BUSINESS TALK: HARNESSING GENERATIVE AI WITH DATA ANALYTICS MATURITY

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ABSTRACT

Generative AI applications offer transformative potential for business operations, yet their adoption introduces substantial challenges. This paper utilizes the CBDAS data maturity model to pinpoint pivotal success factors for seamless generative AI integration in businesses. Through a comprehensive analysis of these factors, we underscore the essentials of generative AI deployment: cohesive architecture, robust data governance, and a data-centric corporate ethos. The study also highlights the hurdles and facilitators influencing its implementation. Key findings suggest that fostering a data-friendly culture, combined with structured governance, optimizes generative AI adoption. The paper culminates in presenting the practical implications of these insights, urging further exploration into the real-world efficacy of the proposed recommendations.

KEYWORDS

Artificial Intelligence, Generative AI, Analytics, Maturity Model, Big Data

1. INTRODUCTION

Recent advancements in natural language processing (NLP) have resulted in a rapid development and deployment of generative AI applications, including chatbots like ChatGPT and virtual assistants, across various industries [1]. Literature highlights the potential of generative AI in revolutionizing customer engagement, improving operational efficiency, and its role as a decision-making tool in businesses [2]–[4]. Generative AI has been shown to significantly enhance customer engagement by providing personalized and interactive experiences. Some authors have demonstrated that generative AI enables organizations to establish stronger connections with customers, enhance satisfaction levels, and build long-term relationships [3], [5], [6]. By leveraging advanced natural language processing capabilities, generative AI systems can engage customers in meaningful conversations, understand their preferences, and deliver tailored solutions, resulting in higher levels of customer satisfaction and loyalty. Moreover, the integration of generative AI systems has been found to drive improvements in operational efficiency. Generative AI helps automating repetitive tasks, provides real-time information, and streamlines operational processes [2], [4]. By doing so, organizations can reduce manual efforts, minimize errors, and accelerate decision-making processes, leading to enhanced operational efficiency and cost savings.

Generative AI also plays a vital role in business decision-making. Academic literature, including studies by Catelluccio [7] and Davenport [4], emphasizes that AI, with its advanced analytics and natural language processing capabilities, assists organizations in data-driven decision-making. By analyzing vast amounts of data and extracting valuable insights, generative AI systems provide organizations with recommendations and actionable intelligence to support strategic choices and operational processes, ultimately leading to more informed and effective decision-making. However, the adoption of generative AI poses certain challenges that need to be addressed. Some authors highlight issues such as data privacy and security concerns, ethical considerations, algorithmic bias, and the need for continuous monitoring and improvement to ensure optimal performance and user satisfaction [8], [9]. Organizations must carefully navigate these challenges to ensure responsible and ethical implementation of generative AI systems. Successful integration of generative AI also requires organizational readiness and effective change management. Arrieta et al. [10] and Castelluccio [7] emphasizes the importance of aligning generative AI initiatives with overall business strategies, establishing appropriate governance structures, and fostering a culture that embraces data-driven decision-making and innovation. Organizations need to proactively address the organizational and cultural changes necessary to support the implementation and ongoing management of generative AI systems.

Thus, the main question guiding this paper is: "What are the primary drivers and barriers to the effectiveness of generative AI integration as a decision-making tool in companies?" To address this question, we conduct a comprehensive review of the success factors for generative AI integration in companies, by leveraging the Consensual Big Data Maturity Assessment System (CBDAS) maturity model [11]. We introduce the CBDAS model and its application specifically to generative AI, providing an overview of the key factors crucial for successful generative AI integration in companies. Subsequently, we delve into each critical success factor in detail, examining the specific requirements for implementing generative AI, identifying the inhibitors and enhancers that influence its implementation, and discussing the actions that organizations can undertake to ensure successful implementation. Through our analysis, we identify a well-integrated architecture, robust data governance, and a data-friendly corporate culture as critical factors for achieving successful generative AI implementation.

The structure of this paper is organized as follows. In the subsequent section, we present a comprehensive literature review encompassing the CBDAS maturity model and generative AI technologies. This review explores the current and potential applications of generative AI in the business domain. Moving forward, Section three provides an overview of the critical success factors for generative AI integration in companies. Section four further examines each critical success factor, delving into the specific requirements, inhibitors, and enhancers for successful implementation. Additionally, we propose actionable measures that organizations can take to ensure success. Finally, in the concluding section, we discuss the implications of our findings for practitioners, drawing on the insights provided by the aforementioned academic literature, and offer concluding remarks and suggestions for future research.

2. LITERATURE REVIEW

2.1. The Consensual Big Data Assessment System

The CBDAS is a consensual framework [11] designed on a theoretical framework that outlines the key success factors (CSFs) of data analytics [12], [13]. This framework encompasses the factors and sub-domains, and the criteria of success of big data initiatives. The structure of the CBDAS consists of two sections: the first section assesses the current maturity levels of enterprises at various levels of granularity – from factor to subdomain level - while the second section evaluates the relative importance of the CSFs for industry experts. The assessment system is comprised of 59 questions, with 44 questions focusing on the maturity levels of the CSFs and sub-domains and 15 questions addressing the underlying business needs. The results are obtained through a standardized questionnaire with one closed-ended question per item and analyzed using software such as Cognito, Zapier, and Google Sheets. The CBDAS is a quantitative method that generates 156 potential outcomes based on the combination of sub-domain maturity levels and their interdependencies. The second section of the questionnaire evaluates the importance of each factor using the analytic hierarchy process (AHP) which evaluates individuals' and groups' judgments and converts them into numerical values for objective comparison. The output of the AHP is used as input to evaluate the relevance of each organizational area from the manager's perspective, recognizing that the relevance of each factor may vary depending on context and may not be applicable to all organizations.

2.2. Data Maturity Models: Evaluating the Drivers and Drainers of Generative AI Integration

In recent years, the proliferation of generative AI applications has sparked recognition of their transformative potential in revolutionizing business operations [3], [14], [15]. However, the successful adoption and implementation of generative AI systems present significant challenges for organizations [3], [4], [16], [17]. To address these challenges effectively, organizations need to identify and analyze the critical success factors that influence the effectiveness of generative AI as a decision-making tool [4], [8]. This is where data maturity models come into play.

Data maturity models, such as the Consensual Big Data Assessment System (CBDAS) maturity model [11], provide a framework to assess and evaluate the maturity levels of organizations in terms of their data capabilities [18]–[21]. By applying data maturity models like CBDAS, organizations gain a comprehensive understanding of their strengths and weaknesses in relation to generative AI integration [16], [22]. They can identify the drivers that contribute to successful implementation, such as clear data strategies, well-integrated architectures, robust IT infrastructure, user-friendly interfaces, skilled analytical workforces, collaborative organizational structures, and data-driven corporate cultures. Simultaneously, organizations can uncover the potential drainers, including inadequate data strategies, fragmented architectures, insufficient IT infrastructure, complex interfaces, inadequate workforce competencies, siloed organizational structures, and resistance to data-driven decision-making.

Understanding the drivers and drainers of generative AI integration through the lens of data maturity models empowers organizations to make informed decisions and take strategic actions [8], [14], [23]. It enables them to address the challenges effectively and leverage the drivers to maximize the benefits of generative AI as a decision-making tool.

The CBDAS maturity model, as an example of a data maturity framework, outlines key success factors (CSFs) that contribute to the effectiveness of data analytics initiatives, including generative AI integration [24]. By utilizing the CBDAS model, organizations can assess the maturity levels of various factors and sub-domains that are critical for the successful implementation of generative AI. By soliciting expert opinions through a standardized questionnaire, organizations can gain insights into the factors that industry experts consider critical for achieving successful outcomes in generative AI integration. This assessment enables organizations to align their efforts with expert opinions, ensuring they address the most impactful drivers and mitigate potential drainers effectively.

Through the CBDAS questionnaire, organizations can collect data on a range of factors, such as data strategy, integrated architecture, IT infrastructure, human data interface, analytical human workforce, integrated organization, and data-friendly corporate culture [11]. Analyzing the responses to these questions enables organizations to generate valuable insights about their data maturity levels and the specific factors that drive or drain the effectiveness of generative AI integration.

2.3. Generative AI and business applications

The current academic literature offers valuable insights into the applications of generative AI in the business domain. Vaswani et al. [6] highlight how generative AI can revolutionize customer engagement by providing personalized and interactive experiences, leading to stronger connections with customers and enhanced satisfaction levels. Korzynski et al. [25] further emphasize the potential of generative AI in improving customer engagement through efficient and effective communication. These studies suggest that generative AI can help organizations build long-term relationships with customers and drive business growth [26]. Moreover, some authors discuss the current and potential applications of generative AI in streamlining operational processes [3], [27]. By automating repetitive tasks and providing real-time information, generative AI reduces manual efforts, minimizes errors, and accelerates decision-making processes. Korzynski [25] highlight the efficiency gains that organizations can achieve by integrating generative AI systems into their operations. These studies demonstrate how generative AI can enhance operational efficiency and improve overall business performance.
Generative AI is also recognized as a valuable tool for data-driven decision-making in the business domain. Chui and Malhotra [27] discuss how generative AI leverages advanced analytics and natural language processing capabilities to analyze large volumes of data, extract meaningful insights, and provide recommendations. By accessing relevant information and generating real-time insights, generative AI empowers decision-makers to make informed choices and drive strategic and operational success. While maturity models have been widely used in various domains to assess organizational readiness and maturity, their specific application to generative AI is not extensively discussed in the current literature [3], [20], [28]. However, as the field continues to evolve, the adoption of maturity models could provide a valuable framework for evaluating how organizations can leverage generative AI for business advantages, considering the associated risks and benefits [3], [10]. Future research can explore the potential connections between maturity models and generative AI to identify specific factors and assessment criteria relevant to its successful implementation.

It is important to note that the field of generative AI is rapidly evolving, and further research is needed to fully explore its potential applications and implications in different business settings. The studies mentioned above serve as foundational references, and future research can build upon them to deepen our understanding of the current and potential applications of generative AI in various industries.

3. CRITICAL SUCCESS FACTORS FOR GENERATIVE AI

In the absence of extensive existing literature on maturity models for generative AI analysis, we propose the Consensual Big Data Assessment System (CBDAS) framework as a trial to equip businesses with the necessary instruments for the efficient adoption of generative AI [11]. This framework aims to provide a structured approach for organizations to evaluate the risks and inhibitors associated with generative AI implementation and assess the requirements for successful deployment.

We leveraged the Consensual Big Data Assessment System (CBDAS) framework as our foundational basis, encompassing its critical success factors such as data strategy, integrated architecture, IT infrastructure, human data interface, analytical human workforce, integrated organization, and data-friendly corporate culture. Our aim is to leverage this framework as a starting point to construct a practical case-based framework that serves as a foundation for understanding inhibitors and risks associated with an organization's adoption of generative AI. The breadth of domains proposed in the framework allows for the incorporation of adjacent aspects from big data analytics into the realm of generative AI maturity. While there is limited explicit literature on the integration of big data analytics and generative AI maturity, the integration of these two fields presents an opportunity to enhance the understanding of generative AI within the broader context of data analytics maturity [29], [30]. This integration can facilitate a holistic approach to harnessing the potential of generative AI and its interplay with big data analytics, leading to more informed decision-making and improved organizational outcomes.

By considering these critical success factors and their specific requirements, organizations can effectively deploy generative AI, ensuring compliance with information security standards and mitigating risks related to proprietary data. This comprehensive approach will facilitate the successful implementation of generative AI in domains such as productivity, content creation, and knowledge transfer, enabling organizations to harness its advantages while minimizing potential challenges.

Table 1. Critical Success Factors Requirements for Generative AI.

Critical Success Factor	**Requirements for Generative AI**	**Actions for Success**
Data Strategy	- Clear understanding of business objectives and data requirements for generative AI - Alignment of generative AI with overall data strategy - Robust data privacy policies and procedures - Strong data procurement and utilization strategy - Develop a clear business case and roadmap for generative AI - Align generative AI with overall data strategy and business objectives - Establish robust data privacy policies and procedures - Develop and implement a comprehensive data procurement and utilization strategy	- Develop a clear business case and roadmap for generative AI - Align generative AI with overall data strategy and business objectives - Establish strong data privacy policies and procedures - Develop and implement a comprehensive data procurement and utilisation strategy
Integrated Architecture	- Well-integrated architecture to support multiple data domains - Robust data quality processes - Flexible DevOps processes to enable rapid deployment and updates - Comprehensive data management and governance practices	- Develop and implement a well-integrated architecture to support generative AI - Establish robust data quality processes - Adopt flexible DevOps processes to enable rapid deployment and updates of generative AI - Develop and implement comprehensive data management and governance practices
IT Infrastructure	- Robust data security and risk management practices	- Establish robust data security and risk management practices

	- Sufficient storage and computational resources - Appropriate cloud-based solutions and big data infrastructure	- Ensure sufficient storage and computational resources are available - Select appropriate cloud-based solutions and big data infrastructure
Human Data Interface	- Easy-to-use and accessible generative AI interfaces - Comprehensive business intelligence systems, analytical toolkits, and data visualization platforms - Guidelines and documentation on data access and usage	- Develop and implement easy-to-use and accessible generative AI interfaces - Adopt comprehensive business intelligence systems, analytical toolkits, and data visualisation platforms - Establish guidelines and documentation on data access and usage
Analytical Human Workforce	- Skilled and competent analytical workforce - Well-defined job families and training guidelines for analytical roles - Corporate-wide development framework for analytical competencies	- Ensure the analytical workforce is skilled and competent - Develop and implement well-defined job families and training guidelines for analytical roles - Establish a corporate-wide development framework for analytical competencies
Integrated Organization	- Collaboration on generative AI across the organisation - Clear power and knowledge flows	- Foster collaboration on generative AI across the organisation - Ensure clear power and knowledge flows
Data-friendly Corporate Culture	- Data-driven decision-making - Openness to new technologies - Willingness to experiment and learn	- Foster a data-driven decision-making culture - Cultivate an openness to new technologies - Encourage experimentation and learning with generative AI

4. RESULTS

Within the CBDAS framework, one factor particularly relevant to generative AI adoption is the establishment of a dedicated internal setup that ensures all use cases relating to leveraging generative AI are channelled in a reliable, secure, and cost-effective manner. This includes implementing a use case intake form, vetting the environment and services to ensure InfoSec compliance and governance, enabling knowledge management sharing, and ensuring a thorough understanding of the generative AI processes [22], [31].

For the IT infrastructure factor, organizations need to establish an environment where generative AI can ensure data are stored securely, and models can be built within the organization's proprietary environment. This includes vetting and ensuring the level of governance, InfoSec compliance, and reliability of the OpenAI Azure offering [6]. It also involves understanding the expected outcomes by identifying the types of problems that can yield good results when using generative AI. Pilot use cases should be tracked and leveraged through knowledge and documentation sharing, and comprehensive training materials should be delivered to facilitate the deployment and usage processes of generative AI models. Additionally, organizations can leverage and build on the learnings from previous projects to enhance productivity, content creation, and knowledge transfer within the organization [32], [33]. By considering these critical success factors and their specific requirements, organizations can effectively deploy generative AI, ensure compliance with InfoSec standards, and mitigate risks associated with the use of proprietary data. This comprehensive approach will facilitate the successful implementation of generative AI in areas such as productivity, content creation, and knowledge transfer, enabling organizations to leverage its advantages while minimizing potential challenges.

Actionable measures that organizations can take to ensure success in the implementation of generative AI, considering the critical success factors discussed within the CBDAS framework should be:

- **Establish a dedicated internal setup:** Implement a use case intake form to systematically capture and evaluate use cases for generative AI. Vet the environment and services to ensure compliance with InfoSec standards and governance. Enable knowledge management sharing through collaborative platforms and establish clear communication channels. Foster a thorough understanding of generative AI processes through training and knowledge transfer programs.
- **Build a robust IT infrastructure:** Create an environment that supports secure data storage and model building within the organization's proprietary infrastructure. Vet and ensure the governance, InfoSec compliance, and reliability of the OpenAI Azure offering. Invest in appropriate storage and computational resources to handle the demands of generative AI. Implement cloud-based solutions and big data infrastructure as needed.
- **Understand expected outcomes and identify use cases:** Conduct a thorough analysis to identify the types of problems that can yield favorable results when using generative AI. Track and leverage pilot use cases, learning from their outcomes and applying insights to future implementations. Share knowledge and document the outcomes of use cases to facilitate organizational learning and continuous improvement.
- **Provide comprehensive training and support:** Deliver training materials that cover the deployment and usage processes of generative AI models. Offer training programs to equip the workforce with the skills and competencies required to navigate within generative AI, including understanding prompt design and other relevant concepts. Establish a corporate-wide development framework for analytical competencies specific to generative AI.
- **Leverage insights from previous projects:** Learn from previous experiences and projects to enhance productivity, content creation, and knowledge transfer within the organization. Identify and leverage best practices, lessons learned, and successful strategies from previous generative AI initiatives. Adapt and refine approaches based on the specific requirements and context of the organization.

By implementing these actionable measures, organizations can enhance their chances of success in deploying generative AI. These measures address the specific requirements outlined in the critical success factors and contribute to building a solid foundation for generative AI implementation. Regular monitoring, evaluation, and adaptation of these measures based on evolving needs and emerging insights will further ensure the long-term success and continuous improvement of generative AI initiatives within organizations [34]–[36].

5. CONCLUSIONS

The paper concludes with important implications for practitioners in the field of generative AI. The adoption of maturity models, specifically the CBDAS framework, can serve as a valuable tool for organizations seeking to leverage generative AI for business advantages. The identified critical success factors, including the establishment of a dedicated internal setup, robust IT infrastructure, understanding of expected outcomes, comprehensive training and support, and leveraging insights from previous projects, provide actionable measures for organizations to ensure successful implementation. Practitioners should consider these recommendations to enhance their ability to deploy generative AI effectively, ensure compliance with InfoSec standards, and mitigate risks associated with proprietary data. By doing so, organizations can tap into the potential benefits of generative AI in domains such as productivity, content creation, and knowledge transfer.

However, further research is needed to investigate the effectiveness of these recommendations in real-world business settings. Future studies can explore the implementation of these measures and evaluate their impact on the successful adoption and utilization of generative AI. Additionally, examining the connection between maturity models and generative AI can provide valuable insights into specific factors and assessment criteria relevant to its implementation.

By bridging the gap between academic research and practical application, future research can contribute to a deeper understanding of how organizations can leverage generative AI for business advantages and navigate the associated challenges. This will ultimately support practitioners in making informed decisions and driving successful implementation of generative AI in diverse business settings.

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