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Wydział Bezpieczeństwa, Logistyki i Zarządzania
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Institute of Organization and Management
Faculty of Security, Logistics and Management
Military University of Technology
in Warsaw

Exploring employees' accountability in knowledge management systems enhanced by generative artificial intelligence

Badanie odpowiedzialności pracowników podczas używania systemów zarządzania wiedzą wspieranych przez generatywną sztuczną inteligencję

Robert Strelau
Warsaw School of Economics, Poland
rstrel@sgh.waw.pl; ORCID: 0000-0001-8815-3447

Abstract:
Research objectives and hypothesis/research questions
The study aims to understand managerial attitudes toward accountability when using GenAI-driven data for decision-making and to identify procedures or regulations that could minimize erroneous data usage.
Research methods
Employing a qualitative approach, the study collected insights from senior managers through interviews. Participants shared perspectives on employee responsibility for GenAI-informed decisions and suggested methods to ensure data accuracy. The analysis of these insights facilitated the development of a potential framework for GenAI adoption in KM.
Main results
Findings reveal that most managers view employees as ultimately accountable for decisions, although they acknowledge GenAI as a supportive rather than a substitutive tool. The need for clear guidelines, thorough testing phases, and the implementation of verification procedures emerged as key strategies for minimizing the risks of inaccurate or false data. Managers also highlighted the importance of well-defined roles, with explicit boundaries for GenAI usage.
Implications for theory and practice
The study contributes to theoretical discourse by pinpointing potential accountability structures in GenAI-driven decision-making and by proposing a framework that addresses data verification challenges. Practically, it offers organizations a structured approach to integrating GenAI into KM, emphasizing the need for precise regulations, testing protocols, and ongoing oversight. These insights encourage further exploration of the ethical and social dimensions of GenAI in business settings.
Keywords: accountability, decision-making, generative AI, knowledge management systems, large language models

Abstrakt:
Cel badań i hipotezy/pytania badawcze
Celem badania jest zgłębienie nastawienia kadry zarządzającej do kwestii odpowiedzialności za decyzje oparte na danych z GenAI oraz identyfikacja procedur czy regulacji, które mogłyby minimalizować ryzyko błędów.
Metody badawcze
W badaniu wykorzystano podejście jakościowe, pozyskując opinie wyższej kadry zarządzającej z wywiadów. Uczestnicy przedstawiali swoje poglądy na temat odpowiedzialności pracowników za decyzje podejmowane przy wsparciu GenAI oraz wskazywali sposoby zapewnienia wiarygodności danych. Analiza zebranych wypowiedzi posłużyła do opracowania koncepcyjnego modelu wdrażania GenAI w zarządzaniu wiedzą.
Główne wyniki
Wyniki pokazują, że większość menedżerów postrzega pracowników jako ostatecznie odpowiedzialnych za podejmowane decyzje, choć jednocześnie traktuje GenAI jako narzędzie wspierające, a nie zastępujące człowieka. Wskazano konieczność wypracowania jasnych wytycznych, przeprowadzenia rzetelnych faz testowych oraz wdrożenia procedur weryfikacyjnych w celu zminimalizowania ryzyka nieścisłych bądź fałszywych danych. Menedżerowie podkreślali także znaczenie klarownego podziału ról oraz ustalenia granic zastosowania GenAI.
Implikacje dla teorii i praktyki
Przeprowadzone badanie wzbogaca dyskusję teoretyczną, wskazując potencjalne struktury odpowiedzialności w procesie podejmowania decyzji wspomaganych przez GenAI, a także proponując ramy rozwiązania problemu weryfikacji danych. Z perspektywy praktycznej wyniki sugerują usystematyzowany sposób wdrażania GenAI w zarządzaniu wiedzą, z naciskiem na precyzyjne regulacje, protokoły testowania oraz bieżący nadzór. Otrzymane wyniki zachęcają do dalszego badania wymiarów etycznych i społecznych związanych z wykorzystaniem GenAI w biznesie.
Słowa kluczowe: odpowiedzialność, podejmowanie decyzji, generatywna SI, systemy zarządzania wiedzą, duże modele językowe

Introduction

Knowledge management (KM) has evolved significantly from its conceptual inception to a pivotal management practice and scientific discipline in modern organizations. As early as the 1990s, Drucker (1992) emphasized the transformation of society into a "knowledge society", where knowledge is even more important asset than traditional resources like capital, labor, and land. In this landscape, KM has become a critical process for harnessing and leveraging this vital resource effectively to deliver products or services to clients in line with business strategy (du Plessis, 2007). The advent of Generative Artificial Intelligence (GenAI) holds the potential to revolutionize various industries, with KM (KM World, 2023). GenAI significantly boosts organizational productivity by revolutionizing work processes, creation, and management. Understanding the opportunities and risks, and assessing the social and cultural impacts, is crucial for the responsible and effective deployment of GenAI (Naqbi, Bahroun, Ahmed, 2024).

The ability of GenAI to generate valuable and contextual content from existing datasets introduces new horizons for KM, enabling organizations not only to utilize their collected information more efficiently but also to foster innovation and create new value (Benbya, Strich, Tamm, 2024). In databases such like Proquest, Scopus or Emerald there is a visible lack of literature concerning "knowledge management" and "generative artificial intelligence" what makes it a significant research gap. What is more, a critical issue that emerges with the use of GenAI is the question of accountability – specifically, who takes responsibility for decisions made based on data generated by these systems, as discussed by Wach, Duong, Ejdys et al. (2023), referencing to Amariles and Baquero (2023) or Short and Short (2023).

The objective of this article is to identify the attitudes of management towards responsibility for decisions based on data provided by GenAI. The structure of the article begins with a discussion on the capabilities of GenAI in the realm of KM and addresses the associated challenges, including accountability issues. This is followed by a presentation of the research methodology and a discussion of the findings. The next part presents a potential framework for implementing GenAI in organizations, based on respondent feedback, that minimizes error risks what is suggested by Nazeer, Subal, Liu et al. (2023) and Alavi, Leidner and Mousavi (2024). The article concludes with a summary of the research and suggestions for future directions in the field.

1. Knowledge management in the era of GenAI

GenAI encompasses a set of sophisticated algorithms capable of creating realistic and seemingly new content such as text, images, or audio. These algorithms operate on foundation models, which are extensively trained on vast amounts of unlabeled data in a self-supervised manner to identify underlying patterns across a wide range of tasks (Boston Consulting Group, 2023; Google, 2023). GenAI leverages deep learning models to produce human-like content in response to complex and varied prompts, encompassing different languages and instructions (Lim, Gunasekara, Pallant et al., 2023). Feuerriegel, Hartmann, Janiesch and Zschech (2024) note that while GenAI models are central to modern AI applications, they are initially incomplete and require continual fine-tuning and specific adjustments through various systems and applications to enhance their effectiveness and adaptability in practical scenarios.

The adoption of GenAI in KM brings a lot of opportunities for organizational processes. GenAI can quickly organize information and boost transfer knowledge, especially tacit knowledge (Korzynski, Mazurek, Altmann et al., 2023). Thanks to that, managers can better analyze information, and a new tools like ChatGPT – enhance personalization and integration of knowledge in organization (Alavi, Leidner, Mousavi, 2024). Benbya, Strich and Tamm (2024) highlight GenAI's can transform information from diverse formats like documents, audio, and video to uncover hidden patterns and insights, which can significantly enhance organizational learning and decision-making processes. Ghimire, Kim and Acharya (2024) point out the benefit of saved time. GenAI not only automates routine tasks but also frees up employees to focus on more strategic activities. Quan, Li, Zeng et al. (2023) noticed that it leads to better product design and delivery, tailored to meet customer needs more effectively.

Despite the considerable advantages, there is a myriad of challenges. Hu, Zhang and Zhang (2023) note an inherent level of randomness in responses, which brings the risk of errors. Ghimire, Kim and Acharya (2024) highlight the risk of "hallucination" in GenAI, where the system might generate non-existent information due to inadequate or noisy data. Alavi, Leidner and Mousavi (2024) point out with the use of GenAI organizations can lose control over crucial knowledge, since models are trained on vast amounts of data. Benbya, Strich and Tamm (2024) say that GenAI carries the risk of misunderstanding the business context, which could negatively impact the further decision-making and strategic processes.

As a result, a key problems concerning an accountability for decisions based on GenAI (Benbya, Strich, Tamm, 2024). Nazeer, Sumbal, Liu et al. (2023) suggest that rational procedures need to be established to determine when GenAI should make decisions and when humans should intervene. Organizational procedures should ensure that data is indeed accurate, and GenAI should be adapted to present it correctly as it is used (Alavi, Leidner, Mousavi, 2024). Based on these threads, another aspect has been proposed – the feasibility of implementing GenAI in the context of data verification—balancing the time saved on data acquisition against the time spent on verification.

2. Research methods

A qualitative method was chosen in order to capture a broader perspective of the phenomenon and to provide valuable insights by considering the diverse viewpoints of the studied population or phenomena (Sułkowski, Lenart-Gansiniec, 2021). The research took the form of a standardized interview with open-ended questions, giving respondents the freedom to elaborate on their answers and propose multiple possible options for each question. Building on the previously mentioned literature, the following research questions were formulated:

- **RQ1:** Who should be held accountable for decisions made in an organization based on data provided by GenAI?;
- **RQ2:** What potential procedures or regulations could be implemented to minimize the risk of making erroneous decisions in organizations using data from a GenAI system?;
- **RQ3:** How can data presented by GenAI be verified to maintain the benefits of minimized data acquisition time while ensuring reliability and accuracy?

To facilitate responses to the research questions, a case scenario (A company implements GenAI to enhance KM and a manger decides based or GenAI report. However, the systems hallucinate missing data, which leads to a misleading decision) was prepared and presented to the participants prior to addressing the queries. In the study, respondents were able to provide a variety of responses, often contradictory, as different scenarios emerged in their answers.

The group of respondents included individuals holding senior managerial positions (Senior Manager, Director, or CEO). The rationale behind the selection of these participants lies in their anticipated responsibility for making decisions concerning the implementation of GenAI systems within their firms. The sample was selected randomly, resulting in 22 respondents. The amount of participants is considered as enough to uncover and understand the major issue for a grounded theory study (Bernard, 2013). Data collection methods: 18 interviews via telephone or MS Teams, and 4 participants provided their responses in written form. Out of the total, 20 respondents were given the opportunity to review the research questions and a descriptive case scenario prior to participating, which facilitated more informed and reflective responses. Due to time constraints, 2 participants did not have this preparatory opportunity. During the research, notes were taken on respondents' answers and quotes, which were later structured (in MS Excel), coded and analyzed to capture the phenomenon. This structured approach not only ensured the systematic collection of data but also facilitated a comprehensive analysis.

The study was conducted over a two-week period (15.04-30.04.2024) and 22 participants were interviewed (5 from small companies – 10-49 employees; 7 from medium companies – 50-249, 10 from big companies – 250+ employees). The average level of familiarity with Gen AI was reported as 2.95 on a scale from 1 to 5, where 1 represents very low familiarity and 5 represents very high familiarity (none of the respondents rated their familiarity at the extremes of this scale – neither 1 nor 5). Respondents in this study were Polish, representing wholly Polish organizations or the Polish branches of international corporations.

3. Results

The variability of the scenarios discussed in the responses underscores the nuanced understanding and interpretation of responsibilities and the potential implications of AI-driven decisions. This aspect of the research emphasizes the need for a comprehensive analysis to grasp fully the multifaceted impact of AI in decision-making processes within different organizational contexts. To question no. 1 a significant portion of the respondents identified the decision-making manager ("a person who makes a final decision", "a person who asks an AI tool and makes a decision", "a manager, because he/she should verify and correct the report") as the primary individual responsible for decisions based on GenAI data. This responsibility was attributed to their direct engagement with the GenAI system's output, as well as their role in analyzing the situation and assessing the report's credibility. Also, some of them indicated that the way decision makers prompted (to give a command to GenAI) may affect the presented results.

Furthermore, a notable group pointed to "a person or a team responsible for the implementation of the GenAI system in the organization". They argued that those who integrate and oversee the operational aspects of the GenAI system should also bear accountability for the outcomes of the decisions derived from it. This suggests a shared responsibility that extends beyond the individual making the final decision to include those who facilitate the system's functionality.

Another perspective emerged because respondents emphasized the accountability of the person who decided to deploy the GenAI system, often referring to individual(s) as the "CEO" or "board" justifying "as they decided to implement such technology", and what was sometimes added "they didn't manage to train employees properly". This indicates a recognition of the significance of the initial decision to adopt such technologies and its impact on subsequent operational and strategic choices.

A critical remark from a senior manager of a large company highlighted the early stage of GenAI development, expressing skepticism about the readiness of serious firms to rely on such technologies for crucial decision-making ("At responsible company nobody uses AI, or at least does not say about it loudly"). This skepticism underscores the ongoing debate about the maturity and reliability of GenAI systems, reflecting broader concerns about their current utility in high-stakes environments.

The diversity of responses collected in this study underscores the multi-layered nature of responsibility associated with the use of GenAI systems in organizational decision-making. This range of perspectives reflects an understanding that responsibility is not isolated to a single role but is distributed across different functions within the organization. The full list of responses on accountability have been systematically organized and presented in Table 1.

In response to the question no. 2 the study identified 24 possible solutions and procedures. The most frequently highlighted was the crucial phase of meticulous testing, underlining the necessity of verifying input versus output data as a fundamental practice to ensure accuracy. The scenario phase, where known solutions are tested to see if the GenAI can generate and present the necessary data for making specific decisions, was noted as another effective method for verification ("in testing phase some well know scenarios should be developed and tested if the solutions generated are correct").

Table 1. Responses to question no. 1

Who should be held accountable for decisions made in an organization based on data provided by GenAI?		
No.	**Answer**	**Responses**
1.	The decision-maker	14
2.	The person/team responsible for implementing the GenAI system	9
3.	The person making the decision to implement AI in the company	6
4.	Department head (manager's supervisor)	2
5.	The person/team entering data into the system	1
6.	People responsible for the lack of training for employees	1
7.	One should not look for someone to blame, but rather draw conclusions	1
8.	Insurance company	1
9.	Department responsible for data verification	1
10.	This technology is at too early a stage to consider its implementation	1

Source: own study

Additionally, respondents stressed the importance of forming "a dedicated team responsible for implementing GenAI within the organization, which would oversee the entire AI implementation process and continually monitor its operation within the organization to conduct regular audits". For larger projects, employing external experts and academic representatives as supportive resources could be beneficial and those in charge of implementation should understand the algorithms and operational methodologies. During the testing phase, it should be assessed the accuracy of data presented by GenAI and the permissible level of deviations, which should be not higher 5% to balance the risk and benefits from data processing automation ("5% of potential deviation could be reasonable to maintain the effectiveness and time saving ratio"). Respondents pointed the necessity of "clear definition of the technology's application boundaries – what it can and cannot be used for". This includes precisely defining the roles of managers versus the AI, clearly delineating the types of decisions that can be based on data provided by GenAI and establishing a threshold for decision-making risk that should not be exceeded. In this context, respondents believed that a good approach would be to estimate the potential risk versus the potential benefits of time and cost savings for each decision based on data provided by GenAI. Decisions should then be made based on this data where the risk is considered acceptable to the organization ("risk when potential financial loss is low could be acceptable, however, an organization should define this level individually"). Some respondents suggested that decisions based on GenAI data should undergo multiple levels of acceptance (two or three levers), which additionally minimize the potential risk.

Moreover, the importance of specialized verification units was mentioned. Such units would be responsible for checking the integrity and accuracy of the data used by GenAI systems. The regular verification of prompts used by employees, and that decisions validated by domain-specific experts, particularly in cases involving non--standard data or decisions was also recomended. In instances where the data or decision context is unusual or falls outside of standard operational parameters, the respondents advised against using GenAI as a support mechanism. This conservative approach ensures that GenAI is only utilized in scenarios where its application is well-understood and deemed reliable.

Before GenAI is implemented across the entire organization "some pilot programs should be conducted in selected departments, to check how the technology works and what are some potential problems". Employees who will use the tool should undergo comprehensive training that clearly explains how the system operates, highlights potential pitfalls, and teaches how to detect anomalies. There were also opinions that "such tools should be used only by experienced employees who have a good understanding of the organization", as this could enable them to better identify potential errors.

Respondents also emphasized the importance of promptly addressing errors reported by users and delving into the challenges faced by employees, IT staff, and the GenAI systems themselves. This is essential for continuous improvement and error elimination. It was mentioned that each error should be meticulously analyzed to eliminate its cause, enhance the accuracy of the systems, and establish best practices.

Furthermore, it is also worth mentioning the need to expand the role of the compliance department as the significance of GenAI within the organization grows. This expansion would ensure that the system's operations comply with legal regulations and internal procedures. The full list of structured responses is presented in Table 2.

In response to the question No. 3, respondents suggested ten potential methods. The most common solution involved "the use of an independent system, such as a second GenAI system or automated verification formulas, to create a cross-verification mechanism". They highlighted this approach, noting that such tools should be regularly checked due to their lack of 100% accuracy. Implementing a second, independent model could enhance data correctness by providing a fail-safe against the first system's potential errors.

Respondents suggested that data generated by GenAI "should initially be verified by a specialized team dedicated to managing the GenAI systems". This team would be responsible for the initial scrutiny and validation of the information before it is used for decision-making.

Table 2. Responses to question no. 2

What potential procedures or regulations could be implemented to minimize the risk of making erroneous decisions in organizations using data from a GenAI system?		
No.	**Answer**	**Responses**
1.	A meticulous and detailed testing phase	6
2.	Establishment of a special unit for the implementation of GenAI	5
3.	Specifying what GenAI will be used for and what it will not be used for	4
4.	Outlining the process of using AI	4
5.	Continuous audits conducted by a special team regarding AI operations and its data access	4
6.	Detailed acknowledgement of the system and algorithm from a technical perspective to fully understand its operation before it is implemented in the organization	3
7.	Implementation of a double-check procedure for data verification	3
8.	Pilot programs in selected departments	3
9.	Training and workshops for employees, focusing on the strengths and weaknesses of AI, how to work with GenAI, search for and verify potential errors	3
10.	Verification of input data	3
11.	Drawing conclusions from emerging errors and seeking best practices	2
12.	Analysis of potential scenarios and consequences, assuming a potentially erroneous decision and analyzing whether it is worthwhile to use data from GenAI	2
13.	Determining the tool's effectiveness and an acceptable error level	2
14.	Establishing a method for data verification	2
15.	Acceptance of decisions at 2 or 3 levels	2
16.	Only experienced employees may use AI systems	2
17.	Expanding the role of the compliance department to include aspects related to the use of GenAI	2
18.	Support from external experts, researchers during implementation	1
19.	Identifying issues faced by AI, the IT department, and employees	1
20.	Verifying prompts by two independent experts	1
21.	Rapid response by the team to problems reported by users	1
22.	Generated reports should go through the controlling department before being received by a manager	1
23.	Verification of decisions by specialists in the respective field	1
24.	In case of unusual data or decisions, consult the expert team	1

Source: own study

Some individuals indicated that tools like GenAI should be treated as assistants, where manual verification of all data by the person receiving the report remains essential. This manual check ensures an additional layer of accuracy, mitigating the risks associated with relying solely on automated systems. Additionally, interviewees mentioned that experienced employees could effectively identify anomalies in the data, supporting the notion that GenAI should be restricted to those who are well-versed in the business process and organizational context. This approach aligns with the broader theme of maintaining stringent control over the access to use, ensuring that its application is both effective and secure.

Answerers recommended that the GenAI tool should explicitly identify the sources of each piece of data it used, allowing for either random or comprehensive verification of these data sources – "this method ensures the traceability and credibility of the information used by GenAI". Additionally, other respondents emphasized the need for random verification checks, with one highlighting the effectiveness of checking elements such as dates and times to detect anomalies.

Table 3. Responses to question no. 3

How can data presented by GenAI be verified to maintain the benefits of minimized data acquisition time while ensuring reliability and accuracy?		
No.	**Answer**	**Responses**
1.	Two LLM tools cross-checking each other or other formulas/applications for data verification (cross-verification)	6
2.	Verification of output data by the GenAI project team	5
3.	Manual verification by an employee	4
4.	An experienced employee will identify anomalies in the reports presented	4
5.	Indicating the sources of all data and their (random) verification	3
6.	Random data checking	3
7.	Using two different prompts about the same thing and comparing the results	2
8.	Expert verification of the report	2
9.	Expert verification of the decision	2
10.	Checking parameters such as dates and times	1

Source: own study

Another responses indicated the usefulness of using two different prompts that ask for the same information to see if the data presented in both versions of the report are consistent. This technique can also help in cross-verifying the reliability of the output provided by GenAI. It was also suggested that reports generated by GenAI "should be reviewed by an expert in the relevant field", or that any significant decision based on the report should be validated by such an expert.

This step adds a layer of specialist scrutiny to the process, ensuring that the insights provided by GenAI are both accurate and applicable. Multilevel verification aligns with the procedure suggested as an answer on the second question.

It is also worth noting a critical viewpoint regarding verification. One respondent expressed a concern that if the system and data correctness need to be verified post-implementation, it questions the utility of deploying the system at all. This perspective suggests that robust verification should be an integral part of the implementation phase, to prevent redundant checks post-deployment. Detailed responses to this question have been systematically compiled and are presented in Table 3.

Thanks to these comprehensive answers it was possible to propose an implementation model, which is presented in the following part of the article.

4. Potential framework of implementing GenAI into organization to enhance knowledge management process

The framework proposed in this chapter is designed based on the findings from the research study described earlier. The primary aim of this framework is to guide organizations in implementing GenAI within the realm of KM, particularly focusing on decision-making processes and the minimization of error risks. By integrating both research outcomes and scholarly discussions, the framework seeks to provide a robust methodology for organizations aiming to leverage GenAI effectively and responsibly.

The proposed framework begins with the creation of a dedicated team comprising individuals deeply familiar with the organizational processes. This knowledge is crucial for identifying the potential benefits that GenAI can bring to KM within the organization. The team should also include individuals who are well-versed in GenAI technology, including IT representatives responsible for the technical aspects of the system's implementation. This blend of operational and technological expertise is essential for effectively integrating GenAI into the organization's existing structures and workflows.

With the deployment of GenAI, it is imperative to expand the role of the compliance department within the organization. Representatives could be GenAI Team members or serve as consultants. This expansion is essential to ensure that the use of GenAI software adheres to legal requirements as well as internal organizational procedures. The compliance department must closely not only give directions towards implementation, but also monitor the integration and operation of GenAI to prevent any legal or ethical breaches, ensuring that the technology not only enhances operational efficiency but also aligns with regulatory standards and organizational values.

The next critical step in the framework is the selection of an appropriate GenAI tool that aligns with the project's goals. This involves assessing various available solutions to determine which system best matches the specific needs and objectives of the organization. For large-scale projects, it may be beneficial to seek external assistance from both the system providers and independent experts and researchers. This external support can help in developing detailed procedures and processes that are tailor-made for the specific context of the organization. Such collaboration can provide a more nuanced approach to the integration of GenAI, ensuring that the implementation is robust, contextually appropriate, and poised for long-term success.

Once the appropriate GenAI software has been selected, the next essential step in the framework involves thoroughly acquainting the team with the capabilities of the chosen technology. It is imperative that the team understands how the GenAI system functions to fully exploit its potential and ensure it meets the organization's needs. This includes a deep dive into the system's features, limitations, and any requirements for integration with existing technologies. Following this, there is a need to establish a specialized unit responsible for the input and verification of both incoming and outgoing data. This unit plays a critical role in maintaining the integrity and accuracy of the information processed by the GenAI system. They ensure that the data feeding into GenAI is of high quality and that the outputs are reliable and valid for making informed decisions.

The testing phase forms a pivotal part of the framework. This phase should be comprehensive, involving rigorous scenario testing to check the GenAI system's responses under various conditions. Verification of the accuracy of these responses is crucial to confirm that the system behaves as expected. Additionally, the development of a prompt database that users will interact with should be considered. This database should be well-structured and designed to trigger the most relevant and accurate responses from the GenAI system. The testing phase should also aim to fine-tune the accuracy of the GenAI system, ensuring that it performs optimally within the specific operational context of the organization.

Based on the outcomes of these tests, precise definitions need to be established regarding the scope of GenAI's application within the organization. This includes determining who is authorized to use the tool, defining the roles of users versus the capabilities of the GenAI, and specifying which decisions can be reliably made using data generated by the GenAI and which will still require traditional data-gathering methods. Establishing these boundaries ensures that the technology complements rather than complicates the decision-making process.

The process for data verification within the organization must also be clearly established. This could involve a variety of approaches, such as verification by the users themselves, selected experts, a special data verification department, or through the implementation of automated verification tools. Each method has its advantages and would depend on the organizational structure and the critical nature of the data being processed.

Finally, a procedure for accepting decisions based on data obtained from GenAI systems needs to be formalized. This procedure should include multiple levels of approval, reflecting the complexity and importance of the decisions. By instituting a robust acceptance process, organizations can ensure that decisions made with the assistance of GenAI are both thoughtful and well-validated, thereby reducing the risk of errors and enhancing the decision-making process.

The implementation process should also include selecting pilot departments where the GenAI software will be initially tested. This strategic approach allows for controlled, real-world testing of the software, providing valuable insights into its functionality and the adjustments needed before a wider rollout. Pilot departments can serve as benchmarks, illustrating the benefits of GenAI and highlighting potential pitfalls in a contained environment, thereby mitigating broader organizational risk.

Training for employees is a critical step in the successful integration of GenAI into organizational processes. Such training sessions should not only highlight the capabilities and operational guidance of GenAI but also raise awareness about potential risks associated with its use. Employees should be taught how to verify the data generated by GenAI and identify indications of inaccuracies. This educational approach ensures that staff are well-equipped to leverage GenAI effectively while maintaining vigilance over its outputs.

Continuous audits and verification of prompts are essential for maintaining the integrity of the GenAI system. Regular reporting on AI performance and providing ongoing support to users are crucial for adapting and optimizing the use of GenAI within the organization. Additionally, continuous data evaluation helps in making informed decisions about whether to expand the program to other departments. Such decisions should consider whether to broaden or narrow the tasks performed by GenAI and the range of decisions made based on data from the system.

Additionally, it is crucial to learn from any issues or errors that arise during the operation of GenAI. Organizations should be proactive in identifying these challenges and implement solutions that improve the functioning of GenAI. This involves a continuous improvement cycle where feedback from system errors and user experiences drives the development of software updates and process adjustments. By addressing these issues promptly and effectively, the organization can enhance the reliability and utility of GenAI, making it a valuable tool in the decision-making processes and broader KM framework.

The entire process, with its steps and components, is illustrated in Figure 1. This visual representation helps in understanding the sequential and interconnected actions required to successfully implement and manage GenAI within an organizational context, ensuring a clear and structured approach to embracing this transformative technology.

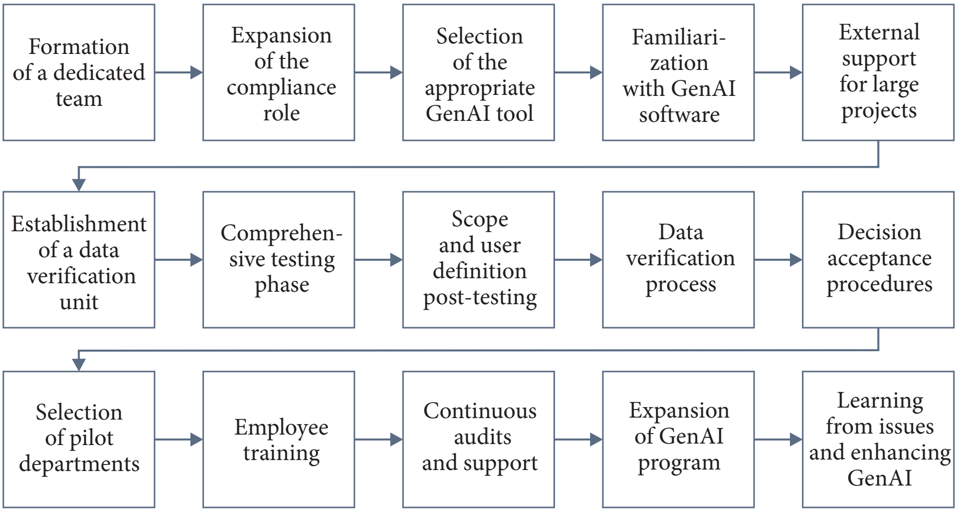

Fig. 1. Framework of implementing GenAI into organization process to minimize risk of misleading data and bad decisions based on them

Source: own study

Summary

This study provides diverse perspectives of senior management regarding accountability for decisions made based on data presented by GenAI. While nearly two-thirds of respondents indicated that the employee responsible for a decision should bear the accountability, the study revealed a multi-layered nature of this responsibility, clearly indicating that it can be transferred to other units within the organization. These findings underscore the complexity of integrating GenAI into decision-making processes, prompting a need for clearly defined accountability frameworks.

To address this complexity, a structured model was developed, offering organizations the flexibility to adjust and refine it according to their specific needs. By detailing methods for verifying GenAI-generated data – yet preserving the time-saving advantages of AI – this study also provides a practical blueprint for mitigating errors avoiding over compromising efficiency. Notably, implementing robust data verification procedures and establishing clear guidelines on roles and responsibilities emerged as critical recommendations for enterprises seeking to harness GenAI.

From a theoretical standpoint, the research advances current knowledge by identifying the individuals and units potentially accountable for GenAI-based decisions and by proposing procedural safeguards to minimize risks. For practitioners, the findings affirm the value of well-defined accountability measures, cross-departmental collaboration, and ongoing employee training in effectively deploying GenAI. As GenAI technology is still in development and companies are just beginning to explore its potential, this study will support the definition of the level of responsibility and the process of implementing GenAI in KM. By adopting these recommendations, organizations can capitalize on GenAI's benefits while safeguarding decision quality and maintaining clear lines of accountability.

Limitations: Micro-enterprises were excluded from research scope which may have overlooked the unique challenges and perspectives of these smallest business units. Participants were all from Poland, which could limit the generalizability of the findings to other cultural or economic contexts. The average self-assessed familiarity of the participants with GenAI technology was relatively low, at 2.95 out of 5. This suggests that the results might have differed if the respondents had a higher level of understanding or experience with GenAI.

Building on these qualitative insights, subsequent research will adopt a quantitative design to examine managers at all organizational levels, using the findings from this study to inform broader empirical validation. A critical component of this follow-up will be a deeper assessment of the proposed model's effectiveness, culminating in its practical validation within real-world organizational contexts.

Further research should also enhance generalizability, it will be important to expand the sample to encompass a more diverse range of organizations, thereby capturing variations in size, industry, and operational context. Additionally, incorporating multiple case studies – particularly from micro-enterprises and other underrepresented sectors – could offer deeper insights into the adaptability and practical implications of GenAI. Finally, future studies should aim to clarify the extent to which GenAI is intended to replace or augment human roles within organizations, especially in the area of KM.

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