https://doi.org/10.34074/rere.00509

Research Article

Is the Service Sector Ready for Generative AI? A Descriptive Qualitative Assessment

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ABSTRACT

This research examines barriers and solution approaches relating to the deployment of Generative Artificial Intelligence (GAI) in contact centre businesses in the Australasian region. We find six main barriers to implementation and six key methods of strategies to solve the challenges with regard to obstacle responses from management and non-management staff, with a qualitative descriptive analysis of 53 obstacle and 30 solution responses. The most common were Data Quality and Availability (83.0 percent), Integration and Infrastructure (77.4 percent), and Cost and Resource Constraints (71.7 percent). The data shows that there is a strong relationship between the barriers to implementation, as, in fact, data challenges were co-occurring with infrastructure problems (34 instances) and trust concerns (33 instances) often. The solution strategies are not only fragmented but the maximum prevalence is just 16.7%, indicating there is a lack of agreement on the best implementation pathways between stakeholders. The findings suggest a paradox: stakeholders are highly aware of the governance priorities, but they are unable to describe concrete governance mechanisms and innovation frameworks. Our discussion provides evidence-based suggestions for organisations that have struggled with GAI adoption in customer-service situations, focusing on the prioritization of data foundations, integrated capability development, partnership-based strategies, and operationalised governance models for organisations that have struggled with GAI adoption in customer-service situations.

Keywords: Generative AI, Service Sector, Contact Centres, Adoption Barriers, Readiness, and Governance

INTRODUCTION

GAI is a revolutionary technological paradigm with the potential to have a large impact on customer service activities. As mentioned by McKinsey and Company (2023), GAI has the potential to add up to 2.6 to 4.4 trillion USD to the global economy and can automate tasks that now take up 60 to 70 percent of the efforts by employees. GAI will, in particular, transform the way services are provided in contact centre settings, where customer engagement becomes the central business activity, with the benefit of personalisation, faster response times, and increased operational efficiency (Bamberger et al., 2023; Brynjolfsson et al., 2023).

Despite this potential for transformation, the adoption of GAI is low in the contact centre industry. According to survey data, of 1000 US organisations, 62 percent of organisations have yet to adopt GAI tools in work-related tasks (DISCO, 2023), and 50 percent of GAI integration will occur between 2030 and 2060, with the median being 2045 (Chui et al., 2023). This adoption lag is evident even in light of evidence showing that significant productivity gains could be achieved as a result of such adoption. Research by Brynjolfsson et al. (2023) found that the use of GAI-based conversational assistants by customer support agents led to a 14 percent productivity gain, with an even larger impact for novice and low-skilled employees.

There appears to be a mismatch between realised potential and actual adoption implies that there are major barriers to implementation beyond technical feasibility. Research into these barriers and viable solution strategies is an important need for organisations that wish to use GAI as a competitive advantage. These implementation dynamics can best be studied in the context of contact centres, which are expected to have the highest GAI adoption rates in the customer service industry (Chui et al., 2023) and where customer experience is the main priority of AI-driven change efforts (Gartner, 2023).

This research addresses a notable gap in current knowledge regarding the barriers faced by organisations in adopting GAI technologies and the solution strategies they consider effective. Al-though much of the existing literature describes GAI capabilities and theoretical frameworks, there is limited empirical evidence on practitioner-identified barriers and solutions. Through a systematic review of open-ended stakeholder responses from contact centre organisations in the Australasian region, we offer grounded insights that can be used to drive evidence-based implementation strategies.

The two key questions our research investigates are:

1. What are the major challenges preventing GAI application in the contact centre environment? and
2. What solution strategies do stakeholders consider effective in addressing these challenges?

Through qualitative analysis, including thematic coding, word frequency analysis, and co-occurrence analysis, we map the landscape of challenges and solutions, revealing patterns that provide actionable insights for practitioners.

THEORETICAL BACKGROUND AND CONTEXT

Contact centres are key to customer engagement, influencing brand reputation and satisfaction through personalized interactions (Talbot, 2021). They face challenges like fluctuating productivity, high turnover (with annual attrition costs of 10, 000 to 20,000 USD per agent), and costly training (Buesing et al., 2020). With customer experience as the top priority, noted by 38% of respondents.

Empirical studies show GAI's potential. Brynjolfsson et al. (2023) introduced a GAI assistant to 5,179 agents, boosting productivity by 14%, especially among new and low-skilled workers. This resulted in a 25% reduction in turnover and case escalation, indicating GAI's ability to address human capital challenges and improve service quality across many industries.

However, GAI implementation in contact centres faces challenges. The need for human interaction and relationship-building creates a tension between automation and service quality, as conversations require both AI-supported pattern-matching and human empathy, judgment, and adaptability. Successfully addressing this requires understanding both technical barriers and organizational readiness.

Implementation obstacles in technology adoption literature

Technology adoption literature highlights key barriers to GAI implementation. The TOE framework (Tornatzky & Fleischer, 1990) identifies technological readiness, organizational capabilities, and environmental factors as key determinants. The Technology Acceptance Model (TAM) stresses perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003), while diffusion of innovations theory focuses on relative advantage, compatibility, and complexity (Rogers, 2003).

Recent AI research points to barriers like resource constraints of time, people and money, data issues, integration challenges, and ethical concerns (Rjab et al., 2023). However, most studies examine AI broadly, rather than focusing specifically on GAI in customer service, leaving gaps this study aims to address.

Governance and ethical considerations

GAI implementation presents governance challenges requiring proactive management. Wach et al. (2023) highlight concerns like regulatory compliance, data privacy, intellectual property protection, algorithmic bias, and misuse. The rapid adoption of tools like ChatGPT, which reached 100 million users (globally) in two months in 2023 (Hu, 2023), often outpacing governance development.

Effective governance requires addressing multiple dimensions: unbiased training data, reducing algorithmic bias, maintaining human oversight, protecting intellectual property, and ensuring clear accountability (Janssen et al., 2020; Mondal et al., 2023). They also suggest that organizations must balance innovation with risk mitigation, requiring frameworks that turn principles into actionable policies.

METHODOLOGY

Research design and data collection

The research design adopted in this study was a qualitative-methods research design that using open ended questionnaire as a qualitative data collection tool to examine the GAI application in contact centre businesses in the Australasia region. The qualitative approach used allowed obtaining open-ended qualitative replies, thus providing a story on the issue of implementation challenges (Dawadi et al., 2021; Schoonenboom & Johnson, 2017).

Purposive sampling was used to recruit participants via personalized email messages and LinkedIn messages to both the managerial and non-managerial employees of the contact centre organizations in regulated industries like legal, healthcare, education and finance. in . This sampling plan helped to reach out to the stakeholders who had a first-hand experience and an informed opinion on the problem of GAI implementation (Palinkas et al., 2013). The survey was done online between July and August of 2023 resulting in an 88% response rate.

The composition of the respondents included 62 percent managerial level respondents and 38 percent non-managerial employees, with the largest percentages being insurance, information technology, and healthcare. This composition offered both strategic decision-making (managerial) and operational implementation (non-managerial) levels of view.

Survey instrument

The questions developed in the survey Included? two main open-ended questions that were studied within the frame of this qualitative analysis:

> **Q6:** "What are the challenges that your business encounters in adopting generative AI?" (Multiple selection based on pre-defined options, open-ended expansion).
>
> **Q8:** "What are, in your opinion, the specific actions, strategies, or measures that will help your organization to overcome the possible barriers and challenges to deploying generative AI?" (Open-ended question).

Question 6 had 53 responses with 273 total selections under obstacles categories, and Question 8 had 30 responses. The survey also included the quantitative data on the readiness to organizational governance and considerations, and this allowed triangulation to be used to confirm the qualitative results.

Analytical framework

The inductive thematic analysis was used in qualitative analysis based on the valid methodologies of using thematic analysis in accordance with the existing guidelines on thematic analysis use (Braun & Clarke, 2006, 2022). All responses were subjected to exhaustive preprocessing, such as to lower ase, punctuation marks, tokenization and extensive stop word removal based on an extended list of non semantic words over 400. This preprocessing resulted in fine corpora of 1,361 extracted meaningful words of obstacle responses and 257 words of solution responses. Three complementary techniques were incorporated in the analytical framework:

Thematic Coding: The responses were coded into six pre-defined obstacles themes (Technical Expertise & Skills, Data Quality & Availability, Cost & Resource Constraints, Integration & Infrastructure, Trust & Reliability, Ethical Concerns and Legal Concerns) and six themes of solutions (Training & Education, Pilot Projects & Testing, Governance & Policy, Collaboration & Partner-ships, Investment & Resources, Change Management). These themes were informed by theoretical perspectives in adoption of technology, organizational change and implementation of AI literature. The coding involved the application of the keyword matching algorithms which have been tested with the manual classification.

Word Frequency Analysis: The most repeated words in the responses after removing stop words and minimum length filtering (≥ 4 characters) were used in the quantitative assessment to determine the most common words mentioned. They were supported by frequency distributions that assisted the thematic coding findings and identified relevant ideas in the discourse of stakeholders.

Co-occurrence Analysis: Co-occurrence matrix recorded where more than one theme of obstacles was observed in individual responses clarifying interrelations between barriers. Co-occurrence frequencies were normalized to correct different rates of prevalence of the same theme and relationship strengths could be compared.

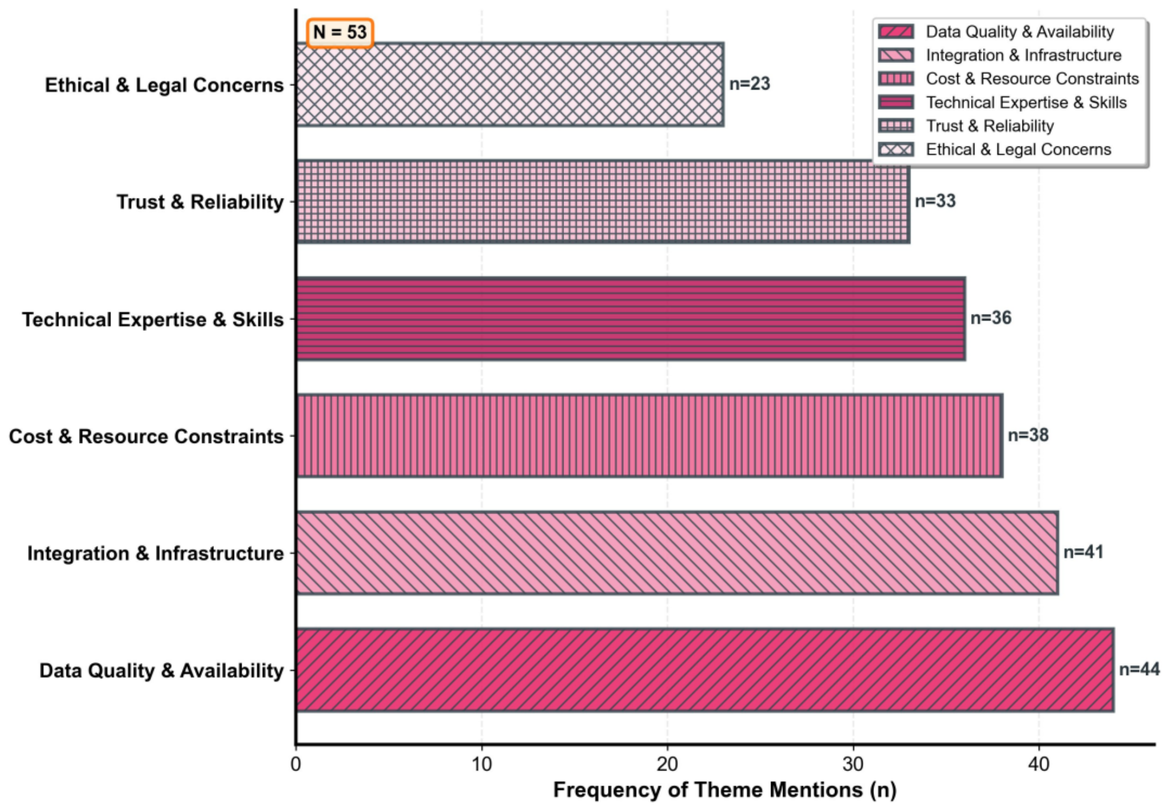
FINDINGS: IMPLEMENTATION OBSTACLES

Thematic distribution of obstacles

The thematic content analysis of 53 obstacle responses indicated that six major thematic groups are present that depict clear hierarchical trends that reflect the existence of focused stakeholder issues. The full distribution of obstacle themes is given in Figure 1.

The most common concern was Data Quality & Availability, which was identified by 83.0 percent of the respondents (n=44). The datum highlights a general understanding that General Artificial Intelligence (GAI) systems are essentially data-dependent, and the quality of output is necessarily limited by the nature of input data. The challenges that were highlighted by respondents included completeness, accuracy, relevance and accessibility of data by the organization. The concerns that were represented were fragmentation of data in legacy systems, lack of consistency in quality standards, lack of historical data to use in training and organizational silos that limit access to data. In the second place, with 77.4 percent (n=41), Integration & Infrastructure indicated intense apprehension about technical compatibility and system architecture as well as the issues of integrating AI capabilities into the existing technological ecosystems. This theme includes the limitations of legacy systems, platform compatibility problems, API integration difficulties, and architectural difficulties connected to developing smooth AI-driven workflows.

Figure 1: Distribution of Implementation Obstacle Themes (N=53)



The Cost & Resource Constraints were reported by 71.7 percent of the respondents (n=38), which included a high start-up capital and continual operation costs. The theme is a financial investment of technology purchase, infrastructure building, acquisition of talents with specialization, an extensive training program and maintenance of systems.

Technical Expertise & Skills 67.9 percent of respondents (n=36) are emphasizing dimensions of critical human capital. The theme includes gaps in knowledge in data science, machine learning engineering, AI system management, and new competencies in prompt engineering and AI ethics.

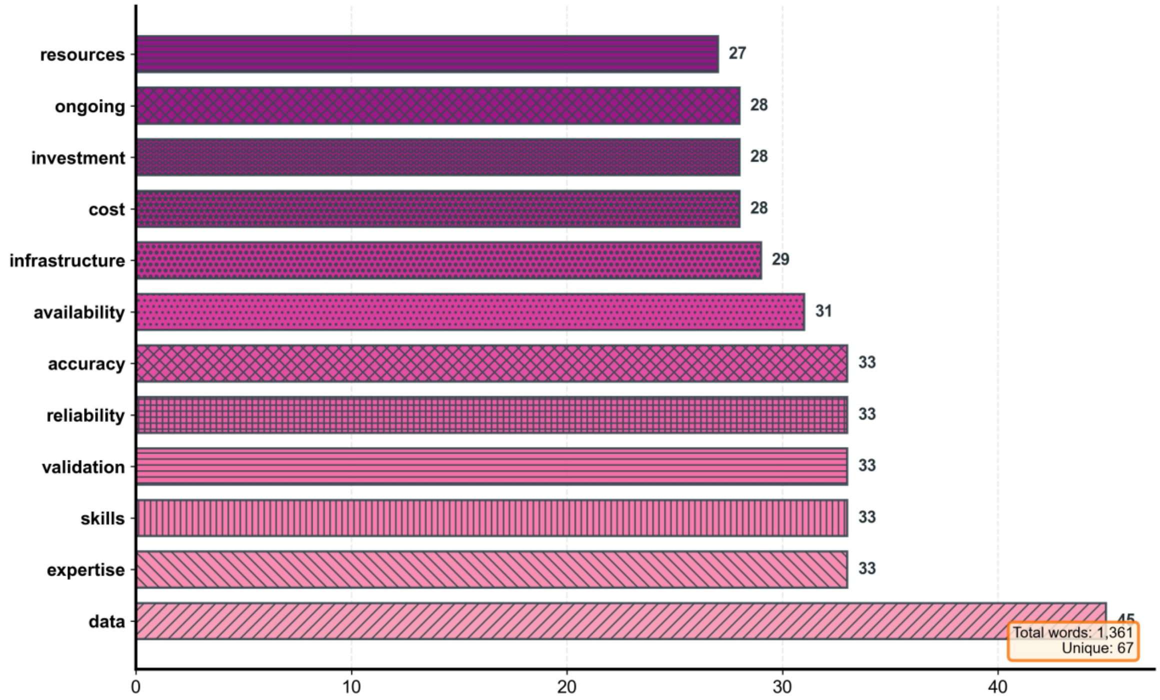
The issue of Trust and Reliability presented in 62.3% of the answers (n=33) shows the fears of the reliability of the AI system, the correctness of the output, and the trust in the use of algorithms in decision making. A need to be explainable, a validation system, a fallback system under AI failure, and the definition of the liabilities of AI-made mistakes were highlighted by the respondents.

Ethical & Legal Concerns ranked lowest (43.4% (n=23)) but still indicated a large minority. The theme consists of regulatory compliance uncertainty, privacy protection requirements, intellectual property issues, risk of algorithmic bias, and general implications to the society.

Word frequency analysis: obstacle discourse

Through lexical analysis, excellent pre-processing produced 67 unique meaningful terms out of the 1,361 word corpus, which brought out salient concepts in stakeholder thinking. Figure 2 represents the frequency distribution of the most common more meaningful words.

Figure 2: Word Frequency Distribution for Implementation Obstacles



Data was the most used word (45 times) which is a very powerful argument to consider the focus of the data on the implementation issues and supports the fact that Data Quality & Availability is the most important topic in the thematic coding. Close clustering was also observed in human capital terms: the frequency of the terms expertise (33 instances) and skills (33 instances) was the same, indicating that the stakeholders also perceive technical competencies and practical expertise as one and the same condition.

Quality and reliability terms also tended to fall together: the word validation (33), reliability (33) and the word accuracy (33) also had the same frequency, which means that the issue of system dependability is regularly looked into by the stakeholders on a variety of levels. A few words connected with infrastructure, such as platforms (29), infrastructure (29), and financial terms, such as cost (28), investment (28), ongoing (28), etc., had a lower but still significant frequency.

Figure 3 illustrates an alternative visualization of the predominance of key terms in a word cloud form.

Figure 3: Word Cloud Visualization of Implementation Obstacles

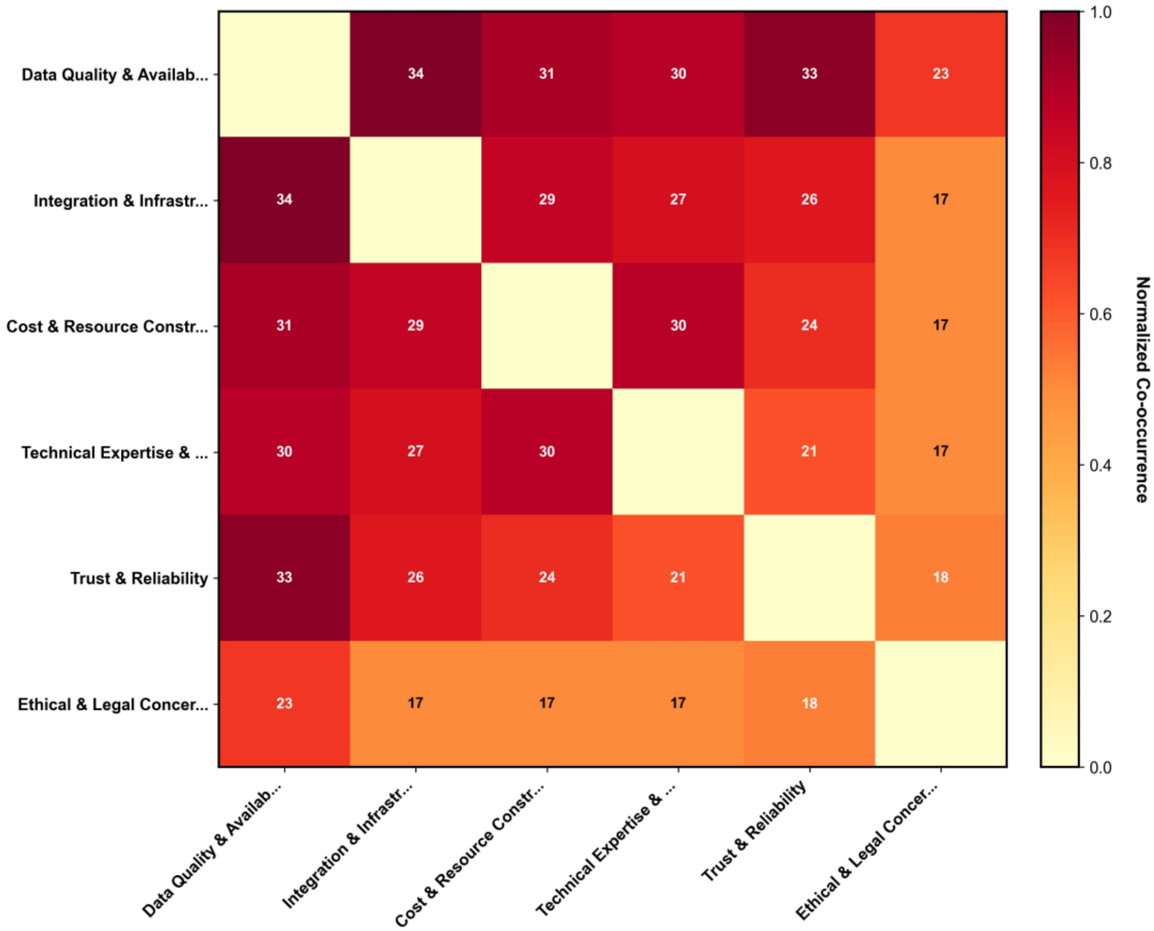
Co-occurrence patterns: interconnected obstacles

The co-occurrence analysis indicates that the implementation barriers are seldom present alone. The co-occurrence matrix (Figure 4) records the occurrences of multiple themes in individual responses, that is, which barriers are clustered in the consciousness of stakeholders.

The highest number of co-occurrences (34 cases) was between Data Quality and Availability and Integration and Infrastructure, indicating that data related issues are inherently tied to the problem of system integration. The close relationship between the concept of Data Quality and Availability and the concept of Trust and Reliability (33 instances) proves that trust issues are usually based on the uncertainties in data quality.

The concept of Data Quality & Availability was often placed with the concept of Cost & Resource Constraints (31 times) and the concept of Technical Expertise & Skills (30 times), which is to show that data issues demand considerable resource involvement and expertise in areas beyond technology purchases alone. These co-occurrence patterns reveal that the implementation barriers are a networked system, and not isolated barriers.

Figure 4: Normalized Co-occurrence Matrix of Obstacle Themes



FINDINGS: SOLUTION STRATEGIES

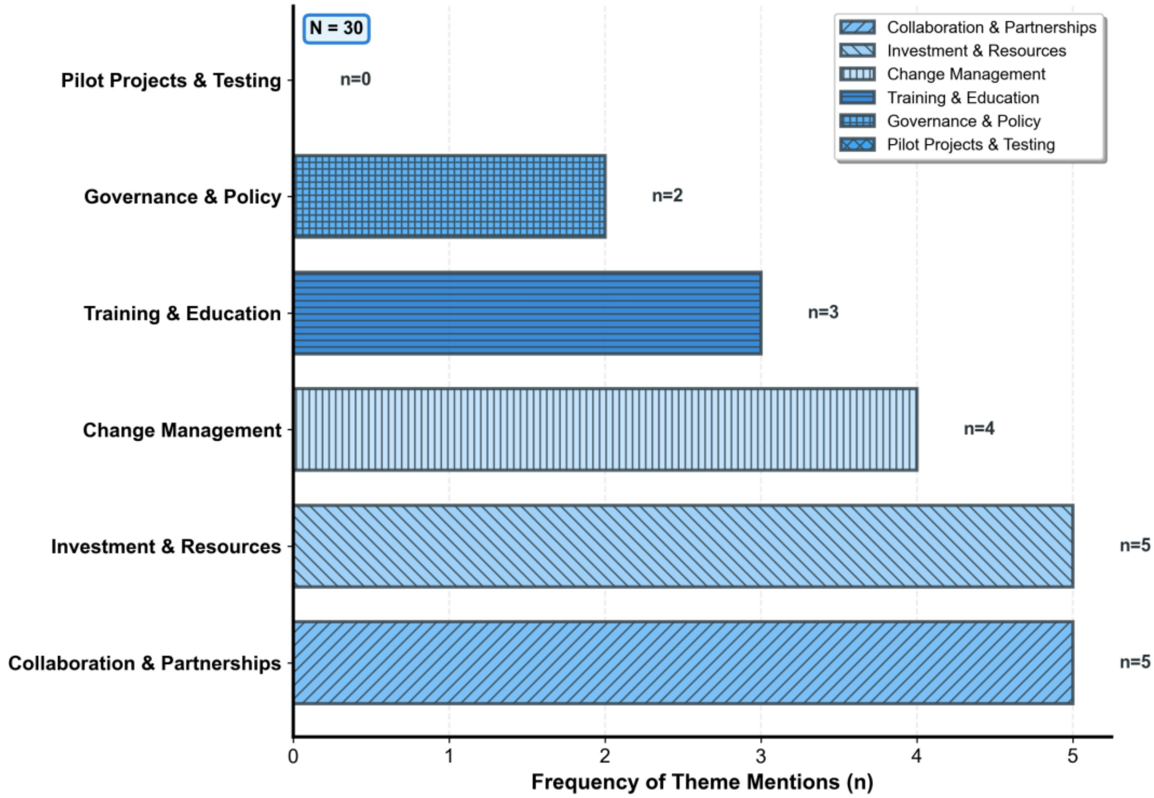
Thematic Distribution of Solutions

The 30 solution responses were also analyzed to find out the six strategic approaches and the results of the analysis have indicated variation among significantly different patterns than the obstacle responses (Figure 5). The decreased response rate (N=30 and N=53) and decreased number of words (257 and 1,361 words) in itself is an outcome of the study—it was more difficult to explain the solutions than to notice the problems.

Both Collaboration & Partnerships and Investment & Resources had 16.7 percent of responses each (n=5), and are the joint-primary solution methods. Collaboration includes using outside AI vendors, teaming with consultants in technology, and industry consortia. The investment is an indicator of appreciation of the fact that successful adoption entails huge resource commitments.

Change Management was mentioned in 13.3% of responses (n=4), with transformation dimensions being human-centered, whereas Training & Education was also mentioned in 10.0 percent of responses (n=3). Governance & Policy appeared in 6.7% of responses (n=2), while Pilot Projects & Testing received no explicit mentions (0.0%) — a striking absence given pilot-driven implementation is a widely promoted best practice.

Figure 5: Distribution of Solution Strategy Themes (N=30)



Word frequency analysis: solution discourse

Patterns of lexical analysis of responses in solutions were quite distinct compared to obstacles (Figure 6). The word human was used most often (5 times) as it focused on the stakeholder acknowledgment that the AI solutions should not eliminate human factors. The word cost (5 instances) was equally common, which shows that the consideration of finances is most important even during the proposal of solutions.

The vocabulary richness is remarkable - the number of unique words, 190 out of 257 in total, shows that the conceptualizations of solutions are very diverse, and there is no real consensus on the particular method. This is in contrast to obstacle responses whereby terminology was more clustered which indicates a better understanding of challenges rather than solutions. Figure 7 is a word cloud visualization of solution discourse.

Figure 6: Word Frequency Distribution for Solution Strategies

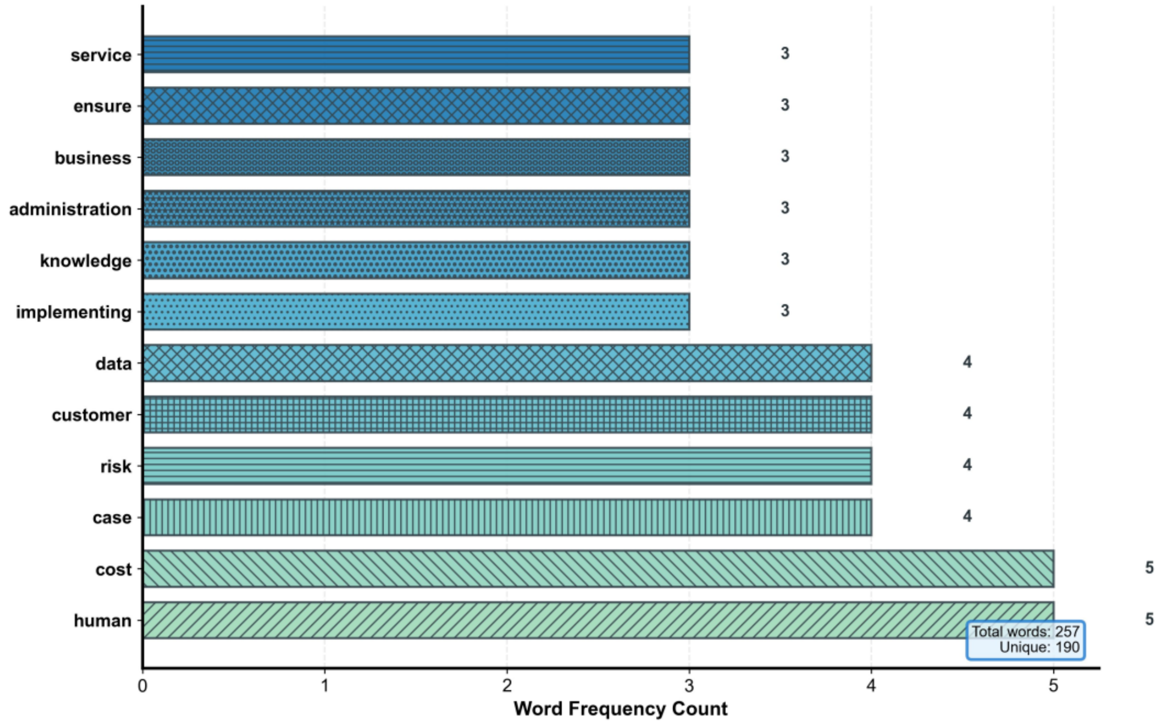


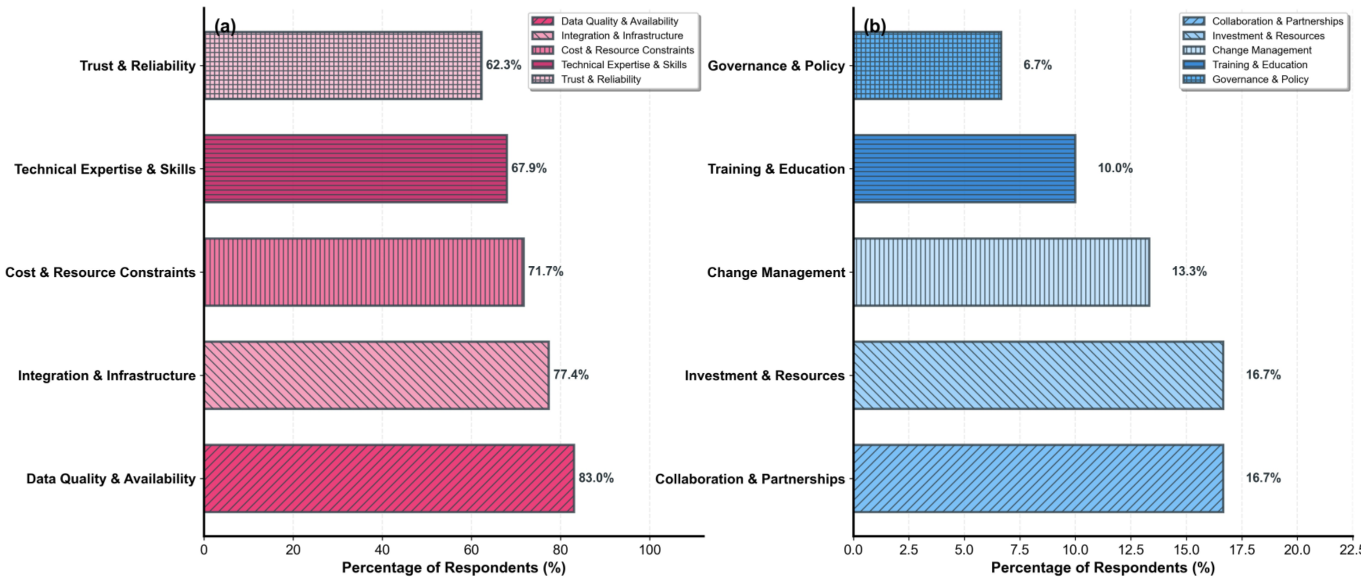
Figure 7: Word Cloud Visualization of Solution Strategies

DISCUSSION

The solution fragmentation paradox

The comparative analysis shows a clear asymmetry: obstacles exhibit a high concentration (with prevalence ranging from 43.4% to 83.0%), while solutions are scattered (with prevalence peaking at 16.7%). Figure 8 presents a side-by-side comparison of the key themes. This gap suggests that organizations have a more unified understanding of the challenges they face than they do of the most effective ways to address them, creating both challenges and opportunities for knowledge sharing and consolidation.

Figure 8: Comparative Thematic Analysis: (a) Implementation Obstacles; (b) Solution Strategies



The fragmentation observed can be attributed to several factors. Firstly, the implementation of artificial intelligence represents a highly complex organizational transformation, where universal solutions are rare. Secondly, the early stage of generative AI adoption means that best practices are still in their formative stages. Thirdly, articulating solutions demands a higher level of expertise compared to the relatively lower level of expertise required to identify the obstacles.

The data-infrastructure nexus

The strongest emerging pattern links data quality, infrastructure integration, and trust issues. Data Quality Availability (83.0%) and Integration Infrastructure (77.4%) were the most prominent, showing the need for simultaneous focus on data governance and infrastructure modernization.

However, responses related to solutions reveal a lack of a direct approach to this connection. Although Data Management (4 responses) emerged as a solution theme, it was significantly less emphasized than the prevalence of the associated barrier would suggest is necessary. This disconnect highlights potential gaps in solution development or an acknowledgment that data-infrastructure issues may not have easily applicable solutions.

The innovation challenge

A qualitative study on barriers established scepticism about the possibility of AI to transform business models and perceived constraints that need human decision-making to make strategic choices. Yet solution responses did not depict much activity in innovation enablement. The total lack of Pilot Projects & Testing as a solution theme is particularly striking, since the literature on innovation focuses on experimentation and fast prototyping.

The governance implementation gap

Quantitative results showed a high level of agreement that data governance, privacy, and security are important factors (82.69% agreement), and the same level of prioritisation was achieved with fairness and bias reduction (84.61% agreement). Nonetheless, solution responses based on qualitative solutions were slightly involved with Governance & Policy (6.7%, n=2). The lack of connection presents a governance paradox: stakeholders recognize the importance of governance but offer minimal description of governance mechanisms or structures.

IMPLICATIONS FOR PRACTICE

The analysis has a number of implications that can be applied to the contact-centre organisations:

1. **Prioritise Data Foundations:** The sheer amount of data quality issues (83.0%) and the high rate of co-occurrences necessitates the development of solid data governance, data quality assurance, and availability infrastructure before even starting to deploy AI.

2. **Embracing Implementation Strategies that are integrated:** When obstacles are interconnected as shown by extensive theme co-occurrences, cross-functional teams should be sought by organisations to undertake integrated strategies that cater to various dimensions at a time.

3. **Build Hybrid Expertise Models:** Due to talent constraints and cost limits, organisations must seek hybrid approaches which integrate internal capacity building through training, external capacity building through partnerships, and knowledge-capture systems.

4. Frame AI as Augmentation: Due to the continued focus on human judgment and AI complementary roles, effective change management needs to frame AI as a labor force aug-mentation and not replacement.

5. **Build Innovation Capabilities:** Determined innovation gaps need to be actively addressed, which means that experimentation, rapid prototyping, and psychological safety of productive failures should be encouraged, and mechanisms to systematically find transformative use cases should be established.

6. **Operationalise Governance:** Organisations must turn principles into tangible policies, allocate specific responsibilities, and entrench governance across lifecycles of implementation.

LIMITATIONS

There are a number of limitations of this study that should be mentioned. The size of the sample of solution strategies (N=30) is much smaller than the sample of obstacles (N=53), which could restrict the generalisability. Thematic coding was based on the use of keywords and was classified based on the keywords and this might not represent subtle semantic differences. The sample composition was biased towards the managerial levels (62 percent), which may not reflect the views of the frontline. Cultural and linguistic differences in the Australasia region can also bring about response differences which are not exhaustively represented. Lastly, the responses are based on perceptions expressed and not organisational capabilities, which is prone to social desirability bias.

CONCLUSION

This qualitative study is an empirical demonstration of the complex nature of the issues that organisations encounter when adopting generative AI in contact-centre services. The fact that the majority of the issues are related to data quality issues (83.0%), integration difficulties (77.4%), and resource limitations (71.7%) will indicate that the complexity of the implementation is not limited to the technical aspect.

The disjointedness of solution strategies (maximum 16.7% prevalence) is an indicator of a new area where the best practices are still disputed and situation-specific. Organisations are forced to cope with this ambiguity by means of systematic testing, cross-sector knowledge and adaptive implementation frameworks that recognise the existence of interdependent systems of barriers.

The critical insights that have come out of this analysis are: (1) data and infrastructure issues are an integrated nexus which has to be given attention simultaneously; (2) the lack of expertise necessitates hybrid models between internal development and external partnerships; (3) innovation capabilities need to be intentionally cultivated and not just an operational efficiency focus; (4) governance has to shift towards an operationalised practice and not just an abstract principle.

To practitioners, this discussion highlights that effective implementation of generative AI demands organisational preparedness on a broad scale in terms of technical infrastructure, data governance, talent capabilities, cultural preparedness and governance structures. The findings show that organizations that treat AI implementation as a holistic change are better positioned for long-term success.

REFERENCES

Bamberger, S., Clark, N., Ramachandran, S., & Sokolova, V. (2023). *How generative AI is al-ready transforming customer service*. BCG Global. https://www.bcg.com/

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Braun, V., & Clarke, V. (2022). Thematic analysis: A practical guide. *QMiP Bulletin*, *1*(33), 46–50. https://doi.org/10.53841/bpsqmip.2022.1.33.46

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative AI at work*. https://doi.org/10.48550/arXiv.2304.1177110.48550

Buesing, E., Gupta, V., Higgins, S., & Jacobson, R. (2020). *Customer care: The future talent factory*. McKinsey & Company.

Chui, M., Roberts, R., & Yee, L. (2023). *The economic potential of generative AI: The next productivity frontier*. McKinsey & Company.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org//10.2307/249008

Dawadi, S., Shrestha, S., & Giri, R. A. (2021). Mixed-methods research: A discussion on its types, challenges, and criticisms [doi: 10.46809/jpse.v2i2.20]. *Journal of Practical Studies in Education*, *2*(2), 25–36. https://doi.org/10.46809/jpse.v2i2.20

Gartner. (2023). *Definition of digital transformation*. https://www.gartner.com/en/information-technology/glossary/digital-transformation

Hu, K. (2023). *ChatGPT sets record for fastest-growing user base*. Reuters.

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy artificial intelligence [doi: 10]. *Government Information Quarterly*, *37*(3), 101493. https://doi.org/10.1016/j.giq.2020.101493

McKinsey & Company. (2023). *The economic potential of generative AI: The next productivity frontier*. McKinsey Digital. https://www.mckinsey.com/capabilities/

Mondal, S. K., Das, S., & Vrana, V. (2023). How to bell the cat? A theoretical review of generative artificial intelligence towards digital disruption in all walks of life. *Technolo-gies*, *11*(2), 44. https://doi.org/10.3390/technologies11020044

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2013). Purposeful sampling for qualitative data collection and analysis in mixed method implemen-tation research. *Administration and Policy in Mental Health and Mental Health Services Research*, *42*(5), 533–544. https://doi.org/10.1007/s10488-013-0528-y

Rjab, A. B., Mellouli, S., & Corbett, J. (2023). Barriers to artificial intelligence adoption in smart cities: A systematic literature review and research agenda. *Government Information Quarterly*, *101814*. https://doi.org/10.1016/j.giq.2023.101814

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Schoonenboom, J., & Johnson, R. B. (2017). How to construct a mixed methods research design. *Kölner Zeitschrift für Soziologie und Sozialpsychologie*, *69*(S2), 107–131. https://doi.org/10.1007/s11577-017-0454-1

Talbot, P. (2021). *How call centers can make or break brand loyalty*. Forbes.

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). *User acceptance of information technology: Toward a unified view* (Vol. 3). JSTOR. https://doi.org/10.2307/30036540

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J., & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(2), 7–30. https://doi.org/10.15678/eber.2023.110201