Challenges in Developing AI-Integrated Information System Ecosystems

Rayfran Rocha Lima, André Fernandes, Luiz Cordovil

Sidia Institute of Technology
Manaus – AM – Brazil

{rayfran.lima, andre.fernandes, luiz.cordovil}@sidia.com

Abstract: *With the advent of Large Language Models (LLMs) and the popula- rization of tools such as Chat-GPT, Llama, and DeepSeek, a technological race has emerged in which companies strive to integrate Artificial Intelligence (AI) into their information systems (IS) to create smarter solutions. However, this trend often overlooks essential challenges and prerequisites. This paper addres- ses five key challenges: (i) the need for developers with AI expertise; (ii) mana- ging client and user expectations to prevent direct comparisons with tools like Chat-GPT; (iii) understanding that not all problems can be solved with AI; (iv) the costs associated with developing AI-based systems, including infrastructure, time, effort, and result quality; and (v) the lack of integration strategies and ar- chitectures that ensure dependable, ethical, and socially aligned incorporation of AI into Information Systems. By discussing these aspects, we aim to provide a critical and comprehensive perspective on the responsible integration of AI into organizational ecosystems.*

Palavras-chave*: Inteligência Artificial (IA), Modelos de Linguagem de Grande Escala (LLMs), Sistemas de Informação (SI), Desenvolvedores com expertise em IA, Desafios éticos e sociais.*

1. Introduction

The rapid advancement of Artificial Intelligence (AI) has fundamentally transformed the way organizations develop and integrate information systems [George and George 2023]. Large-scale AI models, particularly LLMs like Chat-GPT, Llama, and DeepSeek, respectivelly launched in 2022, 2023, 2025, have demonstrated the ability to enhance automation, improve decision-making, and optimize user interactions. As a result, companies across industries are actively seeking to embed AI into their information ecosystems to gain a competitive edge. However, this accelerated adoption often overlooks fundamental challenges, leading to inefficient implementations, increased costs, and misaligned expectations [Perales 2024].

The challenges discussed in this paper are the outcome of a feasibility and risk analysis (FRA) for a project aimed at developing an AI-supported information sys- tem ecosystem within a large software development company. Although this project had addressed these challenges in prior phases, a new FRA was necessary due to the launch of new technologies and the rapid pace of change in the AI-based environment [Agarwal

2018]. This analysis gathered insights from industry professionals with more than 10 years of experience in AI-based solutions, identifying key challenges and critical factors that influence AI adoption in enterprise environments.

One of the most critical issues in AI integration is the assumption that AI can be seamlessly incorporated into any system without significant modifications. Unlike traditional software, AI-driven systems require continuous adaptation, extensive validation, and robust data governance to ensure reliable performance [Habbal et al. 2024]. Moreover, the widespread use of generative AI tools has fueled unrealistic expectations among stakeholders, contributing to dissatisfaction when enterprise AI applications fail to match the fluency and flexibility of consumer-oriented models such as ChatGPT or Llama [Malheiros et al. 2024].

Additionally, AI adoption poses significant technical, financial, and workforce-related challenges. Organizations must navigate the shortage of specialized professionals, the high computational costs of AI models, and the inherent limitations of AI in complex decision-making scenarios [Pesovski et al. 2024, Oprea et al. 2024]. These challenges demand a structured, transparent, and context-aware approach to AI deployment, ensuring that its implementation aligns with real business needs, ethical principles, and regulatory constraints, rather than being driven by technological hype.

This paper presents a critical analysis of five key challenges in the development of AI-integrated Information System (IS) ecosystems. These include: (i) the shortage of developers with AI expertise; (ii) the gap between client and user expectations and the actual capabilities of enterprise AI systems; (iii) the misconception that AI is a universal solution; (iv) the high infrastructure, operational, and maintenance costs of AI-based systems; and (v) the absence of integration strategies and architectures that ensure dependable, ethical, and socially aligned incorporation of AI into IS. By addressing these aspects, the paper contributes to the agenda for responsible digital transformation and sustainable adoption of AI in enterprise environments.

2. Background

The integration of Artificial Intelligence (AI) into information systems has gained significant traction, particularly with the rise of Large Language Models (LLMs) such as Chat-GPT, Llama, and DeepSeek. Organizations increasingly seek to embed AI capabilities to enhance automation, decision-making, and user interactions across various domains [Yuan et al. 2023, Chen et al. 2024]. However, the integration of AI into information systems presents unique challenges that go beyond the traditional adoption of new technologies.

One of the primary challenges is the misalignment between AI capabilities and business needs. Many organizations embark on AI adoption driven by market trends or competitive pressure, often overestimating its applicability and failing to conduct feasibility analyses [Oprea et al. 2024]. This results in implementations where AI either does not provide tangible value or requires continuous adjustments due to evolving requirements. Unlike conventional software solutions, AI models are inherently probabilistic and require continuous validation and adaptation to maintain performance and reliability [Habbal et al. 2024].

Another critical challenge involves data governance and infrastructure demands. AI-integrated systems rely on vast amounts of high-quality data, demanding robust data management strategies, security measures, and compliance with regulatory fra- meworks [Pesovski et al. 2024]. Furthermore, large-scale AI models impose significant computational costs, requiring substantial investments in hardware and cloud resources [Pesovski et al. 2024]. These costs often escalate unpredictably, particularly in scenarios where AI inference is performed at scale.

The shortage of AI expertise poses a major barrier to successful integration. Unlike traditional software development, which follows deterministic execution paths, AI-driven systems require specialized knowledge in areas such as model selection, bias mitigation, and explainability [Habbal et al. 2024]. The lack of qualified professionals capable of maintaining and optimizing AI models can lead to inefficient deployments, increasing operational risks.

There is a growing gap between user expectations and actual AI performance. The widespread use of generative AI tools has contributed to unrealistic assumptions regarding AI's capabilities, leading to dissatisfaction when enterprise AI applications fail to deliver similar levels of fluency or adaptability [Malheiros et al. 2024]. Managing these expec- tations requires a clear communication strategy, focusing on AI's real-world constraints and gradual deployment strategies to ensure alignment with business objectives.

Addressing these challenges requires a structured approach to AI adoption, balancing innovation with feasibility. This paper examines these critical aspects, providing insights into the expertise required for AI-driven system development, the complexities of managing expectations, the need for problem-specific AI deployment, and the cost considerations essential for sustainable implementation.

3. Challenges

3.1. Expertise in AI Development

The successful integration of artificial intelligence (AI) into information systems necessitates specialized expertise across multiple stages of the development lifecycle. From gathering and documenting user requirements to designing AI-driven solutions, developers must navigate complex challenges to ensure the effective application of AI technologies [Heyn et al. 2023]. For instance, AI can enhance predictive analytics, automate decision-making processes, and optimize user interactions. However, these benefits can only be realized when AI is properly aligned with business needs and technical constraints [Ros-Arlanzo´n and Perez-Sempere 2024]. The implementation phase involves critical steps such as dataset creation and preprocessing, model training and optimization, rigorous testing, and the deployment and continuous maintenance of AI services in production environments. Each of these tasks requires a distinct skill set, making expertise in AI development a key determinant of success.

A major challenge in AI adoption is the shortage of qualified professionals, as the field spans diverse subdomains like machine learning, deep learning, NLP, computer vision, and reinforcement learning [Cisterna et al. 2024]. Since few individuals possess deep expertise across all areas, companies must build diverse teams to cover essential AI competencies. The rapid evolution of AI further demands continuous learning and up-skilling, making workforce development increasingly difficult. Without addressing these gaps, organizations risk deploying inefficient and unreliable AI solutions. Strategic workforce planning, AI education investment, and interdisciplinary collaboration are essential to overcoming these challenges [Malheiros et al. 2024].

3.2. Managing User and Client Expectations

The rapid proliferation of AI conversational agents, such as Chat-GPT, has contributed to unrealistic user expectations, often leading to the misconception that AI is limited to chatbot functionalities [Zhang et al. 2024]. While conversational AI is a prominent application, enterprise AI solutions extend far beyond simple text interactions, encompassing predictive analytics, classification, recommendation systems, decision automation, and seamless integration with enterprise APIs [Abitbol et al. 2024]. Unlike standalone chatbot applications, these AI-driven solutions require scalability, security, and regulatory compliance to ensure robust and ethical deployment in business environments [Pesovski et al. 2024].

A major challenge in AI adoption is the discrepancy between expectations and actual performance. Many organizations anticipate immediate and transformative results, underestimating the need for extensive data preparation, domain-specific tuning, and ongoing monitoring [Metz and Grant 2024]. This often leads to frustration when enterprise AI systems fail to match the fluency and adaptability of consumer-facing models like Chat-GPT [Cisterna et al. 2024, Malheiros et al. 2024]. To mitigate these challenges, organizations should implement incremental AI deployment strategies, set clear communication frameworks to manage expectations, and invest in AI literacy for both end-users and decision-makers [Aydın and Karaarslan 2023].

Effective adoption of AI also depends on user experience and system interpretability. By ensuring that AI capabilities align with real business needs and providing transparency regarding system limitations, organizations can foster trust and ensure that AI solutions generate sustainable value rather than temporary technological enthusiasm [Aydın and Karaarslan 2023].

3.3. AI is Not a Universal Solution

Despite the rapid advancements in artificial intelligence (AI), it remains a specialized tool rather than a universal solution. AI excels in tasks such as pattern recognition, predictive analytics, natural language processing, and autonomous decision-making. However, its effectiveness is largely dependent on the availability of structured or semi-structured data, where patterns can be systematically identified and leveraged for automation. In contrast, AI struggles in scenarios requiring contextual reasoning, ethical judgment, or high levels of human creativity, as these tasks involve abstract concepts that extend beyond predefined datasets [Khan et al. 2023].

Several real-world applications highlight these limitations. In medical image analysis, deep learning models can detect anomalies in X-rays and MRIs with high accuracy. However, clinical diagnosis remains a challenge, as it requires an understanding of patient history, social determinants of health, and ambiguous symptoms that AI cannot fully interpret [Rahardja et al. 2024]. Similarly, AI-powered chatbots effectively handle routine inquiries but fail in nuanced, emotionally charged conversations, frustrating users who expect human-like comprehension [Zhang et al. 2024].

AI misapplications also raise ethical and operational concerns. Automated hi- ring systems, for instance, can introduce biases by reinforcing patterns found in histo- rical training data, leading to discriminatory resume screenings that disadvantage underrepresented groups [Nugent and Scott-Parker 2022]. Likewise, AI-driven fraud detection, despite its efficiency, often generates excessive false positives, mistakenly flag- ging legitimate transactions and causing disruptions that necessitate human intervention [Rani and Mittal 2023].

These cases illustrate that AI should be viewed as a complementary tool rather than a replacement for human expertise. Organizations must critically assess whether AI is the most suitable approach for a given problem, considering alternatives such as rule-based systems, statistical models, or human-in-the-loop solutions when appropriate. A balanced integration strategy ensures that AI enhances, rather than diminishes, decision-making effectiveness while mitigating its inherent limitations.

3.4. Costs and Resource Allocation

The deployment of AI systems entails significant infrastructure and resource allocation challenges, particularly for organizations requiring on-premise solutions to safeguard trade secrets and prevent industrial data leaks. Unlike cloud-based AI, which benefits from scalable resources and managed services, on-premise deployment demands specialized hardware, including GPUs, TPUs, and high-performance storage, leading to higher upfront and maintenance costs [Pesovski et al. 2024]. Additionally, maintaining competitive AI performance necessitates dedicated data centers, energy consumption planning, and continuous system upgrades, further increasing operational complexity.

The computational demands of large-scale AI models make efficiency a key determinant of economic feasibility. For instance, DeepSeek-V2 employs the Mixture-of-Experts (MoE) architecture, achieving a 42.5% reduction in training costs and a 93.3% decrease in key-value cache memory usage, improving inference efficiency compared to traditional dense models [DeepSeek-AI 2024]. When compared to other widely used models, such as Gemini and GPT, DeepSeek stands out for its lower operational cost, despite exhibiting slower execution in certain tasks. Conversely, Claude, while offering higher performance, comes at a significantly greater expense, making cost-effective alternatives like DeepSeek more attractive for enterprise applications [Gao et al. 2025].

Beyond computational resources, AI implementation requires substantial investment in data processing and system integration. Organizations must allocate resources for secure data handling, preprocessing, model training, and validation, all of which demand specialized expertise and iterative development cycles [Gupta and Rathore 2024]. Insufficient investment in data security, model optimization, and performance monitoring can result in unreliable AI outputs, increasing operational risks and regulatory compliance challenges [Yigitcanlar et al. 2023].

To ensure sustainable AI adoption, organizations must adopt a balanced approach that aligns security, cost efficiency, and performance. Strategies such as optimized model selection, hardware acceleration, and robust internal governance can help mitigate financial and technical risks while maximizing AI-driven value.

3.5. Integration Strategies and Architectures for AI in IS Ecosystems

Despite increasing interest in AI-driven solutions, one of the most pressing challenges is how to technically and organizationally integrate AI into existing Information System (IS) architectures. Unlike conventional software components, AI modules require continuous retraining, validation, and interpretability, which pose unique architectural constraints [Heyn et al. 2023]. The integration of AI into IS ecosystems may demand for hybrid architectures that can handle probabilistic outputs, feedback loops, and large-scale data processing while ensuring modularity and explainability [Chakraborty et al. 2023].

Common approaches include API-based integration of cloud AI services, on-premise AI modules embedded into enterprise systems, and middleware orchestration layers that bridge AI inference engines with traditional business logic and data layers. These solutions must account for data governance, auditability, and performance trade-offs [Atoum 2025]. In the Brazilian context, these integrations must also comply with local regulatory frameworks, such as the LGPD and the emerging AI regulation frameworks, demanding a cross-disciplinary approach to system design [Belli et al. 2023].

Future research should explore reference architectures, integration patterns, and organizational practices that can support scalable, ethical, and context-aware deployment of AI-based IS.

4. Final Remarks

The integration of Artificial Intelligence (AI) into Information System (IS) ecosystems of- fers significant opportunities but also introduces complex challenges that require careful consideration. This paper has examined five challenges that influence the effectiveness of AI-driven solutions, underscoring the importance of strategic planning, technical prepara- tion, and informed decision-making to ensure a dependable, ethical, and socially aligned incorporation of AI into IS.

For organizations aiming to implement AI-based ecosystems, a realistic and structured approach is essential. Successful AI integration demands investment in AI literacy, workforce specialization, and sustainable deployment strategies to ensure long-term viability. Moreover, AI adoption should be driven by business needs rather than technological trends, with a strong focus on data security, model reliability, and cost-efficiency, particularly for industries where data protection and compliance are paramount.

Future research should prioritize the development of cost-effective AI deployment frameworks, optimization techniques for on-premise execution, and methodologies to enhance explainability and interpretability in AI-driven decision-making. Additionally, interdisciplinary collaboration among AI researchers, software engineers, and business strategists is crucial to aligning AI capabilities with organizational objectives and industry-specific constraints.

Ultimately, strategic AI integration must balance innovation, feasibility, and sustainability. Organizations that emphasize structured implementation, continuous monitoring, and ethical AI practices will be better positioned to harness AI's transformative potential while mitigating risks. By proactively addressing the challenges outlined in this study, businesses can build AI-powered ecosystems that deliver long-term value, efficiency, and competitive advantage.

Acknowledgments

This paper is a result of the Research, Development & Innovation Project performed at Sidia Institute of Science and Technology sponsored by Samsung Eletroˆnica da Amazoˆnia Ltda., using resources under terms of Federal Law No. 8.387/1991, by having its disclo- sure and publicity in accordance with art. 39 of Decree No. 10.521/2020.

References

Abitbol, R., Cohen, E., Kanaan, M., Agrawal, B., Li, Y., Bhamidipaty, A., and Bil- gory, E. (2024). Kmodels: Unlocking ai for business applications. arXiv preprint arXiv:2409.05919.

Agarwal, P. K. (2018). Public administration challenges in the world of ai and bots. Public Administration Review, 78(6):917–921.

Atoum, I. (2025). Revolutionizing ai governance: Addressing bias and ensuring accountability through the holistic ai governance framework. International Journal of Advanced Computer Science & Applications, 16(2).

Aydın, O¨ . and Karaarslan, E. (2023). Is chatgpt leading generative ai? what is beyond expectations? Academic Platform Journal of Engineering and Smart Systems, 11(3):118–134.

Belli, L., Curzi, Y., and Gaspar, W. B. (2023). Ai regulation in brazil: Advancements, flows, and need to learn from the data protection experience. Computer Law & Security Review, 48:105767.

Chakraborty, S., Talukder, M. B. U., Hasan, M. M., Noor, J., and Uddin, J. (2023). Bigru-ann based hybrid architecture for intensified classification tasks with explainable ai. International Journal of Information Technology, 15(8):4211–4221.

Chen, Y., Lehmann, C. U., and Malin, B. (2024). Digital information ecosystems in modern care coordination and patient care pathways and the challenges and opportunities for ai solutions. Journal of Medical Internet Research, 26:e60258.

Cisterna, D., Gloser, F.-F., Martinez, E., and Lauble, S. (2024). Understanding professional perspectives about ai adoption in the construction industry: A survey in germany.

In ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, volume 41, pages 347–354. IAARC Publications.

DeepSeek-AI (2024). Deepseek-v2: A strong, economical, and efficient mixture-of-experts language model. arXiv preprint, arXiv:2405.04434.

Gao, T., Jin, J., Ke, Z. T., and Moryoussef, G. (2025). A comparison of deepseek and other llms. arXiv preprint, arXiv:2502.03688.

George, A. S. and George, A. H. (2023). A review of chatgpt ai's impact on several business sectors. Partners universal international innovation journal, 1(1):9–23.

Gupta, R. and Rathore, B. (2024). Exploring the generative ai adoption in service industry: A mixed-method analysis. Journal of Retailing and Consumer Services, 81:103997.

Habbal, A., Ali, M. K., and Abuzaraida, M. A. (2024). Artificial intelligence trust, risk and security management (ai trism): Frameworks, applications, challenges and future research directions. Expert Systems with Applications, 240:122442.

Heyn, H.-M., Knauss, E., and Pelliccione, P. (2023). A compositional approach to creating architecture frameworks with an application to distributed ai systems. Journal of Systems and Software, 198:111604.

Khan, B., Fatima, H., Qureshi, A., Kumar, S., Hanan, A., Hussain, J., and Abdullah, S. (2023). Drawbacks of artificial intelligence and their potential solutions in the healthcare sector. Biomedical Materials & Devices, 1(2):731–738.

Malheiros, P. S., Lima, R. R., and Oran, A. C. (2024). Impact of generative ai technologies on software development professionals' perceptions of job security. In Proceedings of the XXIII Brazilian Symposium on Software Quality, pages 169–178.

Metz, C. and Grant, N. (2024). Old friends become rivals in big tech's race for ai. The New York Times, pages B1–B1.

Nugent, S. E. and Scott-Parker, S. (2022). Recruitment ai has a disability problem: anticipating and mitigating unfair automated hiring decisions. In Towards trustworthy artificial intelligent systems, pages 85–96. Springer.

Oprea, S.-V., Nica, I., Baˆra, A., and Georgescu, I.-A. (2024). Are skepticism and moderation dominating attitudes toward ai-based technologies? American Journal of Economics and Sociology, 83(3):567–607.

Perales, M. C. (2024). A brief note on japan's ai race, the copyright dilemma, and generative ai impact on authorship. Interface-Journal of European Languages and Literatures, 24.

Pesovski, I., Santos, R., Henriques, R., and Trajkovik, V. (2024). Generative ai for customizable learning experiences. Sustainability, 16(7):3034.

Rahardja, U., Sunarya, P. A., Aini, Q., Millah, S., and Maulana, S. (2024). Technopreneurship in healthcare: Evaluating user satisfaction and trust in ai-driven safe entry stations. Aptisi Transactions on Technopreneurship (ATT), 6(3):404–417.

Rani, S. and Mittal, A. (2023). Securing digital payments a comprehensive analysis of ai driven fraud detection with real time transaction monitoring and anomaly detection. In 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), volume 6, pages 2345–2349. IEEE.

Ros-Arlanzo´n, P. and Perez-Sempere, A. (2024). Evaluating ai competence in specialized medicine: Comparative analysis of chatgpt and neurologists in a neurology specialist examination in spain. JMIR Medical Education, 10:e56762.

Yigitcanlar, T., Agdas, D., and Degirmenci, K. (2023). Artificial intelligence in local governments: perceptions of city managers on prospects, constraints and choices. Ai & Society, 38(3):1135–1150.

Yuan, J., Yang, C., Cai, D., Wang, S., Yuan, X., Zhang, Z., Li, X., Zhang, D., Mei, H., Jia, X., et al. (2023). Rethinking mobile ai ecosystem in the llm era. arXiv preprint arXiv:2308.14363.

Zhang, R. W., Liang, X., and Wu, S.-H. (2024). When chatbots fail: exploring user coping following a chatbots-induced service failure. Information technology & people, 37(8):175–195.