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ARTIFICIAL INTELLIGENCE AND AUTOMATION IN STARTUP BUSINESS PROCESSES: EVIDENCE FROM THE US AND EU

ШТУЧНИЙ ІНТЕЛЕКТ ТА АВТОМАТИЗАЦІЇ В БІЗНЕС ПРОЦЕСАХ СТАРТАПІВ: ПРАКТИКА США ТА ЄВРОПЕЙСЬКОГО СОЮЗУ

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The article examines the role of artificial intelligence and automation in early-stage startup processes under conditions of uncertainty and limited resources. The study focuses on how AI-enabled infrastructure supports problem discovery, hypothesis testing, iterative learning, and demand validation. Using the Plan–Do–Check–Act framework as a theoretical foundation, the research conceptualizes startups as learning-oriented process systems rather than static organizational entities. Comparative analysis of startup practices in the United States and the European Union highlights institutional differences in AI adoption and process automation. The findings demonstrate that artificial intelligence, when embedded into core startup processes, reduces experimentation costs, accelerates feedback loops, and improves decision-making quality. The study contributes to entrepreneurship and digital transformation research by framing AI and automation as infrastructural elements of early-stage startup development.

Keywords: artificial intelligence, automation, startup processes, early-stage startups, PDCA cycle, digital transformation, entrepreneurship.

У статті досліджується роль штучного інтелекту та автоматизації в процесах розвитку стартапів на ранніх етапах за умов високої невизначеності та обмежених фінансових і організаційних ресурсів. Обґрунтовано, що основні причини невдач стартапів пов’язані не з технологічною неспроможністю продуктів, а з неефективним виявленням проблем цільової аудиторії, недостатньою валідацією ринкового попиту та повільними циклами організаційного навчання. Метою дослідження є визначення можливостей використання штучного інтелекту та автоматизації як інфраструктурних елементів процесів стартапу для зниження рівня невизначеності та підвищення ефективності управлінських рішень. Теоретичною основою дослідження є цикл Plan–Do–Check–Act, який розглядається як процесна модель ітеративного навчання та адаптації в підприємницькому середовищі. Стартапи концептуалізуються як навчально орієнтовані процесні системи, здатні до постійного перегляду гіпотез і коригування бізнес-рішень, а не як статичні організаційні структури з фіксованими бізнес-моделями. У роботі показано, що інтеграція штучного інтелекту та автоматизації у ключові процеси стартапу, зокрема виявлення проблем, формування та перевірку гіпотез, розробку мінімально життєздатного продукту та ранню валідацію попиту, сприяє зниженню вартості експериментів, прискоренню зворотного зв’язку та підвищенню якості управлінських рішень. Проведено порівняльний аналіз практик використання штучного інтелекту в стартап-екосистемах США та Європейського Союзу, який виявив відмінності між ринково-орієнтованою моделлю швидкого тестування та більш інституційно врегульованим підходом до цифровізації процесів. Окрему увагу приділено обмеженням і ризикам використання штучного інтелекту в стартапах, зокрема проблемам якості даних, надмірної залежності від автоматизованих рішень та регуляторним вимогам. Зроблено висновок, що штучний інтелект і автоматизація доцільно розглядати як інфраструктурні елементи процесів стартапу, які підвищують ефективність навчання, але не замінюють підприємницьке судження.

Ключові слова: штучний інтелект, автоматизація, процеси стартапів, цикл PDCA, стартапи на ранніх етапах, цифрове підприємництво, діджиталізація.

Formulation of the Problem. Early-stage startups operate in conditions of heightened uncertainty, limited financial and human resources, and accelerated decision-making requirements. Empirical evidence indicates that the majority of startup failures occur during the initial stages of development, with insufficient understanding of market demand and ineffective validation processes identified as the primary causes of early venture collapse [1; 3]. These challenges highlight the structural vulnerability of startups at the formative stage, where strategic errors incur disproportionately high costs.

Traditional approaches to startup development rely heavily on manual market research, intuition-driven hypothesis formulation, and fragmented feedback mechanisms. While such methods may be effective in stable or resource-rich environments, they are poorly suited to early-stage ventures facing dynamic markets and rapid changes in customer behavior. Studies on entrepreneurial experimentation emphasize that the high cost of learning and limited number of feasible iterations significantly constrain startup survival and growth [11].

At the same time, contemporary startups increasingly operate within digital ecosystems where large volumes of market-relevant data are continuously generated. Reports by McKinsey & Company and the OECD demonstrate that artificial intelligence and automation technologies are becoming integral to organizational processes, enabling faster data processing, decision support, and operational efficiency [6; 8; 9]. However, in the context of early-stage entrepreneurship, the application of AI remains fragmented and is often limited to isolated tasks rather than integrated into core startup processes.

This situation reveals a fundamental problem: despite the availability of advanced digital technologies, early-stage startups lack systematic, process-oriented frameworks that integrate artificial intelligence and automation into their core mechanisms of problem discovery, hypothesis testing, and validation. Existing entrepreneurial models insufficiently address how AI-enabled infrastructures can reduce uncertainty, lower experimentation costs, and support continuous learning under resource constraints.

Accordingly, the central problem addressed in this study is the absence of a coherent conceptual framework that positions artificial intelligence and automation as infrastructural elements of early-stage startup processes.

Addressing this problem is essential for improving the effectiveness of startup experimentation, enhancing decision-making quality, and increasing the likelihood of achieving sustainable product–market fit in highly uncertain environments.

Analysis of Recent Research and Publications. Recent research on entrepreneurship and startup development has extensively examined the challenges associated with uncertainty, limited resources, and early-stage decision-making. A significant body of literature focuses on the causes of startup failure, emphasizing inadequate demand validation, lack of product–market fit, and inefficient learning processes as dominant factors influencing early venture collapse [1; 2; 3]. These studies collectively underline the importance of structured experimentation and evidence-based decision-making in early-stage entrepreneurship.

Another important stream of research addresses process-oriented management frameworks, particularly the application of the Plan–Do–Check–Act cycle in organizational learning and continuous improvement. Scholars such as Peças, Silva, and Henriques conceptualize PDCA as a dynamic mechanism for iterative learning, highlighting its relevance in environments characterized by high uncertainty and frequent feedback loops [12]. Subsequent studies further extend this framework by incorporating digital technologies, proposing enhanced PDCA models suitable for modern, data-intensive organizational contexts [13]. These contributions provide a theoretical foundation for understanding startups as learning systems rather than static production units.

Parallel to this, entrepreneurship literature has developed the concept of Minimum Viable Product and validated learning as central mechanisms for reducing uncertainty in early-stage ventures. Rao emphasizes that MVP-based experimentation enables startups to test hypotheses with minimal resource expenditure, although he also notes limitations related to incomplete feedback and front-end fuzziness in problem definition [11]. This line of research highlights the need for complementary mechanisms that improve the quality and speed of feedback in early experimentation.

In recent years, increasing scholarly and institutional attention has been devoted to the role of artificial intelligence and automation in business processes. Reports published by McKinsey & Company demonstrate that

AI adoption is expanding across marketing, product development, and operational functions, reflecting a broader shift toward data-driven and automated decision-making [8; 9]. Similarly, analyses conducted by the OECD and the European Commission indicate that digital technologies, including AI, are becoming critical enablers of productivity and competitiveness, particularly for small and medium-sized enterprises [6; 7].

Despite these advances, the existing literature reveals several limitations. Research on AI adoption largely focuses on established organizations, while early-stage startups remain underrepresented in empirical studies. Moreover, artificial intelligence is predominantly examined as a set of discrete tools rather than as an integrated infrastructural layer shaping core entrepreneurial processes. Studies addressing startup experimentation and PDCA-based learning rarely incorporate AI-enabled automation as a structural component of these frameworks [11; 12; 13].

Overall, the reviewed literature demonstrates substantial progress in understanding startup failure dynamics, iterative learning models, and the growing role of artificial intelligence in organizational processes. However, it also reveals a gap at the intersection of these research streams. Specifically, there is limited theoretical and empirical integration of AI-enabled automation with process-oriented frameworks for early-stage startup development. Addressing this gap provides the foundation for the present study and motivates further examination of artificial intelligence and automation as infrastructural elements supporting startup experimentation and validation.

Highlighting Previously Unresolved Parts of the Overall Problem. Despite the extensive body of research on startup failure, iterative learning, and digital transformation, several critical aspects of early-stage startup development remain insufficiently explored. Existing studies predominantly analyze these phenomena in isolation, resulting in fragmented explanations that fail to capture the systemic nature of early-stage entrepreneurial processes.

First, while the Plan–Do–Check–Act cycle is widely recognized as an effective framework for continuous improvement and organizational learning, its application to early-stage startups remains conceptually underdeveloped. Most PDCA-related studies focus on mature organizations, manufacturing systems, or quality management contexts, where processes are relatively stable and data availability is high [12; 13]. In contrast, early-stage startups operate under extreme uncertainty and incomplete information, conditions that challenge traditional PDCA assumptions and require adaptive, technology-enhanced implementations.

Second, research on Minimum Viable Product and validated learning emphasizes rapid experimentation but provides limited guidance on how feedback quality and learning speed can be systematically improved. As noted by Rao, MVP-based approaches often suffer from front-end fuzziness, where problem definition and demand signals remain ambiguous despite iterative testing [11]. The literature offers limited insight into how advanced data-processing capabilities, such as artificial intelligence, could mitigate these limitations by enhancing early-stage sensing and evaluation mechanisms.

Third, although artificial intelligence and automation are increasingly examined in the context of organizational efficiency and decision support, their role in early-stage entrepreneurship remains underrepresented. Institutional and industry reports primarily analyze AI adoption in established firms, focusing on productivity gains and cost optimization [6; 8; 9]. As a result, AI is typically conceptualized as a set of discrete tools rather than as an integrated infrastructural layer capable of reshaping core startup processes, including problem discovery, hypothesis testing, and validation.

Finally, comparative perspectives on AI-enabled startup development across institutional contexts remain limited. While studies acknowledge differences between startup ecosystems in the United States and the European Union, few analyses explicitly examine how regulatory environments, market structures, and digital maturity influence the integration of AI and automation into early-stage startup processes [5; 7; 15; 16]. This gap restricts the transferability of best practices and limits the development of context-sensitive entrepreneurial frameworks.

Taken together, these unresolved issues point to the absence of a coherent conceptual approach that integrates process-oriented learning frameworks with AI-enabled automation in the context of early-stage startups. Addressing this gap requires rethinking artificial intelligence not merely as an auxiliary technology, but as an infrastructural element that supports continuous experimentation, reduces uncertainty, and enhances learning efficiency under resource constraints. The present study seeks to contribute to this unresolved area by proposing an integrated perspective on AI-enabled startup processes grounded in iterative learning and comparative institutional analysis.

Summary of the Main Material. The analysis of early-stage startup development demonstrates that the primary challenges faced by new ventures are rooted in high uncertainty, limited resources, and the elevated cost of experimentation. Empirical evidence confirms that inadequate problem discovery, weak demand validation, and inefficient feedback mechanisms are the dominant factors leading to early-stage startup failure [1; 3]. These challenges necessitate process-oriented approaches that reduce uncertainty and support continuous learning under constrained conditions.

From a theoretical perspective, early-stage startups can be conceptualized as learning systems operating through iterative cycles of hypothesis formulation, experimentation, evaluation, and adjustment. The Plan–Do–Check–Act framework provides a suitable foundation for modeling such processes, as it emphasizes structured experimentation and feedback-driven improvement [12; 13]. However, traditional PDCA implementations assume stable processes and sufficient data availability, conditions that are rarely present in early-stage entrepreneurial contexts. Consequently, the effectiveness of PDCA in startups depends on the integration of mechanisms capable of accelerating data collection, analysis, and evaluation.

Artificial intelligence and automation address these limitations by functioning as infrastructural elements embedded within startup processes. AI-enabled systems support continuous aggregation and analysis of unstructured market data, enabling more systematic problem discovery and demand assessment. By automating data processing and pattern recognition, artificial intelligence reduces reliance on intuition-driven decision-making and enhances the informational basis of early-stage planning activities [8; 9]. This integration strengthens the planning and evaluation stages

Fig. 1. The Plan–Do–Check–Act framework

Source: formed based on [12; 13]

of the PDCA cycle, improving the quality of hypotheses subjected to experimentation.

In the context of hypothesis testing and MVP development, AI and automation significantly reduce the marginal cost of experimentation. Automated workflows enable rapid creation of digital interfaces, content assets, and feedback channels, allowing startups to test value propositions and pricing assumptions with minimal resource expenditure. These capabilities align with the principles of validated learning emphasized in entrepreneurship research, while simultaneously mitigating the problem of front-end fuzziness through improved feedback quality and analytical depth [11].

Early-stage marketing and validation processes further benefit from AI-enabled automation. Artificial intelligence supports search engine optimization, geographic targeting, and content marketing by enabling continuous analysis of search behavior, user engagement, and regional demand patterns. These processes transform marketing activities into structured experiments that generate actionable feedback for both product and strategy development. As a result, marketing becomes an integral component of the learning cycle rather than a separate promotional function [8; 14].

Comparative analysis of startup practices in the United States and the European Union illustrates that, despite institutional and regulatory differences, both ecosystems increasingly rely on artificial intelligence and automation to support early-stage experimentation. U.S. startups typically prioritize speed, market-driven validation, and rapid iteration, leveraging AI-enabled tools to maximize experimentation frequency [8; 15]. European startups, operating within more structured regulatory environments, adopt AI in alignment with digitalization and compliance frameworks promoted by public institutions [5; 7; 16]. In both contexts, AI-enabled infrastructure serves as a mechanism for reducing uncertainty and improving process efficiency.

At the same time, the integration of artificial intelligence into early-stage startup processes introduces notable limitations and risks. Data quality constraints, overreliance on automated outputs, organizational readiness challenges, and regulatory considerations may undermine the effectiveness of AI-enabled systems if not carefully managed [6; 7; 8]. These risks underscore the importance of aligning AI adoption with process design, human judgment, and institutional context.

Table 1

Comparative Characteristics of AI-Enabled Startup Practices in the United States and the European Union

Dimension	United States	European Union
Ecosystem scale	Largest global startup ecosystem; high concentration of unicorns and venture capital	Smaller absolute scale; fewer unicorns, but broad geographic distribution
Growth dynamics	Moderate relative growth; mature and competitive ecosystems	Higher relative growth rates among top hubs, indicating accelerated expansion
AI adoption in business processes	Widespread adoption across marketing, product, and operations; AI integrated into core workflows	Growing adoption, but uneven across countries and sectors; advanced AI adoption below 30% among SMEs
Approach to experimentation	Strong emphasis on rapid MVP testing, early demand validation, and fast iteration	More structured experimentation, often aligned with public funding and compliance requirements
Role of regulation	Market-driven environment with limited ex-ante AI regulation	Strong regulatory framework (GDPR, emerging AI governance) shaping AI use and data practices
Institutional support	Accelerator-driven and private investment-led support structures	Policy-driven support via EU programs and national innovation initiatives
Cost of experimentation	Lower relative cost due to scale, capital access, and widespread automation	Higher relative cost mitigated by public funding and digitalization programs

Source: formed based on: [7, 8, 9, 15, 16]

Overall, the synthesized analysis demonstrates that artificial intelligence and automation, when embedded as infrastructural components of startup processes, enhance the effectiveness of iterative learning frameworks such as PDCA and MVP-based development. By reducing experimentation costs, accelerating feedback loops, and improving decision-making quality, AI-enabled infrastructures provide early-stage startups with structural advantages in navigating uncertainty and achieving sustainable market validation.

Conclusions. The results of this study indicate that the main challenges of early-stage startup development arise from high uncertainty, limited resources, and insufficiently structured processes for problem discovery and demand validation. It was established that technological sophistication alone does not determine early-stage success, while the organization of learning and decision-making processes plays a decisive role.

The study demonstrates the relevance of viewing startups as learning-oriented process systems in which iterative experimentation and continuous adjustment are essential. Within this context, the Plan–Do–Check–Act cycle proves to be an effective framework for structuring hypothesis formulation, testing, evaluation, and refinement under conditions of uncertainty. Applying a process-oriented perspective allows early-stage startups to better manage experimentation and reduce the cost of incorrect strategic decisions.

It was found that the integration of artificial intelligence and automation into core startup processes enhances the efficiency of iterative learning by accelerating information collection, reducing manual effort, and improving feedback quality. Artificial intelligence should therefore be considered not as an isolated tool, but as an infrastructural element that supports early-stage decision-making and process coordination.

The comparative analysis conducted in this study revealed differences in the use of artificial intelligence within startup ecosystems of the United States and the European Union. While market-driven environments emphasize rapid experimentation and iteration, more regulated contexts prioritize structured and compliant process automation. Despite these differences, in both cases artificial intelligence contributes to reducing uncertainty and improving the effectiveness of startup processes.

The study also highlights that the adoption of artificial intelligence and automation requires careful alignment with organizational readiness and the preservation of entrepreneurial judgment. Overreliance on automated solutions may weaken strategic sensitivity if not balanced by human interpretation and contextual understanding. The findings of this research may be applied in the design of startup processes and can serve as a foundation for further studies on process-based management and digital infrastructure in early-stage entrepreneurship.

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