Exploring Implementation Parameters of Gen AI in Companies

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Keywords: Gen AI, Adoption, Case Study, LLM, Implementation, Companies.

Abstract: Our work focusses on investigating Gen AI implementation, as the field is developing at such a rapid pace, up to date research on business implementations and outcomes is limited. We systematically evaluate AI applications, analysing challenges/opportunities. We consider adoption beyond pilot projects via a structured approach covering factors such as technological, organizational, and environmental. Our case studies show relevance of data quality, infrastructure, and organizational culture. The paper explores how company leaders can support to create employee trust and deliver on an AI strategy. Companies face competition, customer needs and regulation that shape their technology roadmaps. These complexities are exacerbated by training data problems, internal communications, context challenges and ethics. This research finds that challenges & strategies for responsible Generative AI deployment advocate a holistic and adaptive approach. Which companies need to tailor each application, to achieve desired outcome.

1 INTRODUCTION

Generative artificial intelligence (Gen AI) is a specific application of artificial intelligence. It uses various technologies, such as large language models, reinforcement learning algorithms and generative models. It had been widely applied in companies for customer support, content creation and data analysis (Bandi et al. 2023, Bostrom, N., & Yudkowsky, E. 2014). Literature has investigated the specific ways in which Generative AI is being implemented in businesses and its impact on business outcomes (Agrawal, K, 2023; Alvim, A., & Grushin, B. 2019). However, gen AI implementation involves the design, development, and deployment of systems to achieve specific goals and objectives (Ghimire 2023, Kelleher, J. D., Mac Namee, B., & D'Arcy, A. 2015). This holistic approach is needed to positively affect the effectiveness of generative AI implementation, which is determined by factors such as user satisfaction, system reliability and overall performance (Abbeel, P., & Zaremba, W. 2019). We systematically research Gen AI implementation from organizational perspective, creating much needed insight in this rapidly evolving field.

This work contributes to research on the application of AI. The findings provide insights into how generative AI is used. It shows benefits and challenges of implementation, and impact on business outcomes. The study will inform development of best practices for the implementation and help companies make informed decisions about the adoption of AI. The research will aid with addressing application challenges of gen AI tech in companies, help identify benefits and support the impact assessment of gen AI.

In the past only few companies adopted and deployed AI applications beyond pilot projects (Anon, 2020). This has changed with the launch of OpenAI as it is now on every company's radar. Organizations face challenges in adopting and deploying AI, coming technological, organizational, or environmental readiness gaps. Caused by government regulations, infrastructure costs, resources, or reliance on external partners (Alsheibani et al., 2018). In addition, there can be organizational obstacles with stakeholders prioritizing automation to reduce costs, but managers may prefer augmentation, leading to a potential paralysis in deployment (Dedrick et al., 2013; Shollo et al., 2020). The use of AI may challenge cultural norms and act as a barrier for managers and customers to accept AI technologies (Dwivedi et al., 2019). To understand the dynamics involved in organizations adopting AI and developing AI capabilities, investigation into the socio-technical arrangements and processes through which AI applications are developed and deployed will help (Holton & Boyd, 2019). Therefore, a deeper understanding of these challenges and cultural obstacles, as well as strategies to overcome them, is crucial, leading us to the question of research of this paper:

Voorneveld, M.
Exploring Implementation Parameters of Gen AI in Companies.
DOI: 10.5220/0012618300003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 665-673
ISBN: 978-989-758-692-7; ISSN: 2184-4992

What parameters to implement gen AI are used and how do companies overcome its challenges? This research will focus on cultural norms and changes in organizational structures impact the adoption and deployment of AI in business operations. This study can benefit academic researchers, practitioners, and policymakers working in the field of artificial intelligence and its applications in business by addressing how companies can use generative AI. What the potential benefits of generative AI are and the related challenges companies face using generative AI. The execution sequence of this research has linked a theory for key metrics to measure the impact of AI in business and compare findings with theory to provide suggestions. This paper will continue with a literature review, followed by a methodology, before displaying the outcomes and conclusions.

2 BACKGROUND

As gen AI continues to advance, it becomes crucial to have a comprehensive understanding for assessing its performance and evaluating its outputs. Early discussion with a VP at an organization implementing AI solutions for corporate clients drew attention to the industry's game-changing technology investments. It highlights the ongoing rapid industrial revolution propelled by Generative AI, citing Microsoft's substantial investment as a testament to its transformative potential. Emphasizing the urgency for businesses to integrate Generative AI to avoid obsolescence, it acknowledges Microsoft's decision to make Azure the exclusive cloud provider as potentially limiting accessibility. The interview underscores the need for flexibility in adoption and deployment strategies. Generative AI's profound impact extends to daily software interactions, prompting the next challenge of effectively incorporating it into enterprise environments. This is referred to as Case Study 0 and they recognized the achievement in this domain, inviting discussions on the future of AI, deep learning, and generative AI. This company envisions the possibilities of running a Smaller GPT models, highlighting potential benefits in reduced data centre footprint, power consumption, and maintenance compared to the larger Generative AI models. Emphasizing the need to tailor a solution to specific requirements such as sustainability or financial advantages can to enterprise settings if that is required.

To provide a systematic approach for assessing generative AI, incorporating relevant concepts, methods, and metrics are required from existing literature. There are different types of generative AI models and their underlying principles which should be assessed by a variety of evaluation metrics (Goodfellow et al., 2014; Kingma & Welling, 2013; Radford et al., 2019). Metrics that can be used to assess the performance of generative AI models are enablers or inhibitors of AI use, these can be subdivided into three main categories: technological, organizational, and environmental (Enholmm 2021).

2.1 Organizational

Strategic orientation and organizational structure impact the ability to successfully adopt AI. Making organizational culture a key factor in the process to adopt AI (Mikalef & Gupta, 2021). A culture of innovation can encourage learning and development, it is essential for implementing new solutions such as AI (Mikalef & Gupta, 2021). Such changes require the support of leaders preferably company execs to drive adoption (Alsheiabni et al., 2018; Demlehner & Laumer, 2020). Leaders should actively participate in exploring the best applications of AI to establish a culture supporting disruptive adoption (Lee et al., 2019). Through this support initiators of change can have resources allocated to support the adoption of AI.

Making sure organizations are ready for change is essential, to have the necessary resources made available is essential for AI adoption (AlSheiabni et al., 2018). As mentioned, this is in part adequate budget allocation, to an extent without stringent performance targets. Because the early days of new solution adoption requires additional freedom to allow employees to learn while developing the best AI use cases (Pumplun et al., 2019). Core to the organizational capabilities are employees with deep and broad technical skills to create and deploy AI. Who need to be able to collaborate with subject matter experts of existing business processes. This is essential to identify opportunities for AI use cases and advocate their benefits (Pumplun et al., 2019). Internal availability of expertise is a challenge, as it is often allocated to running projects. Clear business goals are required to ensure that technical and managerial staff are trained and have availability to develop AI based solutions for specific business functions (Mikalef & Gupta, 2021).

Employees having trust in systems is crucial for successful implementation, this is especially so for AI. As the impact in companies can be large, with AI replicating partial human cognition or automating laborious tasks there is a risk of changing employees' roles and responsibilities impacting their livelihood (Makarius et al., 2020). Therefore, employees need to understand the purpose of AI and its role. They need to understand how it will affect their responsibilities and be able to see the benefit (Makarius et al., 2020). Building this trust between humans and machines is a challenging task as implementation of solutions rarely considers emotions and empathy, which is an aspect also absent in AI. Additionally, managers need to be able to rely on AI systems, to do so they need a solid understanding of tech (Keding, 2020). Concluding from this all, companies need to develop an AI organizational adoption strategy. To proactively overcome the barriers and be able to reap the benefits of AI adoption, aligning it with existing goals (Finch et al., 2017a; Keding, 2020). Such a strategy can be effective when it includes specific processes, plans, and timeframes for implementation. Requiring organization structural change processes, collaboration options between departments, and data governance improvement plans (Mikalef & Gupta, 2021). In terms of organizational readiness, it is important to define the benefits of the AI solution to the organizational goals and strategy (Pumplun et al., 2019). Where higher levels of adoption and use of AI are observed when there is a strong fit between technology and the business goals. This should be achieved through a use case definition addressing how problems will be solved through AI and enhance business performance (Mishra & Pani, 2020; Alsheiabni et al., 2018). Vice versa, companies must be able to adapt their business processes to requirements of AI for successful implementation.

2.2 Technological

Large data sets are used to train models, putting data at the core of AI development (Schmidt et al., 2020). The quality of this data being used in the training models is crucial. Often the "garbage-in, garbage-out" is a fundamental principle for AI is mentioned (Lee et al., 2019). This can be overcome by dealing with common challenges in data quality, these include completing datasets, labelling data, filtering incorrect entries, and removing noise or other disruptions in the data. Data scientists need to closely collaborate with engineering teams to identify and mitigate data quality problems (Baier et al., 2019). Data can also suffer from an introduced bias at various stages of its use cycle, during generation for instance by priming, through selective collection, or faulty processing, it is essential this is addressed to reduce negative consequences (Ntoutsi et al., 2020).

Utilizing a suitable infrastructure is a requirement in the process of AI adoption. Having sufficient computing power and of the correct instance type, developing workable algorithms that can train on the quality data sets (Wamba-Taguimdje et al., 2020). The algorithms are often complex with data sets being enormous thus requiring massive amounts of computing power (Baier et al., 2019). This has significant impact on companies and most organizations may not have such resources available (Schmidt et al., 2020). To address this many companies are utilizing the services of cloud-based solutions for machine learning infrastructure (Borges et al., 2020). This option has democratized the development of AI, giving organizations access to the necessary resources for AI adoption (Schmidt et al., 2020; Wang et al., 2019). In conclusion, quality data free from bias requires collaboration with data scientists. The right technology infrastructure is essential enablers of AI adoption in organizations. This includes suitable computing power and algorithms, critical for developing quality AI applications, often via cloud-based solutions.

2.3 Environmental

A strong driving factor for AI adoption is that companies seek to gain a competitive advantage over their competition by developing and adopting innovations (Demlehner & Laumer, 2020) Their customers can play a crucial role when demanding specific goods or services. To meet these needs companies must consider how to leverage their knowledge in the process of AI adoption (Coombs et al., 2020).

Government policies and regulations also play a crucial role in shaping the ethical and moral aspects of AI adoption. The General Data Protection Regulation (GDPR), enforced in the European Union (EU) and the European Economic Area (EEA) in May 2018, regulates the processing of personal data and has implications for organizations using AI solutions as they struggle to comply with data protection requirements (Pumplun et al., 2019). GDPR increases the complexity of AI deployment as organizations need to anonymize data sets to comply with the law, which can hinder the use of intelligent, self-learning algorithms. Intellectual property issues related to AI algorithms and data sets can also pose legal challenges to AI adoption (Demlehner & Laumer, 2020). Additionally, industry-specific regulations and external circumstances can impact AI adoption, with highly regulated sectors like healthcare facing additional challenges (Coombs et al., 2020) Addressing ethics is crucial when adopting AI systems possess capabilities displacing human output. As it has the effect of interconnecting humans and machines to a level not previously achieved. In doing so it is essential that applications are developed based on ethical principles and do not contain unknown biases (Coombs et al., 2020). Typical issues with the development of AI are lack of transparency, unconscious bias, and potentially discrimination. Being data-driven AI can produce biased outcomes if the underlying data is unbalanced or inherently discriminatory, but also can be influenced by the biases of system developers (Baier et al., 2019). Public and private bodies can support generating transparency, accountability, safety and security, societal and environmental well-being, design for universal access, and human agency and oversight (European Commission, 2019a; European Commission, 2019b). In conclusion gen AI requires a comprehensive evaluation that considers key concepts, methods, and metrics. These factors will be further detailed in the Methodology section, to understand the performance and reliability of generative AI in complex decision-making processes.

3 METHODOLOGY

For the mutual benefit and protection of Authors and This study employs a qualitative case study approach, where we have set up data collection through in-depth interviews with key AI implementation leader in various companies. These companies are on the forefront of applying gen AI. The companies are AWS, Microsoft, Open AI and the interviews are aimed at determining how they enable the adoption of AI data collected will be analyzed using thematic analysis to identify key themes and patterns in the data. The first step in assessing gen AI implementation is conceptualizing what it is, to provide an overview of the different aspects that need to be considered in the assessment of gen AI. It includes evaluation metrics for diversity and novelty, it looks at the application realism and fidelity. But it also enquires into its robustness and generalization capability, whilst not shying away from ethical considerations on interpretability and explaining ability. Lastly issues like user acceptance usability, and contextual factors are considered. These topics will be addressed by questions and investigation.

Conducting case studies on companies adopting and deploying generative AI, requires a well-defined methodology to gather valuable insights. The method is based on a qualitative data analysis of case study interviews. After a review of existing literature on generative AI adoption and deployment we have identified key parameters, challenges, and best practices discussed in the literature. These have been tailored to the companies selected based on their prominence in the generative AI space, they are AWS, Microsoft, a Tech Unicorn, and OpenAI, selected for their significant contributions. In conducting and reporting this research, we have ensured ethical standards, by obtaining informed consent from interviewees and we anonymize the data to protect the identity of participants.

We have conducted semi-structured interviews with senior leaders or key stakeholders at each company. Based on an interview guide focusing on parameters considered and implementation challenges. The output has been transcribed and applied qualitative analysis tools to generated coded interview data using a thematic analysis approach. To validate the findings, we used multiple data sources (interviews, documents, reports) and we share preliminary findings with interviewees for validation. Finally, we present findings here through a comprehensive report to illustrate key point and provide a detailed discussion of how challenges were overcome. This methodology aims to provide a thorough understanding of the parameters considered and challenges overcome during the generative AI implementation journey in the selected companies. It combines insights from interviews with rigorous qualitative data analysis to enhance the credibility and reliability of the research.

3.1 Organizational

The integration of gen AI into an environment, such as a website, application, or messaging platform, requires the evaluation of realism and fidelity of generative AI outputs. This includes metrics such as human perception-based evaluations and cross checking this with the output (Xu et al., 2018). Also, an adversarial evaluation is required (Lucic et al., 2018), and domain-specific evaluations are beneficial (Zhu et al., 2017). This will help measure how realistic output is compared to reference material considered true or real data. The assessment of the robustness in gen AI models requires adversarial robustness (Madry et al., 2017) or out-of-distribution detection (Hendrycks et al., 2018), and transfer learning evaluation (Donahue et al., 2019). These can assess how well the generative AI models perform under different conditions and domain shifts.

3.2 Technical

Generative AI can understand natural language, interpret the user intent, and generate appropriate responses, to do so it has technical requirements. These are determined by the context of a specific domain or industry, the availability and quality of data, the complexity of decision-making tasks. However human involvement in decision making processes and the contextual factors can significantly influence performance, reliability, and usability of gen AI. Besides this assessing the diversity and novelty of generative AI outputs, including metrics such as diversity score is vital, also novelty scoring is important (Li et al., 2021). These metrics allow for a quantification of to what extent to which the outputs generated are relevant, diverse and novel.

3.3 Environmental

Gen AI implementation metrics such as user satisfaction, system reliability, and performance create an impression of the environment (Davis, 1989), also the ease of use is vital (Nielsen, 1993), and usefulness of output (Venkatesh et al., 2003). Assessing these important considerations in practicality and usability for gen AI in real-world settings enables environmental understanding. Also, ethical considerations in the assessment of gen AI must be taken onboard including fairness (Verma et al., 2018), accountability (Doshi-Velez et al., 2017), and interpretability (Ribeiro et al., 2016). These important aspects to consider when evaluating the impact and implications of gen AI have led us to the following questions to understand implementation in real-world applications.

4 OUTCOMES

This study provided a comprehensive understanding of the applications of gen AI technologies in corporate settings. We have asked questions on the implementation and the impact on business outcomes. The results of this study provide insights into the benefits and challenges and inform the development of best practices.

4.1 Organizational

The cases suggest that the successful adoption of generative AI, particularly OpenAI, involves a combination of technical strategies, stakeholder communication, ethical considerations, diversity, interpretability, and refinement based on contextual factors and user feedback.

Diverse Training Data and Robustness: All three interviews emphasize the importance of using diverse training data to address robustness and generalization issues. This includes exposure to a wide range of examples and data distributions, fine-tuning on domain-specific data, and incorporating external inputs.

Interpretability Challenges: Achieving interpretability in generative AI models remains a challenge. While attention mechanisms, saliency mapping, and post hoc analysis are mentioned, there's a recognition that interpretability is an ongoing challenge, and efforts are being made to improve it.

Stakeholder Communication: Clear communication with stakeholders is crucial. Techniques such as visualization, explanations alongside outputs, and clear documentation are mentioned across interviews to make the generated outputs interpretable and understandable to stakeholders.

Continuous Learning for Diversity: Ensuring diversity and novelty in outputs requires continuous learning. This involves not only using diverse training data but also incorporating user feedback, subjective evaluation, and constant updates to the model with new content and inputs.

Contextual Factors Impact Implementation: Contextual factors, such as domain-specific considerations, data availability, complexity of decision-making tasks, and human involvement, have a significant impact on the implementation of generative AI. This impact is seen in the need for collaboration with domain experts, ethical and legal considerations, and the iterative nature of the implementation process.

Human Involvement & Ethical Consideration: Human involvement is consistently highlighted as crucial in the implementation process, not only for providing domain expertise but also for ethical verification. Ethical considerations, including privacy and sensitivity, are integral to the development and deployment of generative AI models.

Speed vs. Verification: The impact of contextual factors, especially ethical and regulatory constraints, can slow down the implementation process. Verification steps, including ethical checks and human interaction, are deemed necessary and contribute to a more cautious and responsible deployment of generative AI.

Iterative Model Refinement: The need for continuous model refinement is evident, with feedback loops from users, experts, and new data being integral to addressing biases, errors, and ensuring the latest input is represented in the outputs.

4.2 Technological

From technical perspective generative AI models are a multifaceted challenge, requiring a combination of qualitative and quantitative methods, a clear understanding of task-specific metrics, and an ongoing commitment to addressing subjectivity and improving evaluation strategies. Stakeholder engagement, transparency, and an iterative approach to model refinement are critical aspects of successful assessment and decision-making in adoption.

Diversity in Assessment Approaches: Interviewees employ diverse approaches for assessing the realism and fidelity of generative AI outputs. While one interviewee did not provide an answer, others use a mix of qualitative and quantitative methods, including visual inspection, metrics like Inception Score and FID, and a combination of both.

Benchmarking Challenges: The evaluation of generative AI models faces challenges due to the lack of definitive benchmarks, ground truth, and objective standards for creativity and novelty. Benchmarking is commonly done through standardized tests or benchmarks, but interviewees acknowledge that benchmark performance may not directly correlate with real-world scenarios.

Evaluation Metrics: Qualitative evaluation, such as visual inspection, is a common method used by interviewees, often complemented by quantitative metrics like Inception Score, FID, perplexity, and diversity metrics. Task-specific metrics are emphasized to ensure that the models perform well in the intended context.

Subjectivity & Lack of Ground Truth: Challenges include the subjectivity in human judgments, difficulty defining evaluation metrics without ground truth, and the potential misalignment between benchmark data and real-world scenarios.

Addressing Challenges: To address challenges involve ensuring high data quality, relevance of evaluation data, and iterative improvement. Engagement with stakeholders, soliciting feedback, and enhancing interpretability are essential.

Using Findings for Improvement: Findings are used to identify strengths, weaknesses, and areas for improvement. Informed decisions are made to refine models, adjust architecture or training parameters, and address limitations.

Engaging Stakeholders: Stakeholder engagement is a recurring theme, emphasizing the importance of considering user feedback, involving domain experts, and aligning models with real-world needs. Collaboration with stakeholders is essential for refining models and making informed decisions.

Continuous Improvement and Documentation: Iterative model refinement is a key strategy, involving continuous monitoring, refinement, and adaptation based on assessment results. Documentation of insights and regular updates contribute to a culture of continuous improvement.

Emphasis on Transparency and Diversity: OpenAI, as mentioned in case 3, actively solicits feedback and insights from diverse perspectives, emphasizing transparency in evaluation practices. This aligns with the broader industry trend toward openness and inclusivity.

4.3 Environmental

Organizations are currently contending with the ethical complexities presented by generative AI models, demonstrating a collective dedication to mitigating biases, fostering user acceptance, and harmonizing models with organizational objectives. The integration of generative AI necessitates the careful navigation of ethical considerations, the assurance of user acceptance and usability, alignment with organizational goals, and the resolution of distinct challenges in gauging effectiveness. A prevalent and unifying element in the implementation process is the ongoing pursuit of improvement, propelled by continuous evaluation, user feedback, and iterative refinement, which stands as a central theme across diverse cases.

Ethical Considerations and Bias Mitigation: All cases recognize the ethical challenges associated with generative AI, particularly in training data and user prompting. Preprocessing training data is a shared concern, including efforts to reduce biases, misinformation, and imbalances. Ongoing monitoring, external audits, and user feedback play crucial roles in ensuring adherence to ethical guidelines and bias reduction.

User Acceptance and Usability: A feedback loop is consistently emphasized across all cases, involving explicit and implicit feedback, user testing, surveys, and interviews. User-centric design principles guide the evaluation of usability, with a focus on continuous improvement based on user input.

Factors for Evaluating User Satisfaction and Usefulness: Different use-cases for generative AI models are acknowledged, including decision-making aid and Retrieval Augmented Generation (RAG). Factors such as effectiveness, efficiency, user interface design, and relevance of outputs are considered for evaluating user satisfaction and usefulness.

Alignment with Organizational Goals: Strategies for alignment vary, with prompt engineering, collaboration, progress reviews, and stakeholder engagement being key themes. Continuous involvement of stakeholders, domain experts, and users is highlighted to ensure that generative AI models align with organizational goals.

Measurement of Effectiveness in Achieving Outcomes: Various evaluation approaches are discussed, including standardized tests/benchmarks, task-specific metrics, and user satisfaction ratings. Challenges in evaluating generative AI models are acknowledged, requiring innovative approaches for effectiveness measurement.

Examples of Assessment Impact: Two cases didn't provide specific examples due to confidentiality or the absence of relevant instances, the third case (OpenAI) highlights the broader impact on the field. Assessment findings influence real-world decision-making, leading to the identification of improvement areas, the development of new evaluation methodologies, and the formulation of guidelines.

Common Theme: Continuous Improvement: Across all aspects, a common theme is the emphasis on continuous improvement. This includes refining models based on user feedback, addressing biases, and iterating assessment methodologies.

5 CONCLUSION & DISCUSSION

Theoretical development provided a systematic approach to assessing gen AI implementation observations. Where we focused on matters such as user satisfaction, system reliability, and performance. By adopting this we have effectively evaluated the implementation of gen AI, this has created insights to aid future projects by making more informed decisions. The interviews in these three different cases have provided valuable insights into the complex landscape of adopting gen AI. Successful adoption often involves a nuanced combination of technical strategies, stakeholder communication, ethical considerations, and a persistent commitment to diversity, interpretability, and refinement based on contextual factors and user feedback.

We see that availability to diversity in training data is a recurring theme, which has been emphasized as it addresses robustness and generalization issues. The potential exposure to a wide range of examples will allow for fine-tuning on domain-specific data for companies. The incorporation of various inputs contributes to the model's adaptability and helps achieve interpretability, but this remains as a common challenge. Attention mechanisms, saliency mapping, and post hoc analysis are being employed, which to us is highlighting the ongoing developments and efforts in the field of AI implementation.

On the organizational side we see that effective stakeholder communication is crucial. When employing tactics to visualize progress, creating explanations alongside outputs this clear documentation can work as championing artifacts within companies. The cases show the importance of cultivating a culture of continuous learning for improving diversity. Companies must involve not only diverse training data but also user and employee feedback, even if it is a subjective evaluation, as these constant updates to models are invaluable.

Context is important to implementation we find, as domain specific considerations are essential to suitable data availability. This is required to deal with the complexity of decision-making tasks due to human involvement. Human engagement is crucial for providing domain specific insight but also for ethical verification. There is a tradeoff between speed and verification which comes up in ethical and regulatory constraints. Where a cautious and responsible deployment of gen AI leads to quality outcomes but hampers impact due to being slower.

From a technical perspective gen AI models present many challenges. To address these requires a combination of solutions, there is need for a clear understanding of task-specific metrics. Also, we find that a commitment to addressing subjectivity and improving evaluation strategies is important. Further the key stakeholder engagement drives the project forward. Where transparency and iterative working helps model refinement, this has emerged as a critical aspect for successful adoption of AI.

We find that both qualitative and quantitative methods are employed to evaluate the realism and fidelity of generative AI outputs. The lack of benchmarks as objective standards for creativity and novelty are not available. Despite these challenges, stakeholders actively engage in continuous improvement, using findings to refine models, adjust architecture or training parameters, and address these limitations to the best of their abilities.

When reviewing the ethical considerations, they have appeared to be at the forefront of organizational priorities. There is a shared commitment to addressing biases, ensuring user acceptance, and aligning models with organizational goals. However bias mitigation strategies linked with user feedback mechanisms, and iterative improvement are considered to have limited impact on resolving these issues. The cases show commitment to transparency, diversity, in ongoing practices, to align with broader industry trends toward openness and inclusiveness.

In conclusion, the cases collectively paint a comprehensive picture of the multifaceted challenges and strategies involved in the adoption of generative AI. Our findings have underscored the need for holistic and adaptive approaches. Where we clearly see emphasis towards ongoing learning, stakeholder collaboration, commitment to ethical and transparent practices. However, the road to responsible deployment of gen AI models is still wrought with ample challenges and opportunities for improvement.

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