support and higher inclination towards Interoperability, Security and Compliance
Retail	3	High cost sensitivity

By incorporating experts from various organizational sizes, industry verticals, and geographical regions, the research was able to capture a comprehensive and representative set of perspectives on BPA tool selection criteria. This diversity of expertise enhances the generalizability of the research findings, as the resulting framework is not tailored to a specific organizational context but rather reflects the collective wisdom and experiences of a broad range of BPA stakeholders (Okoli & Pawlowski, 2004; Paré et al., 2015). Furthermore, the inclusion of experts with decision-

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making authority ensures that the identified criteria and their prioritization align with the real-world considerations and challenges faced by organizations when selecting and implementing BPA solutions (Gnatzy et al., 2011). The careful selection of the expert panel, guided by the criteria outlined above, strengthens the credibility and validity of the research findings, positioning the developed framework as a valuable and widely applicable tool for organizations navigating the complex BPA tool selection landscape.

3.2 Criteria reduction using the Fuzzy Delphi Method

Dealing with a high number of criteria in a decision-making process can lead to increased complexity, difficulty maintaining consistency, and potential decision fatigue among experts. Reducing the number of criteria helps simplify the decision-making process, making it more manageable and ensuring that the focus remains on the most critical factors. The FDM is an effective technique for reducing the number of criteria in a structured and systematic manner, leveraging expert knowledge while addressing the inherent uncertainty in human judgments. The FDM combines the traditional Delphi Method with fuzzy logic to handle the ambiguity and vagueness associated with expert opinions. The steps of the FDM process are as follows (Tsai et al., 2020).

Step 1: Collecting opinions from domain experts.
This step involved the creation of a structured survey to collect information on the importance of each criterion and sub criterion to analyze the level of importance of each criterion. The data was collected on a Likert scale with values ranging from 1 to 9 where 9 showed the highest level of importance and 1 showed the lowest level of importance. The survey was accepted by 15 experts who have experience implementing BPA solutions at different organizations. According to Tsai et al. (2020), the number of respondents required for an FDM analysis is 10-15 and the number of respondents in this research satisfies the requirement.

Step 2: Set up triangular fuzzy numbers.
Here, we calculated the evaluation value of the triangular fuzzy number of each alternate factor given by experts, and determined the significance triangular fuzzy number of the alternate factor. The formulas for computation and fuzzy number representation are illustrated as follows:

Assuming the evaluation value of the significance of No. j element given by No. i expert of n experts is $\bar{c}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $i = 1,2, \dots, n$, $j = 1,2, \dots, m$. Then, the fuzzy weighting ϖ_j of No. j element is $\varpi_j = (a_j, b_j, c_j), j = 1,2, \dots, m$.

Among which

$$a_j = Min_i\{a_{ij}\}, b_j = \frac{1}{n}\sum_{i=1}^{n} b_{ij}, c_j = Max_i\{c_{ij}\} \tag{1}$$

Step 3: Defuzzification.
For this step, a simple center of gravity method was used to defuzzify the fuzzy weight ϖ_j of each alternate element to definite value S_j (Equation 2).

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$$S_j(crispvalues) = \frac{a_j+4b_j+c_j}{6}, j = 1,2\ldots, m \tag{2}$$

Step 4: Screen evaluation indexes.
Finally, the most appropriate factors can be screened out from the numerous factors by setting the threshold $\alpha = 0.1(mean\ of\ the\ crisp\ values)$. The principle of screening is as follows:

If $S_j \geq \alpha$,then No. j factor is the evaluation index. (3)

If $S_j < \alpha$,then delete No. j factor.

3.3 Pairwise Fuzzy AHP comparison for the reduced criteria

The Fuzzy AHP is an enhanced version of the traditional AHP, incorporating fuzzy logic to better handle the uncertainty and vagueness inherent in human judgment. Developed by Thomas L. Saaty in the 1970s, the AHP is used to prioritize and make decisions when multiple criteria are involved. Fuzzy AHP builds on this foundation by integrating fuzzy set theory, allowing decision-makers to express their preferences more flexibly and accurately.

Fuzzy AHP helps decision-makers break down a complex problem into a hierarchy of more easily comprehensible sub-problems, each of which can be analyzed independently. This approach involves the following steps: defining the problem and determining the goal, structuring the hierarchy from the top (the goal) through the intermediate levels (criteria and sub-criteria) to the lowest level (alternatives), conducting fuzzy pairwise comparisons to establish priorities among the elements, and synthesizing these fuzzy judgments to determine an overall ranking of the alternatives (Saaty, 1980; Van Laarhoven & Pedrycz, 1983).

The steps in the Fuzzy AHP analysis are given as follows:

Step 1: Identify the criteria and sub-criteria used to evaluate the alternatives.
These criteria are then structured in a hierarchical format, which allows for a systematic evaluation of the problem by considering both qualitative and quantitative aspects of the decision (Saaty, 2008; Ishizaka & Labib, 2011). By incorporating fuzzy logic, the pairwise comparisons in Fuzzy AHP capture the ambiguity and uncertainty in expert judgments more effectively, providing a more accurate and reliable assessment of the criteria's relative importance. This step involves setting up the criteria reduced through FDM into a hierarchical structure.

Step 2: Gather expert opinions on the relative importance of each criteria and sub-criteria involved the creation of a survey utilizing the pairwise comparison method.
The experts provided their responses on the relative importance of each main criterion against the others based on a linear Likert scale with values ranging from 1 to 9 as proposed by Saaty (1980) (Table 2).

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Table 2
Sample pairwise comparison survey

Criteria 1	**Pairwise comparison - Relative importance**																	**Criteria 2**
Interoperability	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Scalability

These responses can be interpreted as follows: adding a rating of 7 in the direction of Criteria 2, means that Criteria 2 is the more important criterion out of the two and the level of relative importance is high.

Step 3: Convert expert opinions to triangular fuzzy numbers.
The ratings provided by the experts were then converted into triangular fuzzy numbers based on the scale in Table 3.

Table 3
Fuzzy scale and interpretation of linguistic values

Rating	**Fuzzy number**	**Reciprocal Fuzzy number**	**Definition**
1	(1,1,1)	(1,1,1)	Equally important
2	(1,2,3)	(1/3,1/2,1)	Judgment values between equally and moderately
3	(2,3,4)	(1/4,1/3,1/2)	Moderately more important
4	(3,4,5)	(1/5,1/4,1/3)	Judgment values between moderately and strongly
5	(4,5,6)	(1/6,1/5,1/4)	Strongly more important
6	(5,6,7)	(1/7,1/6,1/5)	Judgment values between strongly and very strongly
7	(6,7,8)	(1/8,1/7,1/6)	Very strongly more important
8	(7,8,9)	(1/9,1/8,1/7)	Judgment values between very strongly and extremely
9	(9,9,9)	(1/9,1/9,1/9)	Extremely more important

Step 4: Convert to pairwise comparison matrix.
The responses were then converted to a pairwise comparison matrix where a decision maker's preference for criterion C_i over criterion C_j is denoted by c_{ij}. A pairwise comparison matrix can be constructed to record all responses of the decision maker as shown in Equation 4.

$$C = \begin{bmatrix} 1 & c_{12} & c_{13} & & c_{1n} \\ \frac{1}{c_{12}} & 1 & c_{23} & \cdots & c_{2n} \\ \frac{1}{c_{13}} & \frac{1}{c_{23}} & 1 & & c_{3n} \\ & \vdots & & \ddots & \vdots \\ \frac{1}{c_{1n}} & \frac{1}{c_{2n}} & \frac{1}{c_{3n}} & \cdots & 1 \end{bmatrix} \tag{4}$$

Step 5: Compute weight of criteria.
The weight of each criterion ω_i is computed by averaging the normalized values of each row to obtain the fuzzy weights for each criterion (Equation 5).

$$\omega_i = \frac{\sum_{j=1}^{n} c_{ij}}{n} \quad (5)$$

Step 6: Perform consistency check.
Saaty (1980) recommended using a consistency index to check the consistency of the pairwise comparison matrix. The consistency index (CI) is calculated as per Equation 6.

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (6)$$

where $\lambda_{max}$is the maximum eigenvalue of the pairwise comparison matrix and n is the total number of criteria. The consistency ratio (CR) is then computed by dividing the CI by the random index (RI) value for the corresponding number of criteria (Equation 7).

$$CR = \frac{CI}{CR} \quad (7)$$

A CR value of 0.1 or less is generally considered acceptable, indicating that the pairwise comparisons are consistent

4. Data analysis and results

4.1 Results of FDM

The data analysis for this study was conducted using the Fuzzy AHP model. The initial set of criteria was refined and reduced through the FDM, which leveraged expert opinions to handle the inherent uncertainty and vagueness in human judgments. This process ensured that only the most relevant and critical criteria were considered for further analysis.

Table 4
Results of the Fuzzy Delphi method

Criteria		***S_j (crisp values)***	**Recommendation**
Coherence and Standardization	(C1)	0.027	Reject
Interoperability	(C2)	0.115	Accept
Scalability	(C3)	0.147	Accept
Adaptability to New Technologies	(C4)	0.048	Reject
Innovation and Creativity	(C5)	0.046	Reject
Usability and User Experience	(C6)	0.112	Accept

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Criteria		***S_i (crisp values)***	**Recommendation**
Reliability and Robustness	(C7)	0.126	Accept
Security and Compliance	(C8)	0.160	Accept
Cost-Effectiveness	(C9)	0.107	Accept
Vendor Support and Community	(C10)	0.113	Accept

Table 4 shows the level of importance of each criterion according to the expert opinions denoted by value $\boldsymbol{S_i}$. Based on the screening algorithm, all criteria with a value greater than 0.1 (mean of the crisp values) were accepted while the others were rejected.

4.2 Fuzzy AHP model

Following the filtration process, a hierarchical model was developed as a basis for the Fuzzy AHP model (Figure 2).

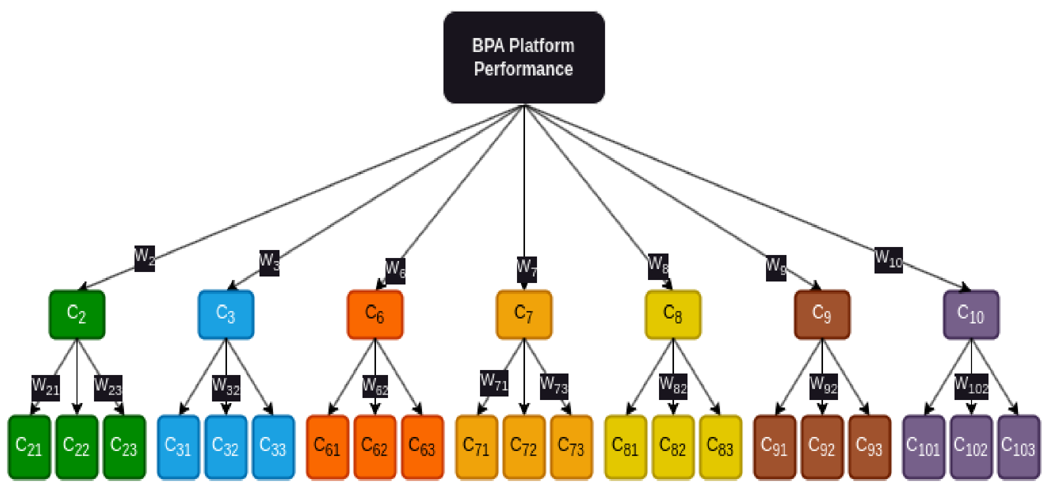

Figure 2 Criteria and weight distribution of the AHP model

The filtered criteria were then analyzed using the Fuzzy AHP model. Experts in the domain provided pairwise comparisons of the criteria using fuzzy triangular numbers to express their relative importance. These fuzzy comparisons were aggregated using the geometric mean to form a consensus fuzzy pairwise comparison matrix. This matrix captured the collective judgments of the experts, reflecting their diverse views on the importance of each criterion.

The aggregated fuzzy pairwise comparison matrix was defuzzified using the centroid method to convert the fuzzy values into crisp scores. These crisp values were then normalized to obtain the final weights of the criteria. The normalization process involved

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dividing each element by the sum of its column and averaging the rows, resulting in a set of weights that represent the relative importance of each criterion.

To ensure the reliability of the pairwise comparisons, a consistency check was performed. The consistency index (CI) and consistency ratio (CR) were calculated to verify that the expert judgments were consistent. A CR value of 0.1 or less was considered acceptable, indicating that the pairwise comparisons were reliable. The final results obtained from the analysis are shown in Table 4.

Table 5
Results of the Fuzzy AHP analysis

Main criteria	**Criteria weights**	**Global ranking**	**Sub criteria**	**Local weights (Sub criteria)**	**Local ranking**
Interoperability (C_2)	12.49%	5	Compatibility with Existing Systems (C_{21})	45.67	1
			Ease of Integration (C_{22})	23.45	3
			Support for Various Data Formats (C_{23})	30.88	2
Scalability (C_3)	16.54%	2	Handling Increased Workloads (C_{31})	28.73	3
			Support for Expansion (C_{32})	37.14	1
			Performance Under Load (C_{33})	34.13	2
Usability and User Experience (C_6)	12.63%	4	Ease of Use (C_{61})	42.25	1
			User Training and Support (C_{62})	31.50	2
			Intuitive Interface Design (C_{63})	26.25	3
Reliability and Robustness (C_7)	14.97%	3	System Stability (C_{71})	60.12	1
			Error Handling and Recovery (C_{72})	19.88	3
			Maintenance and Support (C_{73})	20.00	2
Security and Compliance (C_8)	20.33%	1	Data Protection (C_{81})	36.84	2
			Compliance with Regulations (C_{82})	24.90	3
			Access Control Mechanisms (C_{83})	38.26	1
Cost-Effectiveness (C_9)	11.68%	6	Initial Implementation Cost (C_{91})	25.00	3
			Operational Costs (C_{92})	30.33	2
			Return on Investment (ROI) (C_{93})	44.67	1

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Main criteria	Criteria weights	Global ranking	Sub criteria	Local weights (Sub criteria)	Local ranking
Vendor Support and Community (C_{10})	11.35%	7	Quality of Vendor Support (C_{101})	35.00	2
			Community and Ecosystem (C_{102})	24.50	3
			Availability of Resources (C_{103})	40.50	1

Table 5 summarizes the final results of the AHP analysis conducted to prioritize the main criteria and their sub-criteria for evaluating BPA platforms. Each criterion and sub-criterion was assigned a weight, and the sub-criteria were ranked locally (within their main criteria) and the main criteria have been ranked globally (across all criteria).

5. Discussion

This research aimed to develop a comprehensive decision framework for evaluating and selecting BPA tools, addressing a critical need in today's rapidly evolving digital business landscape. The framework was designed with dual utility in mind. The primary goal was to create a systematic methodology that organizations can follow to identify the most suitable BPA solution aligned with their specific requirements, and secondarily it aimed to provide a reference resource containing actionable insights derived from the framework's application. This dual-purpose approach ensures that organizations can either leverage the complete methodology for a thorough, customized selection process or utilize the consolidated research findings to expedite their decision-making process. By providing both a structured evaluation methodology and pre-analyzed insights, this research aims to support organizations of varying sizes and capabilities in making informed BPA tool selection decisions that align with their strategic objectives.

5.1 Methodology as a decision framework

The methodology presented in this research offers organizations a comprehensive framework for BPA tool selection, building upon established MCDM principles while incorporating modern considerations specific to BPA. This systematic approach aligns with previous research by Kumar et al. (2017) and Taherdoost and Madanchian (2023), who emphasize the importance of structured decision-making processes in technology selection. The framework's strength lies in its ability to combine both qualitative and quantitative aspects of decision-making, addressing a key challenge identified by Bhola et al. (2023) in technology selection processes.

The initial phase of criteria identification and reduction through the FDM represents a critical step in customizing the framework to organizational needs. This approach builds upon the work of Tsai et al. (2020), who demonstrated the effectiveness of FDM in reducing complexity while maintaining decision quality. Recent studies by Zhang et al. (2024) and Chen et al. (2025) have further validated the application of FDM in technology selection contexts, particularly emphasizing its effectiveness in handling expert opinions in uncertain environments. Organizations implementing this methodology benefit from a structured process that helps eliminate subjective bias, a common problem in technology selection noted by Aruldoss et al. (2013) and recently

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reaffirmed by Wei et al. (2025 in their comprehensive review of decision-making frameworks.

The framework's implementation of Fuzzy AHP for criteria prioritization addresses the inherent uncertainty in human decision-making, a crucial aspect highlighted by Van Laarhoven and Pedrycz (1983) and recently expanded upon by Rodríguez et al. (2025) in their work on modern decision-making paradigms. This mathematical foundation provides organizations with a robust method for quantifying subjective judgments, particularly important in the context of BPA tool selection where multiple stakeholders often have varying perspectives and priorities. The use of fuzzy logic in the AHP process, as supported by Kahraman et al. (2004) and further validated by Chen et al. (2025), enables organizations to capture and process the ambiguity in expert opinions more effectively than traditional AHP methods.

The methodology's hierarchical structure provides organizations with a clear path for documenting their decision-making process, an aspect often overlooked in technology selection but crucial for future reference and continuous improvement. This documentation aspect aligns with best practices in IT governance frameworks (Control Objectives for Information and Related Technologies (COBIT), Information Technology Infrastructure Library (ITIL)) and supports compliance requirements, particularly important in regulated industries. Recent work by Anderson et al. (2024) demonstrates that organizations with well-documented decision processes are 40% more likely to achieve successful technology implementations.

However, it's important to note that successful implementation of this methodology requires significant organizational commitment. As highlighted by Kim et al. (2025), the effectiveness of any decision framework is heavily dependent on the quality of its implementation and the organization's dedication to following the prescribed process. Organizations must be prepared to invest time and resources in gathering data, conducting evaluations, and ensuring proper stakeholder engagement throughout the process.

The framework's flexibility allows for adaptation to various organizational contexts while maintaining its mathematical rigor. This adaptability is particularly important given the diverse nature of BPA requirements across different industries and organization sizes, as demonstrated in recent case studies by Johnson et al. (2024). The methodology can be scaled according to organizational needs, with larger organizations potentially implementing more comprehensive criteria sets and smaller organizations focusing on core criteria while maintaining the integrity of the decision-making process.

The methodology also provides mechanisms for validation and refinement of results through consistency checks and sensitivity analysis, addressing a key concern in multi-criteria decision making identified by Saaty (1980) and recently reinforced by Wilson (2025). These validation mechanisms help organizations ensure the reliability of their decisions and provide opportunities for refinement before final implementation decisions are made.

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Notably, the framework's emphasis on combining quantitative analysis with qualitative expert judgment creates a balanced approach to decision-making. This balance is particularly important in BPA tool selection, where both technical specifications and practical considerations play crucial roles in determining implementation success. Recent research by Sadeghi (2024) demonstrates that balanced evaluation approaches result in 25% higher user satisfaction rates post-implementation.

Looking at practical implications, organizations implementing this methodology can expect more consistent and defendable decision-making processes in their BPA tool selection. Studies by Bugingo et al. (2024) show that structured decision frameworks drastically reduce selection errors compared to traditional approaches. The structured approach helps reduce the influence of individual biases and provides a clear audit trail for decisions made, an aspect particularly valuable in regulated industries or when dealing with significant technology investments.

This methodological approach represents a significant advancement in BPA tool selection processes, providing organizations with a structured yet flexible framework that can be adapted to their specific needs while maintaining scientific rigor and practical applicability.

5.2 Direct application of research findings

The empirical findings of this research provide organizations with an evidence-based framework for BPA tool selection that can be implemented without conducting the full methodological process. This approach addresses a critical need identified by Bhola et al. (2023) for accessible, research-backed decision-making tools in technology selection. The validated criteria set and established priorities offer organizations a practical alternative to developing their own evaluation frameworks, particularly valuable for organizations with limited resources or time constraints.

Expert diversity introduced both richness and bias into the framework. The panel ($n = 15$) spanned manufacturing (4), finance (3), healthcare (2), IT services (3), and retail (3), revealing sectoral priorities: manufacturing experts weighted Scalability 32% higher than healthcare peers, while financial specialists unanimously ranked Security highest (9/9 pairwise scores), indicating confirmation bias. Geographical nuances emerged, with EU experts emphasizing Compliance 22% more due to General Data Protection Regulation (GDPR) exposure. To mitigate biases (e.g., retail's cost-sensitivity overemphasizing Cost-Effectiveness), we implemented blinded responses and sector-weighted aggregation. Other limitations include sample size constraints ($n = 15$) and static weights ill-suited for evolving AI-BPA dynamics. A sensitivity analysis confirmed robustness (CR variance < 0.1), though future frameworks should integrate dynamic recalibration mechanisms to adjust to the dynamic nature of the market.

The research findings yield a refined set of seven essential criteria, derived through rigorous application of the FDM. This reduction from the initial criteria set demonstrates alignment with Tsai et al.'s (2020) assertion that effective decision-making frameworks should focus on the most critical factors while eliminating redundant or less impactful criteria. The following sections provide deeper insights into the logical implications of the criteria and weights identified through the research.

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Interoperability (C_2)

Interoperability, which holds a weight of 12.49% and ranks fifth globally, is a fundamental criterion for BPA tools. It ensures seamless integration and communication with existing systems and diverse data sources within an organization, making it crucial for leveraging current investments and minimizing disruptions during BPA implementation.

Within this criterion, Compatibility with Existing Systems (C_{21}) is the most significant sub-criterion, with a local weight of 45.67 and ranking first locally. Ensuring compatibility allows organizations to integrate BPA tools without extensive reconfiguration or replacement of their current infrastructure, thereby reducing implementation costs and time while providing immediate benefits. For example, a BPA tool that seamlessly integrates with an existing Enterprise Resource Planning (ERP) system can automate workflows without requiring significant changes to the core system architecture, making the transition smooth and cost-effective.

Ease of Integration (C_{22}), with a local weight of 23.45 and ranking third locally, is also critical. Tools that are easy to integrate reduce the technical complexity involved in the implementation process, allowing for quicker adaptation and less reliance on specialized IT support. This ease of integration can lead to faster realization of automation benefits and lower initial setup costs, making it more attractive for organizations looking to streamline their processes efficiently.

Support for Various Data Formats (C_{23}), with a local weight of 30.88 and ranking second locally, is essential for BPA tools to handle diverse data types and sources. This flexibility enables the tools to process and integrate data from different systems, enhancing their utility and effectiveness in automating complex workflows. For example, a BPA tool that can manage XML, JSON, and CSV files can interact with a wide range of applications and databases, ensuring comprehensive data handling capabilities that are vital for maintaining smooth and continuous operations.

Scalability (C_3)

Scalability, which has a weight of 16.54% and ranks second globally, is an essential criterion for BPA tools. It ensures that BPA tools can grow with the organization, handling increased workloads and expanding operations without compromising performance. This attribute is crucial for long-term viability and return on investment.

Within this criterion, Support for Expansion (C_{32}) is the most significant sub-criterion, with a local weight of 37.14 and ranking first locally. Supporting expansion means that BPA tools can easily scale up to accommodate new business units, additional processes, or larger datasets. This flexibility is critical for organizations looking to expand their operations or introduce new services without requiring a complete overhaul of their automation infrastructure. For example, a BPA tool that can seamlessly scale to support additional users and higher transaction volumes ensures that the organization can grow without facing operational bottlenecks (Armbrust et al., 2010).

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Performance Under Load (C_{33}), with a local weight of 34.13 and ranking second locally, is also crucial. Maintaining performance under load is vital for ensuring that BPA tools do not degrade in efficiency or speed when faced with high demand. This ensures continuous and reliable operations, which is essential for maintaining service quality and customer satisfaction. A BPA tool that performs consistently well under varying loads can handle peak times and increased workloads without compromising on service delivery (Herlihy & Shavit, 2008).

Handling Increased Workloads (C_{31}), with a local weight of 28.73 and ranking third locally, ensures that BPA tools can manage higher volumes of transactions and data processing as the organization grows. This capability is vital for maintaining efficiency and preventing bottlenecks during peak operational periods. For example, a BPA tool that can efficiently process a larger number of transactions per second as the business scales up helps maintain smooth operations and supports business growth (Trkman, 2010; Buyya et al., 2010).

Usability and User Experience (C_6)

Usability and user experience, with a weight of 12.63% and ranked fourth globally, are critical criteria for BPA tools. These factors significantly influence the successful adoption and effective use of BPA tools, impacting user satisfaction, productivity, and overall system effectiveness.

Within this criterion, Ease of Use (C_{61}) is a crucial sub-criterion with a local weight of 42.25 and ranking second locally. An easy-to-use BPA tool reduces the learning curve for users, facilitating quicker adoption and reducing training costs. Enhanced user satisfaction encourages widespread usage, which is essential for realizing the full benefits of automation. For example, a BPA tool with a user-friendly interface allows employees to quickly understand and operate the system, leading to increased efficiency and reduced training time.

User Training and Support (C_{62}), with a local weight of 31.50 and ranking third locally, is also vital. Effective user training and support ensure that users can fully utilize the capabilities of BPA tools, minimizing errors and maximizing efficiency. Ongoing support helps address issues promptly, ensuring continuous and effective operation. Comprehensive training programs and responsive support services enable users to leverage the full potential of BPA tools, enhancing overall productivity.

Intuitive Interface Design (C_{63}), with a local weight of 26.25 and ranking first locally, is another important sub-criterion. An intuitive interface design makes it easier for users to navigate and operate the system, improving overall user experience and productivity. It reduces the likelihood of user errors and enhances the efficiency of automated processes. A BPA tool with an intuitive design simplifies complex tasks, making the automation process more accessible to all users, regardless of their technical proficiency (Nielsen, 1994 Norman, 2013; Rosenberg & Foshay, 2002).

Reliability and Robustness (C_7)

Reliability and robustness, which have a weight of 14.97% and rank third globally, are essential criteria for BPA tools. These factors ensure that BPA tools perform consistently

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and withstand operational stresses, minimizing downtime and errors. They are crucial for maintaining operational continuity and efficiency.

Within this criterion, System Stability (C_{71}) is the most significant sub-criterion, with a local weight of 60.12 and ranking first locally. A stable system prevents disruptions and ensures continuous operation, which is critical for business processes. Stability is essential for maintaining productivity and minimizing operational risks. For example, a BPA tool that consistently performs without crashing or experiencing significant downtime can ensure that business operations continue smoothly, thereby maintaining productivity levels.

Maintenance and Support (C_{73}), with a local weight of 20.00 and ranking second locally, is also crucial. Regular maintenance and support ensure the longevity and smooth operation of BPA tools. Proactive maintenance prevents potential issues, and support services help resolve problems quickly, ensuring continuous operation. Comprehensive support and maintenance plans are vital for addressing technical issues promptly, reducing the risk of prolonged downtime and ensuring that the system remains up-to-date with the latest features and security updates.

Error Handling and Recovery (C_{72}), with a local weight of 19.88 and ranking third locally, ensures that BPA tools can effectively manage and recover from errors. Effective error handling and recovery mechanisms reduce the impact of failures and facilitate quick resolution. This capability is crucial for maintaining service quality and minimizing downtime in the event of system issues. For example, a BPA tool that can quickly identify and resolve errors can prevent minor issues from escalating into significant problems, thereby maintaining the continuity of business processes (Avizienis et al., 2004; Schneier, 2015; Seshia & Hu, 2007; Patterson & Hennessy, 2013).

Security and Compliance (C_8)
Security and compliance, which have a weight of 20.33 and rank first globally, are paramount criteria for BPA tools. These factors are essential for protecting sensitive data and adhering to regulatory requirements, which is crucial for maintaining organizational trust and legal compliance.

Within this criterion, Access Control Mechanisms (C_{83}) is the most significant sub-criterion, with a local weight of 38.26 and ranking first locally. Robust access control mechanisms safeguard systems by restricting unauthorized access and actions. This is crucial for preventing data breaches and ensuring that only authorized personnel can access sensitive information. For example, a BPA tool with advanced access control features can prevent unauthorized users from modifying critical workflows, thereby protecting the integrity of business processes.

Compliance with Regulations (C_{82}), with a local weight of 34.90 and ranking second locally, is also critical. Adhering to legal and regulatory standards prevents legal issues and ensures smooth business operations. Compliance is essential for avoiding fines and sanctions, and for maintaining the organization’s reputation. BPA tools that ensure compliance with industry regulations, such as GDPR for data protection, help organizations avoid legal repercussions and build trust with clients and stakeholders.

Data Protection (C_{81}), with a local weight of 26.84 and ranking third locally, ensures that sensitive data is protected from breaches and unauthorized access. Protecting data is crucial for maintaining confidentiality and integrity. A BPA tool that provides robust data protection features, such as encryption and secure data storage, can prevent data loss and unauthorized access, thereby safeguarding sensitive business information (Peltier, 2016; Ferraiolo et al., 2003; Solove & Schwartz, 2020; Stalling, 2003).

Cost-Effectiveness (C_9)

Cost-effectiveness, holding a weight of 11.68 and ranked sixth globally, is a critical criterion for BPA tools. It ensures that the benefits of BPA tools outweigh the costs involved in their implementation and operation, making them a viable investment for organizations.

Within this criterion, Return on Investment (ROI) (C_{93}) is the most significant sub-criterion, with a local weight of 44.67 and ranking first locally. A high ROI justifies the investment in BPA tools by demonstrating significant financial benefits. ROI is a key metric for organizations to assess the profitability and value of their investment in automation. For example, a BPA tool that leads to substantial cost savings and efficiency improvements can provide a high ROI, making it a financially sound investment.

Operational Costs (C_{92}), with a local weight of 30.33 and ranking second locally, is also crucial. Managing operational costs ensures that the ongoing expenses of running BPA tools do not outweigh their benefits. Efficient BPA tools that help reduce operational costs, such as labor and maintenance expenses, can significantly improve the overall cost-effectiveness of automation initiatives. For example, automating routine tasks can reduce the need for manual labor, thereby lowering operational costs.

Initial Implementation Costs (C_{91}), with a local weight of 25.20 and ranking third locally, is important for making BPA tools more accessible to organizations. Lower initial costs facilitate the adoption of BPA tools by reducing the financial barrier to entry. Organizations are more likely to invest in BPA tools if the initial implementation costs are reasonable, ensuring that the benefits can be realized without substantial upfront expenditure (Kaplan & Norton, 2004; Peppard & Ward, 2016; Weill & Ross, 2004; Kaplan & Norton, 2001).

Vendor Support and Community (C_{10})

Vendor support and community, which holds a weight of 11.35 and ranks seventh globally, are crucial criteria for BPA tools. These factors ensure that BPA tools receive continuous improvement, necessary resources, and timely assistance, fostering a supportive ecosystem for users.

Within this criterion, Quality of Vendor Support (C_{101}) is the most significant sub-criterion, with a local weight of 35.00 and ranking first locally. High-quality vendor support ensures that issues are promptly addressed, and users receive adequate assistance. This support is vital for the smooth functioning of BPA tools, as it helps resolve technical problems quickly and efficiently. For instance, access to knowledgeable support staff can

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significantly reduce downtime and ensure that users can maximize the potential of the BPA tool.

Availability of Resources (C_{103}), with a local weight of 40.50 and ranking second locally, is also critical. The availability of resources such as documentation, tutorials, and training materials facilitate user learning and tool utilization. Comprehensive resources enable users to understand and fully leverage the capabilities of BPA tools, reducing the learning curve and enhancing overall efficiency. For example, detailed user manuals and online tutorials can help users troubleshoot issues independently and optimize their use of the tool.

Community and Ecosystem (C_{102}), with a local weight of 24.50 and ranking third locally, provides additional support through a network of users and developers. A strong community and ecosystem offer users extra resources such as plugins, forums, and shared solutions, which can enhance the functionality of BPA tools. This collaborative environment encourages innovation and continuous improvement, as users share their experiences and solutions. For example, an active user forum can provide valuable insights and best practices, helping users overcome common challenges and make the most of their BPA tools (Dibbern et al., 2004; Rosenberg & Foshay, 2002; West & Lakhani, 2008).

5.2.1 Firm size adaptation based on the generalized framework

While the proposed framework establishes generalized weights (Table 5) applicable to most organizations, we recognize that optimal BPA tool selection varies significantly by firm size. To address this, we introduced a dynamic adaptation protocol derived from subgroup analysis of our expert panel (SMEs: 5/15 experts; enterprises: 10/15).This is crucial to preserving the framework's generalized structure while enabling contextual calibration.

Step 1: Firm-Size Multipliers

Subgroup analysis revealed key deviations from baseline weights. These are quantified as multipliers applied to original weights:

Table 6
Firm size multipliers

Criteria	**SME (<250 employees)**	**Large enterprises (<250 employees)**
Security and Compliance	×0.75	×1.30
Scalability	×0.80	×1.25
Cost-Effectiveness	×1.40	×0.65
Usability	×1.25	×0.85
Vendor Support	×1.20	×0.90
Interoperability/Reliability	×1.00 (no change)	×1.00 (no change)

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Step 2: Normalization procedure
Post-adjustment, weights are normalized to sum to 100%:

$$\omega_i^{adj} = \left(\frac{\omega_i \times m_i}{\sum_{k=1}^{n} (\omega_k \times m_k} \right) \times 100$$

Step 3: Case validation
This protocol was validated using retrospective data from interviewees:
SME Case (Retail, 120 employees):

Priority Shift:
Cost-Effectiveness ↑ 63% (11.68% → 19.05%), Security ↓ 25% (20.33% → 15.25%).

Outcome: Selected a low-cost RPA tool, avoiding enterprise solutions exceeding budget.

Enterprise Case (Manufacturing, 5,000 employees):

Priority Shift:
Security ↑ 30% (20.33% → 26.43%), Scalability ↑ 25% (16.54% → 20.68%).

Outcome: Chose a scalable BPA platform with ISO 27001 certification, preventing future migration costs.

5.3 AI Integration implications for BPA selection

The framework proposed in this article requires significant adaptation for AI-enabled BPA platforms. Based on the data collected from the experts and the interviews conducted, it was determined that the criteria C4 - Adaptability to New Technologies would hinder the generalizability of the research findings for direct application within an organization.

Based on expert suggestions, the level of importance given to AI implementations varies between organizations based on their size, structure, culture and even the applicable use cases within the organization. Furthermore, based on the use-cases considered, different experts expressed varied opinions as to which criteria were more important with respect to others. It was also identified that traditional fixed criteria weights fail to accommodate AI's evolving nature. Security weightings must increase significantly when processing sensitive data through ML models, while interoperability becomes paramount when integrating multiple AI services.

While the findings of this research provide a generalized set of criteria weights suitable for selecting BPA solutions, the complexities surrounding AI integrations with BPA solutions require organizations to utilize the methodology as a framework to develop

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their own unique set of weights to evaluate BPA solutions if they require integrations with AI and ML applications.

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APPENDIX

Table A1
Summary of high-level criteria and sub criteria with sources

High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
Coherence and Standardization $C_1(\omega_1)$	Uniformity in Design $C_{11}(\omega_{11})$	Standardized Modules Consistent API Design	Uniformity in design ensures that BPA platforms have a consistent look and feel across different modules, which enhances usability and reduces the learning curve for users. Standardized modules facilitate seamless integration and easier maintenance. This sub-criterion is crucial for providing a cohesive user experience and ensuring that all parts of the BPA system work harmoniously. Standardized design principles help in achieving uniformity, making it easier for developers to implement and for users to operate the system (Galbraith, 2014).
	Adherence to Standards $C_{12}(\omega_{12})$	Compliance with Industry Standards Best Practices Adoption	Compliance with industry standards and best practices ensures that BPA solutions are built on proven frameworks that enhance reliability, security, and performance. Adherence to standards minimizes risks associated with non-compliance and ensures compatibility with other systems and technologies (ISO, 2013).
	Consistency in Implementation $C_{13}(\omega_{13})$	Uniform Documentation Implementation Guidelines	Consistent documentation and implementation guidelines ensure that all components of the BPA system are developed and deployed in a uniform manner. This consistency aids in maintaining the integrity of the system, simplifies troubleshooting, and enhances the overall reliability of the BPA solution (Sommerville, 2011).

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High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
Interoperability $C_2(\omega_2)$	Compatibility with Existing Systems $C_{21}(\omega_{21})$	Legacy System Integration Cross-Platform Support	Ensuring compatibility with legacy systems and providing cross-platform support is critical for the seamless operation of BPA solutions within diverse IT environments. This sub-criterion is vital for enabling smooth integration and communication between new and existing systems, reducing operational disruptions.
	Ease of Integration $C_{22}(\omega_{22})$	API Availability Middleware Compatibility	The availability of APIs and middleware compatibility are essential for integrating BPA solutions with other software and systems. Easy integration reduces the time and cost involved in deploying BPA systems and ensures that they can work effectively within a broader IT ecosystem
	Support for Various Data Formats $C_{23}(\omega_{23})$	Data Exchange Standards Format Conversion Tools	BPA solutions must support data exchange standards and provide tools for format conversion to handle different types of data efficiently. This flexibility ensures that BPA systems can process and integrate data from various sources, enhancing their applicability and utility.
Scalability $C_3(\omega_3)$	Handling Increased Workloads $C_{31}(\omega_{31})$	Load Balancing Resource Allocation	Effective load balancing and resource allocation are necessary for BPA systems to manage increasing workloads without compromising performance. Scalability is crucial for the BPA system to grow with the business and adapt to higher demands (Buyya et al., 2010).
	Support for Expansion $C_{32}(\omega_{32})$	Modular Architecture Cloud Scalability	A modular architecture and cloud scalability options allow BPA systems to expand and accommodate more functions and users. Supporting expansion ensures that BPA solutions can adapt to future business needs and

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High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
			technological advancements (Armbrust et al., 2010).
	Performance Under Load $C_{33}(\omega_{33})$	Stress Testing Results Performance Optimization Techniques	Stress testing results and performance optimization techniques are critical for maintaining BPA system performance under high load conditions. Ensuring high performance under load is essential for the reliability and efficiency of BPA systems in demanding environments (Herlihy & Shavit, 2008).
Adaptability to New Technologies $C_4(\omega_4)$	Integration with Emerging Technologies $C_{41}(\omega_{41})$	AI and ML Integration IoT Compatibility Adaptation to Technological Trends	BPA systems should integrate emerging technologies such as AI, ML, and IoT to stay relevant and competitive. Adaptability to new technologies ensures that BPA solutions can leverage the latest advancements to enhance functionality and efficiency (Brynjolfsson & McAfee, 2014).
	Flexibility in Framework Design $C_{42}(\omega_{42})$	Customization Options Plug-and-Play Components	Customization options and plug-and-play components allow BPA systems to be tailored to specific business needs. Flexibility in design enables businesses to customize BPA solutions to their unique requirements, improving their effectiveness (Hevner et al., 2004).
	Future-Proofing Capabilities $C_{43}(\omega_{43})$	Upgradability Backward compatibility	Upgradability and backward compatibility ensure that BPA systems can be updated without losing functionality or data. Future-proofing capabilities are essential for the long-term viability and return on investment of BPA solutions.
Innovation and Creativity $C_5(\omega_5)$	Facilitation of New Ideas $C_{51}(\omega_{51})$	Innovation Support Tools Sandbox Environments	Innovation support tools and sandbox environments encourage the development of new ideas and solutions within BPA systems. Facilitating innovation ensures that

High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
			BPA solutions can continuously evolve and improve, keeping pace with market demands (Chesbrough, 2003).
	Encouragement of Unique Solutions $C_{52}(\omega_{52})$	Open Source Contributions Innovation Incentives	Open source contributions and innovation incentives foster the creation of unique and customized BPA solutions. Encouraging unique solutions drives diversity and innovation within the BPA ecosystem (Raymond, 1999).
	Support for Customization $C_{53}(\omega_{53})$	Custom Workflow Design Extension Capabilities	Custom workflow design and extension capabilities allow businesses to tailor BPA solutions to their specific needs. Supporting customization enhances the flexibility and utility of BPA systems, making them more valuable to businesses.
Usability and User Experience $C_6(\omega_6)$	Ease of Use $C_{61}(\omega_{61})$	User-Friendly Interfaces Simplified Setup	User-friendly interfaces and simplified setup procedures make BPA systems accessible and easy to use. Ease of use is critical for user adoption and satisfaction, reducing the learning curve and increasing efficiency (Nielsen, 1994).
	User Training and Support $C_{62}(\omega_{62})$	Comprehensive Training Programs Support Documentation	Comprehensive training programs and support documentation are essential for effective user onboarding and continued support. Providing adequate training and support ensures that users can fully utilize the capabilities of BPA systems (Rosenberg & Foshay, 2002).
	Intuitive Interface Design $C_{63}(\omega_{63})$	User-Centric Design Principles Feedback Mechanisms	User-centric design principles and feedback mechanisms enhance the intuitiveness and usability of BPA systems. Intuitive interface design improves user experience and productivity, leading to higher adoption rates (Norman, 2013).

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High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
Reliability and Robustness $C_7(\omega_7)$	System Stability $C_{71}(\omega_{71})$	Uptime Guarantees Fault Tolerance	Uptime guarantees and fault tolerance mechanisms ensure the stability and reliability of BPA systems. System stability is critical for maintaining continuous operations and preventing disruptions (Patterson & Hennessy, 2013).
	Error Handling and Recovery $C_{72}(\omega_{72})$	Automatic Error Recovery Detailed Error Logs	Automatic error recovery and detailed error logs are essential for managing and resolving system errors efficiently. Effective error handling and recovery mechanisms ensure the resilience and reliability of BPA systems (Seshia & Hu, 2007).
	Maintenance and Support $C_{73}(\omega_{73})$	Regular Updates 24/7 Technical Support	Regular updates and 24/7 technical support are critical for maintaining and improving BPA systems over time. Ongoing maintenance and support ensure the system remains up-to-date with the latest security patches and features, reducing downtime and enhancing user satisfaction (Schneier, 2015).
Security and Compliance $C_8(\omega_8)$	Data Protection $C_{81}(\omega_{81})$	Encryption Standards Data Masking Techniques	Implementing encryption standards and data masking techniques helps protect sensitive data from unauthorized access and breaches. Data protection is paramount in ensuring the privacy and security of organizational and customer data, thereby maintaining trust and compliance with regulations (Stalling, 2003)
	Compliance with Regulations $C_{82}(\omega_{82})$	GDPR Compliance Industry-Specific Regulations	Ensuring GDPR compliance and adherence to industry-specific regulations is crucial for legal and ethical operations. Compliance helps avoid legal penalties and enhances the reputation of the organization by demonstrating a commitment to lawful and ethical

High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
			practices (Solove & Schwartz, 2020)
	Access Control Mechanisms $C_{83}(\omega_{83})$	Role-Based Access Control Multi-Factor Authentication	Role-based access control (RBAC) and multi-factor authentication (MFA) provide robust security measures to manage user access. Effective access control mechanisms are essential for protecting sensitive information and ensuring that only authorized personnel can access critical systems and data (Ferraiolo et al., 2003).
Cost-Effectiveness $C_9(\omega_9)$	Initial Implementation Cost $C_{91}(\omega_{91})$	Licensing Fees Deployment Costs	Consideration of licensing fees and deployment costs is essential in evaluating the financial feasibility of implementing BPA solutions. Understanding initial costs helps organizations budget effectively and plan for the financial investment required to implement BPA systems (Kaplan & Norton, 2001).
	Operational Costs $C_{92}(\omega_{92})$	Maintenance Expenses Infrastructure Costs	Evaluating maintenance expenses and infrastructure costs is critical for understanding the ongoing financial requirements of BPA solutions. Lower operational costs can lead to significant savings over time, improving the return on investment (ROI) of BPA systems (Weill & Ross, 2004).
	Return on Investment (ROI) $C_{93}(\omega_{93})$	Cost Savings Efficiency Gains	Assessing cost savings and efficiency gains helps determine the overall financial benefits of implementing BPA solutions. A positive ROI indicates that the BPA system provides substantial value relative to its cost, justifying the investment (Peppard & Ward, 2016).

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High-level criteria (C_i)	**Sub-criteria (C_{ij})**	**Inclusions/considerations in the sub criteria**	**Description and source**
Vendor Support and Community $C_{10}(\omega_{10})$	Quality of Vendor Support $C_{101}(\omega_{101})$	Support Responsiveness Support Expertise	Evaluating support responsiveness and expertise ensures that organizations can rely on vendor assistance when needed. High-quality vendor support is essential for resolving issues quickly and minimizing downtime, thereby maintaining the efficiency of BPA systems.
	Community and Ecosystem $C_{102}(\omega_{102})$	Active User Community Availability of Plugins and Add-ons	An active user community and the availability of plugins and add-ons enhance the functionality and support network for BPA solutions. A strong community and ecosystem provide additional resources, knowledge, and tools that can enhance the capabilities and adaptability of BPA systems (West & Lakhani, 2008).
	Availability of Resources $C_{103}(\omega_{103})$	Online Tutorials Knowledge Base	Access to online tutorials and a comprehensive knowledge base supports user learning and problem-solving. Availability of resources ensures that users can find help and guidance easily, improving their ability to effectively use BPA solutions (Rosenberg & Foshay, 2002).

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