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Strategies for Implementing Process Automation with Artificial Intelligence in Startups

ABSTRACT

This study aimed to identify and prioritize the key strategies that enable startups to effectively implement process automation using artificial intelligence (AI), addressing both organizational and technological dimensions. A qualitative research design was employed, using purposive sampling to select 21 participants, including founders, senior managers, and technical experts from technology-driven startups in Tehran, Iran. Data were collected through in-depth semi-structured interviews designed to explore participants' experiences with Al-driven automation adoption. Interviews continued until theoretical saturation was reached. All interviews were transcribed verbatim and analyzed using NVivo 14 through open, axial, and selective coding to generate themes. After the qualitative phase, the identified strategies were subjected to quantitative prioritization; participants rated the relative importance of each strategy, and descriptive statistical analysis was performed using SPSS to establish ranking and mean scores. Six major strategic factors emerged: Strategic Alignment & Vision, Data Governance & Quality, Resource & Infrastructure Readiness, Technology Selection & Integration, Change Management & Culture, and Performance Measurement & Continuous Improvement. Ranking results indicated that Strategic Alignment & Vision was perceived as the most critical (M = 4.72; 22.5%), followed closely by Data Governance & Quality (M = 4.56; 21.7%) and Resource & Infrastructure Readiness (M = 4.31; 20.5%). Technology Selection & Integration (M = 4.18; 19.9%) and Change Management & Culture (M = 3.97; 19.0%) followed, while Performance Measurement & Continuous Improvement (M = 3.85; 18.6%) was ranked lowest but still recognized as essential for long-term success. The study provides a practical, evidence-based roadmap for startups seeking Al-driven process automation. Aligning automation with strategic vision, ensuring robust data governance, and preparing technical and financial infrastructure are foundational. Equally, careful technology selection and fostering cultural adaptability support effective and sustainable automation.

Keywords: Artificial intelligence; process automation; startups; qualitative research; strategy prioritization

Introduction

The emergence of artificial intelligence (AI) and automation technologies is transforming how organizations innovate, optimize operations, and remain competitive in dynamic business ecosystems. Startups, in particular, operate under conditions of uncertainty, limited resources, and high innovation pressure, making them ideal candidates for intelligent process automation to scale efficiently and respond to market shifts. The shift toward automation is driven by the potential of AI to analyze complex data sets, streamline repetitive workflows, and enable predictive decision-making across sectors ranging from finance and healthcare to construction and agriculture [1-3]. In this context, the capacity of young firms to integrate AI-powered process automation is no longer a peripheral advantage but an essential factor for long-term sustainability and growth [4].

The current wave of AI-driven automation goes beyond simple mechanization by embedding machine learning (ML), natural language processing (NLP), and computer vision to improve core decision-making capabilities [5, 6]. Research in human resource development shows that AI-based tools can significantly enhance talent acquisition, training, and performance management, creating more adaptive and learning-oriented organizations [5, 7]. This capability is vital for startups that rely heavily on lean teams and rapid skill development. Similarly, digital transformation literature emphasizes that automation enables business models to adapt dynamically to customer expectations by offering personalized, data-driven experiences and optimized digital campaigns [1].

Despite these opportunities, evidence suggests that adopting Al-based process automation is not without complexity. Founders and managers frequently confront barriers such as unclear technology roadmaps, integration challenges with existing infrastructure, and insufficient leadership commitment [8, 9]. Small and medium-sized enterprises (SMEs), which share operational similarities with startups, report difficulties in aligning automation initiatives with strategic goals, highlighting the need for an explicit vision and clear prioritization [10]. Cultural and organizational resistance also persists; automation initiatives are often perceived as threats to job security and workforce stability [7, 9]. Addressing these human factors is critical for creating a change-accepting culture that embraces rather than resists Al.

Technological readiness forms another core pillar of AI adoption. Research indicates that startups require robust digital infrastructure capable of handling big data and supporting scalable AI deployment [11, 12]. Cloud-based architectures, secure data storage, and modular systems enable rapid experimentation and scaling without prohibitive costs [4]. Yet financial sustainability remains a recurring constraint. New ventures, unlike established corporations, often operate on narrow budgets that can be easily strained by the costs of data engineering, software acquisition, and compliance with privacy regulations [8, 12]. Some founders rely on phased adoption, testing AI tools with limited scope before full deployment, to manage risk and conserve capital [9].

Data governance and quality management stand out as a decisive enabler. Al models rely on clean, comprehensive, and secure datasets; however, startups often lack standardized data processes. Studies in sectors like construction and healthcare reveal that poor data accuracy and fragmented data silos undermine automation success [3, 13, 14]. By contrast, firms that establish clear protocols for data integration, privacy, and validation can leverage Al insights effectively and improve customer trust [11]. Recent frameworks advocate for early investment in data pipelines and robust security measures, even when resources are constrained, to avoid costly reengineering later [12].

Selecting and integrating the right AI technologies is another strategic imperative. AI adoption is no longer limited to large corporations with custom-built solutions; startups can leverage off-the-shelf platforms and low-code tools that reduce the need for extensive coding expertise [4, 15]. Research on enterprise resource planning (ERP) and smart manufacturing shows that intelligent automation solutions can be modular, interoperable, and adaptable to rapidly evolving business models [4, 16]. However, integration remains a frequent pain point; APIs and system compatibility can create unexpected technical debt if not planned carefully [8]. Startups therefore require a deliberate selection process that balances technical sophistication with ease of adoption and long-term flexibility [10].

Equally critical is the cultural and managerial dimension of Al adoption. Startups thrive on agility and creativity, yet introducing automation can trigger fears of redundancy and loss of autonomy among employees. Empirical evidence demonstrates that engaging staff early in the automation process, offering training, and fostering cross-functional

collaboration increase acceptance and reduce resistance [7, 9]. Research in customer engagement further shows that automation should not fully replace human input but rather augment it to maintain trust and creativity [17]. This hybrid model — where humans oversee and refine Al-driven processes — allows startups to maintain flexibility while benefiting from efficiency gains.

Performance measurement and continuous improvement represent the final dimension of successful Al-driven automation. Literature on industry 4.0 and smart production emphasizes the importance of monitoring key performance indicators (KPIs), including process speed, cost savings, and error reduction [16]. In dynamic environments, startups must implement iterative feedback loops to track the effectiveness of Al tools and quickly adjust strategies when outcomes deviate from expectations [18]. Benchmarking against industry practices also supports sustained competitiveness and learning [10]. By establishing continuous improvement systems, startups can evolve beyond initial deployment and unlock long-term value from Al adoption.

Notably, research across industries highlights how contextual factors influence automation strategies. For instance, studies in healthcare and digital health systems show that compliance with regulatory frameworks and patient data privacy are key considerations [13, 19]. Similarly, in finance and banking, Al-enhanced decision-making must align with sustainability and corporate governance principles to maintain ethical and transparent operations [2, 12]. Construction and built environment research indicates that predictive analytics and kinetic façade technologies enable efficiency and comfort while requiring safety-driven implementation models [3, 6]. These sectoral insights inform startups by illustrating transferable best practices and industry-specific risk management.

Given these dynamics, startups must adopt a multifaceted approach to AI-driven process automation, integrating strategic foresight, technical readiness, data governance, cultural adaptability, and performance monitoring. While opportunities to enhance productivity, scalability, and customer engagement are significant, the complexity of technology adoption and organizational change demands evidence-based, context-aware strategies. This study addresses this need by exploring and systematically ranking the key factors that enable effective implementation of process automation with AI in startups, providing actionable guidance for entrepreneurs and managers seeking to navigate the challenges of intelligent automation.

Methodology

This study employed a qualitative research design to explore and develop strategies for implementing process automation with artificial intelligence (AI) in startups. A purposive sampling approach was adopted to select participants who had direct experience in the development, deployment, or management of AI-driven automation processes in early-stage companies. The inclusion criteria focused on founders, senior managers, technical leads, and process optimization specialists from technology-based startups located in Tehran, Iran. A total of 21 participants were recruited, ensuring diversity in organizational size, industry domain, and stage of AI adoption. Data collection continued until theoretical saturation was reached, meaning that no new categories or insights emerged from additional interviews.

Semi-structured interviews were used as the primary method of data collection. An interview guide was developed to elicit rich and in-depth information regarding the motivations, challenges, and strategies related to integrating AI into process automation within startup environments. The guide included open-ended questions addressing topics such as readiness assessment, technology selection, resource constraints, change management, and scalability concerns. Interviews were

conducted individually, either in person or via secure video conferencing platforms when in-person meetings were not possible. Each interview lasted between 45 and 75 minutes and was audio-recorded with participants' consent to ensure accurate transcription and analysis. Field notes were also taken to capture non-verbal cues and contextual details.

The recorded interviews were transcribed verbatim and analyzed using NVivo software version 14 to support systematic qualitative coding and theme development. A multi-stage thematic analysis approach was applied, beginning with open coding to identify initial concepts and codes directly emerging from the data. Axial coding followed to organize these initial codes into broader categories, and selective coding was performed to integrate and refine these categories into coherent themes representing key strategies for implementing Al-driven process automation in startups. Coding was conducted iteratively and collaboratively by the research team to ensure reliability and minimize interpretive bias.

After the qualitative analysis, the identified strategic factors were subjected to a prioritization process to determine their relative importance. The frequency and perceived significance of each factor were quantified based on participants' emphasis during the interviews. These quantitative indicators were then imported into SPSS software for descriptive statistical analysis and ranking. Mean scores and relative weights were calculated, allowing the final set of strategies to be ordered according to their practical relevance and impact as perceived by the participants.

Findings and Results

The study included 21 participants drawn from technology-driven startups located in Tehran, Iran. Of these, 12 (57.1%) were male and 9 (42.9%) were female, reflecting a balanced representation of genders among startup leadership and technical experts. Participants' ages ranged from 26 to 44 years (M = 34.2), with the largest group falling between 30 and 35 years (n = 9; 42.9%), followed by those aged 36–40 years (n = 6; 28.6%), 26–29 years (n = 4; 19.0%), and 41–44 years (n = 2; 9.5%). In terms of professional roles, 8 (38.1%) were founders or co-founders, 6 (28.6%) held senior managerial positions such as operations or technology managers, and 7 (33.3%) were technical specialists including AI engineers and process automation leads. Regarding educational background, the majority held advanced degrees: 11 participants (52.4%) had master's degrees, 7 (33.3%) had bachelor's degrees, and 3 (14.3%) had doctoral qualifications. Sectoral representation was also diverse; 6 participants (28.6%) were from software and IT services, 5 (23.8%) from digital health and medical technology, 4 (19.0%) from fintech and digital payments, 3 (14.3%) from e-commerce and retail tech, and 3 (14.3%) from smart manufacturing and IoT-driven startups. Most participants reported being actively involved in AI-related process automation for 2–5 years (n = 12; 57.1%), while 5 participants (23.8%) had less than two years of direct experience and 4 (19.0%) had more than five years of engagement.

Table 1The Results of Qualitative Analysis

Category (Main Theme)	Subcategory	Concepts (Open Codes)	
1. Strategic Alignment & Vision	Clear automation roadmap	Defining automation goals; Linking AI to business strategy; Setting measurable milestones; Visualizing digital transformation journey	
	Leadership commitment	Founders' long-term vision; Executive sponsorship; Communicating change purpose; Resource allocation by leadership	
	Agile strategic planning	Adapting to fast market changes; Flexible prioritization; Scenario-based planning; Adjusting automation scope dynamically	
	Stakeholder engagement	Engaging board members; Building consensus; Transparent decision-making; Communicating value to employees	
2. Resource & Infrastructure Readiness	Technical infrastructure	Cloud-based platforms; Data storage readiness; Secure integration layers; Modular architecture; Scalable computing resources	
	Financial sustainability	Budget forecasting; Managing cash flow; Seeking external funding; Cost-benefit analysis	

	Skilled workforce	Recruiting AI engineers; Upskilling existing staff; Attracting data scientists; Retaining technica talent	
	Vendor and tool selection	Evaluating automation platforms; Proof of concept testing; Negotiating flexible contracts	
	Regulatory compliance	Data privacy standards; Intellectual property safeguards; Industry-specific rules	
3. Data Governance & Quality	Data availability	Access to operational data; Centralizing data sources; Breaking data silos	
	Data integrity & accuracy	Cleaning raw data; De-duplicating entries; Continuous validation; Avoiding biased datasets	
	Security & privacy	Encryption protocols; Anonymization of personal data; Secure sharing channels	
4. Change Management & Culture	Employee involvement	Early involvement in planning; Continuous feedback loops; Empowering process owners	
	Overcoming resistance	Transparent communication; Addressing job security fears; Celebrating small wins; Offering incentives	
	Learning orientation	Encouraging experimentation; Providing training programs; Promoting digital mindset	
	Cross-functional collaboration	Bridging technical and business teams; Shared ownership of automation; Reducing departmental silos	
5. Technology Selection & Integration	Technology evaluation	Benchmarking AI tools; Assessing vendor maturity; Evaluating interoperability	
	Integration with legacy systems	API development; Middleware use; Minimizing downtime; Incremental system upgrades	
	Scalability & flexibility	Modular Al models; Microservices architecture; Scalable cloud deployment	
	Usability & adaptability	Low-code/no-code tools; End-user friendly interfaces; Adaptive AI workflows	
6. Performance Measurement & Continuous Improvement	KPI development	Process efficiency indicators; AI accuracy metrics; Customer experience scores	
	Monitoring & feedback loops	Real-time dashboards; Error tracking; Regular review meetings; Model retraining cycles	
	Continuous optimization	Automating improvement suggestions; Experimentation culture; Rapid prototyping of enhancements	
	Benchmarking & learning	Learning from competitors; Industry benchmarking; Best-practice sharing	

The first major theme identified was Strategic Alignment and Vision, highlighting the necessity of a clear roadmap for adopting Al-driven process automation in startups. Participants emphasized that without a well-defined strategic direction, automation initiatives easily become fragmented or misaligned with the company's goals. Interviewees discussed the value of linking automation efforts to the overall business strategy, setting measurable milestones, and visualizing a long-term digital transformation journey. One founder noted: "If we don't have a clear roadmap, we just buy tools and hope for the best. But when we mapped our processes first, Al actually started to make sense." Leadership commitment was repeatedly mentioned as a success driver, with executives providing sponsorship, resources, and communication around the change. Stakeholder engagement also surfaced as a subtheme; participants highlighted the need to build consensus and communicate value across the organization. A product manager explained: "We made sure the board understood the return on Al investment early; otherwise, it would be seen as a fancy but unnecessary cost."

The second main theme, Resource and Infrastructure Readiness, reflected the foundational requirements for successful AI-based automation. Technical infrastructure, including secure cloud-based platforms and scalable computing resources, was considered essential for start-ups with limited legacy systems but ambitious automation plans. Financial sustainability emerged as another critical element, as several founders discussed the need to plan budgets and seek external funding to cover technology acquisition and training. "We underestimated the infrastructure costs — not just software but also secure data storage and integration layers," one CTO admitted. Equally important was having a skilled workforce; recruiting or upskilling AI engineers and data scientists was considered vital for reducing dependency on vendors. Regulatory compliance, particularly regarding data privacy and intellectual property, was also mentioned: "We had to think about GDPR-like privacy standards even though we're small, because investors asked about compliance."

The third theme, Data Governance and Quality, addressed the fundamental importance of reliable data as the foundation for automation success. Interviewees repeatedly stated that the quality of available data determined the outcome of their AI initiatives. Many described efforts to centralize data sources, break silos, and clean raw datasets to ensure accuracy. One participant explained: "AI fails without good data; we spent weeks just cleaning and validating before building any model."

Security and privacy also appeared as a pressing concern for young companies aiming to build trust with users and partners. Measures such as encryption, anonymization, and secure sharing protocols were frequently adopted. Participants highlighted that neglecting data governance early could lead to technical debt and reputational damage.

The fourth main theme, Change Management and Culture, underscored the human and cultural side of adopting AI-based process automation. Participants described how early employee involvement, transparent communication, and continuous feedback loops reduced fear and resistance. One operations manager reflected: "At first, the staff thought AI would replace them, but when we included them in redesigning workflows, they became champions." Overcoming resistance was closely tied to fostering a learning-oriented culture, where experimentation and training were encouraged. Cross-functional collaboration between technical and business units also emerged as essential for ensuring that automation aligned with real process needs rather than purely technical ambitions. "Our engineers didn't understand the daily workflow pain points until they worked directly with the sales team," one founder shared.

The fifth theme, Technology Selection and Integration, focused on how startups evaluate and implement AI solutions effectively. Participants described extensive benchmarking of tools and vendors, considering both current needs and future scalability. Many stressed the challenge of integrating AI into existing systems, even when those systems were relatively new. A CTO mentioned: "Integration was trickier than expected — APIs weren't as plug-and-play as advertised." Usability and adaptability were repeatedly emphasized; low-code or no-code platforms were favored to allow non-technical employees to interact with and adjust automation workflows. Another founder commented: "We looked for AI solutions that wouldn't lock us in, so we could pivot if our business model changed."

The final theme, Performance Measurement and Continuous Improvement, captured the importance of ongoing evaluation and refinement after AI-driven automation is implemented. Startups monitored key performance indicators such as process efficiency, AI accuracy, and customer experience outcomes. Interviewees reported creating dashboards and holding regular review meetings to track results and detect issues early. "We don't just launch and leave; we monitor real-time dashboards and tweak the models every month," one participant explained. Continuous optimization was seen as both a mindset and a system, with experimentation and rapid prototyping built into daily operations. Benchmarking against industry practices and competitors also helped maintain momentum and innovation over time.

 Table 2

 Ranking of Strategies for Implementing AI-Driven Process Automation in Startups

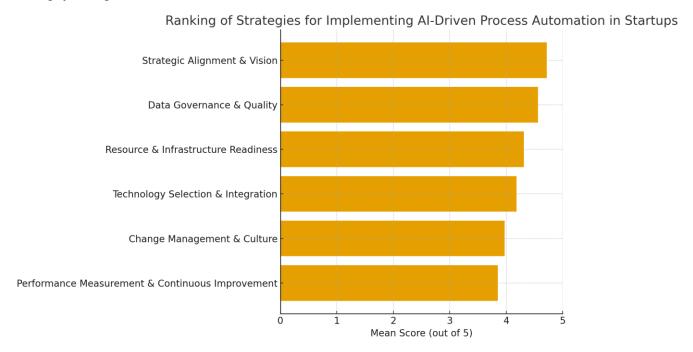
Rank	Strategic Factor (Main Theme)	Mean Score	Relative Importance (%)
1	Strategic Alignment & Vision	4.72	22.5%
2	Data Governance & Quality	4.56	21.7%
3	Resource & Infrastructure Readiness	4.31	20.5%
4	Technology Selection & Integration	4.18	19.9%
5	Change Management & Culture	3.97	19.0%
6	Performance Measurement & Continuous Improvement	3.85	18.6%

(Mean scores calculated on a 5-point Likert scale; relative importance = (mean/total sum of means) × 100)

Following the qualitative coding, the six strategic factors were subjected to a prioritization process using SPSS to determine their relative importance as perceived by participants. The results showed that *Strategic Alignment & Vision* ranked highest (M = 4.72; 22.5%), confirming the essential role of having a clear roadmap and strong leadership in guiding automation initiatives. Close behind was *Data Governance & Quality* (M = 4.56; 21.7%), reflecting the criticality of reliable, secure, and

well-structured data to enable successful AI implementation. *Resource & Infrastructure Readiness* (M = 4.31; 20.5%) was next, emphasizing the need for technical, financial, and human resources to support automation. *Technology Selection & Integration* (M = 4.18; 19.9%) followed, showing that careful evaluation and seamless integration of AI tools are key but slightly less urgent than foundational readiness. *Change Management & Culture* (M = 3.97; 19.0%) ranked fifth, suggesting that while cultural alignment and employee involvement are vital, participants perceived them as slightly less immediate barriers compared to strategic and technical issues. Finally, *Performance Measurement & Continuous Improvement* (M = 3.85; 18.6%) came last, indicating that while important, startups often prioritize getting automation successfully launched before optimizing and benchmarking outcomes.

Figure 1 *Ranking of Strategies*



Discussion and Conclusion

The purpose of this study was to identify and prioritize the critical strategies that enable startups to successfully implement process automation using artificial intelligence (AI). Through an in-depth qualitative analysis with 21 startup founders, technical leads, and managers in Tehran, followed by quantitative prioritization using SPSS, six overarching strategic factors were extracted: Strategic Alignment & Vision, Data Governance & Quality, Resource & Infrastructure Readiness, Technology Selection & Integration, Change Management & Culture, and Performance Measurement & Continuous Improvement. The ranking revealed *Strategic Alignment & Vision* as the most influential factor, followed closely by *Data Governance & Quality* and *Resource & Infrastructure Readiness*.

The finding that strategic alignment and a clear automation roadmap are paramount is strongly consistent with current scholarship. Startups require a clear link between automation efforts and their broader business models to avoid fragmented and costly technology adoption [8, 10]. Our participants emphasized the importance of founders' and leaders' vision, echoing the view that executive sponsorship and clarity of direction enable effective AI investment and integration [1, 5]. This study

also found that engaging stakeholders and building internal consensus early are vital to avoid organizational drift. This is in line with recent work on Al-driven marketing and enterprise transformation, which shows that stakeholder buy-in strengthens adoption by aligning diverse business units [1, 4]. Additionally, the emphasis on agile strategic planning corresponds with the call for iterative and scenario-based strategies to navigate technological and market uncertainty in emerging companies [2].

The second major theme, *Data Governance & Quality*, ranking nearly as high as strategy, reinforces the claim that "Al is only as good as the data behind it." Several participants described investing time in centralizing data and ensuring data accuracy before implementing Al. This mirrors findings in construction and safety automation, where fragmented or poorquality data leads to failed Al deployments [3, 14]. Similarly, studies on Al-big data analytics for building management systems emphasize that robust data governance frameworks are crucial for reliable model performance and user trust [11]. Data privacy and security also emerged as critical concerns; even small startups recognized the need for compliance with privacy norms and intellectual property safeguards. This reflects global calls to build early privacy-by-design and encryption into automation systems to avoid later reputational and legal risk [12, 13].

Resource & Infrastructure Readiness, the third highly ranked theme, underlines the practical constraints faced by startups. Our participants stressed the need for adequate technical foundations, scalable cloud resources, and a financially sustainable adoption path. This aligns with the observation that digital infrastructure is an enabler for AI-driven change and that small firms often underestimate the cost and complexity of integration [8, 11]. Financial readiness is also highlighted in studies on AI adoption in SMEs, where limited budgets can derail automation projects before they reach maturity [9]. The participants' solutions, such as phased adoption and pilot testing before full-scale deployment, reflect industry best practices and risk-mitigation strategies recommended for resource-constrained firms [10]. Human capital readiness also played a key role: founders noted challenges in recruiting and retaining AI specialists, consistent with broader evidence that AI-driven transformation depends on upskilled technical talent and adaptive human resource strategies [5].

The results also revealed *Technology Selection & Integration* as a distinct but slightly lower-ranked theme. Participants emphasized evaluating interoperability, scalability, and adaptability when selecting AI solutions, with a clear preference for low-code and no-code tools. This resonates with findings that startups benefit from modular and flexible technologies that support rapid pivots and minimize vendor lock-in [4, 15]. The integration challenges described — including nonstandard APIs and unexpected technical complexities — mirror research in ERP and automation adoption showing that integration remains one of the most underestimated barriers [8]. By approaching technology selection deliberately and assessing long-term adaptability, startups can reduce technical debt and maintain agility [16].

Cultural readiness and human-centered change management, although ranked fifth, still emerged as a key enabler of successful automation. Fear of job loss, mistrust of algorithms, and resistance to changing workflows were recurring concerns voiced by participants. This aligns with a growing body of literature showing that AI and automation are not purely technical transformations but sociotechnical shifts requiring robust change leadership [7, 9]. Training employees, involving them in redesigning processes, and promoting a digital learning mindset were among the strategies reported by our respondents. These practices echo recommendations for human-centric AI adoption, where technology augments rather than replaces human capabilities [17]. Startups that nurture such adaptive cultures are better positioned to sustain innovation and protect morale during transformation.

Finally, *Performance Measurement & Continuous Improvement* was identified as the least prioritized among the six factors, though still important. The relatively lower ranking does not diminish its significance but indicates that startups often focus first on adoption and scaling before formalizing feedback loops. However, previous research strongly supports the role of metrics and iterative improvement in realizing the full value of automation [16, 18]. Participants who did implement real-time dashboards and regular review meetings reported increased model accuracy and quicker error detection, echoing evidence from smart manufacturing and digital service optimization [10]. Continuous benchmarking and learning from competitors also emerged as effective strategies to maintain relevance and improve automation maturity over time [18].

Overall, these findings align with and extend the existing literature by demonstrating how strategic clarity and data-centric practices, often discussed in large-enterprise contexts, are equally vital but require adaptation for resource-limited startups. Our study highlights the nuanced interplay of technical readiness and organizational culture, showing that while startups tend to focus on immediate survival and agility, long-term success with AI automation also demands deliberate planning, governance, and performance oversight. By ranking these factors, we provide a practical roadmap that synthesizes theoretical insights and lived entrepreneurial experiences.

Despite its contributions, this study has certain limitations. First, the research was conducted with startups located exclusively in Tehran, which may limit the transferability of findings to other geographical or cultural contexts where the regulatory environment, digital maturity, and entrepreneurial ecosystem differ. Second, the sample size, while sufficient for qualitative saturation, remains relatively small for quantitative generalization; the ranking results should be interpreted cautiously and not assumed to represent all startup contexts. Third, the study relied on self-reported experiences from founders and managers, which may carry bias due to retrospective reflection or optimism about their own strategies. Additionally, the ranking was based on perceived importance rather than objective performance outcomes, meaning future research could integrate longitudinal tracking of actual implementation success to validate these prioritizations.

Future research could expand this investigation by incorporating comparative studies across different regions and industries to explore how cultural, sectoral, and regulatory differences influence automation strategies. A mixed-methods design with larger samples could strengthen the generalizability of factor rankings and reveal more subtle variations between startup maturity levels. Further, longitudinal case studies could follow startups through the automation journey to observe the dynamic evolution of strategic priorities, especially how performance measurement and continuous improvement emerge over time. Another promising direction is exploring the human—Al collaboration dimension in greater depth, including psychological readiness, trust-building, and leadership styles that facilitate cultural acceptance. Researchers might also examine investor perspectives and how funding criteria affect automation strategy in early-stage companies.

For startup founders and managers, the findings offer a clear, evidence-informed roadmap to navigate AI-driven process automation. Emphasizing strategic clarity and leadership commitment early can prevent misalignment and wasted resources. Building strong data governance frameworks before deploying AI tools is crucial to avoid costly errors and regulatory risks. Investing in scalable infrastructure and phased adoption helps manage limited budgets while enabling future expansion. Careful evaluation of technology options and planning for integration reduces technical disruption. Equally, fostering a transparent and learning-oriented culture mitigates resistance and empowers employees to contribute to automation success. Finally, although performance measurement ranked lower, embedding continuous feedback and benchmarking

systems from the start can create resilience and long-term value, ensuring that automation evolves in sync with business growth and market shifts.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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References

- [1] W. Suryathi and N. W. R. Mariani, "Revitalizing Marketing Strategies Through the Use of Artificial Intelligence: Analysis of the Effect of Personalization, Market Data Analysis, and Campaign Automation on Sales Conversions," *Escalate*, vol. 1, no. 02, pp. 101-108, 2024, doi: 10.61536/escalate.v1i02.25.
- [2] N. Rane, S. Choudhary, and J. Rane, "Artificial Intelligence-Driven Corporate Finance: Enhancing Efficiency and Decision-Making Through Machine Learning, Natural Language Processing, and Robotic Process Automation in Corporate Governance and Sustainability," 2024, doi: 10.2139/ssrn.4720591.
- [3] A. B. K. Rabbi, Jeelani, Idris, "AI integration in construction safety: Current state, challenges, and future opportunities in text, vision, and audio based applications," *Automation in Construction*, vol. 164, p. 105443, 2024/08/01/2024, doi: 10.1016/j.autcon.2024.105443.
- [4] P. Pokala, "Artificial Intelligence in SAP S/4hana: Transforming Enterprise Resource Planning Through Intelligent Automation," International Journal of Scientific Research in Computer Science Engineering and Information Technology, vol. 10, no. 6, pp. 191-201, 2024, doi: 10.32628/cseit24106169.
- [5] K. Ekuma, "Artificial intelligence and automation in human resource development: A systematic review," *Human Resource Development Review*, vol. 23, no. 2, pp. 199-229, 2024, doi: 10.1177/15344843231224009.

- [6] M. Takhmasib, Lee, Hyuk Jae, Yi, Hwang, "Machine-learned kinetic Façade: Construction and artificial intelligence enabled predictive control for visual comfort," *Automation in Construction*, vol. 156, no. no, p. 105093, 2023/12/01/ 2023, doi: 10.1016/j.autcon.2023.105093.
- [7] A. Semenova, "The Future of Work: Automation, Artificial Intelligence and Information Technology," *E3s Web of Conferences*, 2023, doi: 10.1051/e3sconf/202345105011.
- [8] A. Rawashdeh, M. Bakhit, and L. Abaalkhail, "Determinants of artificial intelligence adoption in SMEs: The mediating role of accounting automation," *International Journal of Data and Network Science*, vol. 7, no. 1, pp. 25-34, 2023, doi: 10.5267/j.ijdns.2022.12.010.
- [9] M. Mabungela, "Artificial Intelligence (AI) and Automation in the World of Work: A Threat to Employees?," *Research in Social Sciences and Technology*, vol. 8, no. 4, pp. 135-146, 2023, doi: 10.46303/ressat.2023.37.
- [10] R. Bukartaite and D. Hooper, "Automation, artificial intelligence and future skills needs: an Irish perspective," *European Journal of Training and Development*, vol. 47, no. 10, pp. 163-185, 2023, doi: https://doi.org/10.1108/EJTD-03-2023-0045.
- [11] Y. Himeur *et al.*, "AI-big Data Analytics for Building Automation and Management Systems: A Survey, Actual Challenges and Future Perspectives," *Artificial Intelligence Review*, vol. 56, no. 6, pp. 4929-5021, 2022, doi: 10.1007/s10462-022-10286-2.
- [12] A. R. A. M. Husain, A. Hamdan, and S. M. Fadhul, "The Impact of Artificial Intelligence on the Banking Industry Performance," in Future of Organizations and Work After the 4th Industrial Revolution: The Role of Artificial Intelligence, Big Data, Automation, and Robotics, 2022, pp. 145-156.
- [13] H. Saiya, S. Doshi, J. Seth, V. Badgujar, and G. Kalme, "Automation of Supply Chain Management for Healthcare," in *Progresses in Artificial Intelligence & Robotics: Algorithms & Applications. ICDLAIR* 2021, vol. 441. Cham: Springer, 2022.
- [14] L. Zhang and H. Li, "Artificial Intelligence in Cost Estimation for Construction Projects," *Automation in Construction*, vol. 125, p. 103573, 2021.
- [15] D. E. Micle *et al.*, "Research on Innovative Business Plan: Smart Cattle Farming Using Artificial Intelligent Robotic Process Automation," *Agriculture*, vol. 11, no. 5, p. 430, 2021, doi: 10.3390/agriculture11050430.
- [16] S. S. Kamble, A. Gunasekaran, A. Ghadge, and R. Raut, "A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs- A review and empirical investigation," *International Journal of Production Economics*, vol. 229, p. 107853, 2020/11/01/2020, doi: 10.1016/j.ijpe.2020.107853.
- [17] L. D. Hollebeek, D. E. Sprott, and M. K. Brady, "Rise of the Machines? Customer Engagement in Automated Service Interactions," *Journal of Service Research*, vol. 24, no. 1, pp. 3-8, 2021, doi: 10.1177/1094670520975110.
- [18] A. R. Wheeler and M. R. Buckley, "The current and future states of automation, artificial intelligence, and machine learning," in *HR without People?*: Emerald Publishing Limited, 2021, pp. 29-44.
- [19] M. A. Mohammed, M. A. Mohammed, and V. A. Mohammed, "Impact of Artificial Intelligence on the Automation of Digital Health System," *International Journal of Software Engineering & Applications*, vol. 13, no. 6, pp. 23-29, 2022, doi: 10.5121/ijsea.2022.13602.